BASIC STUDY ON STORM RUNOFF ANALYSIS BY STORAGE FUNCTION MODELS

PADIYEDATH GOPALAN SARITHA
September 2019

TOKYO METROPOLITAN UNIVERSITY
TOKYO, JAPAN
BASIC STUDY ON STORM RUNOFF ANALYSIS
BY STORAGE FUNCTION MODELS

By

Padiyedath Gopalan Saritha

A dissertation submitted in partial fulfilment of the
requirements for the Degree of Doctor of Engineering in Civil
and Environmental Engineering

Under the guidance of

Prof. Akira Kawamura

Department of Civil and Environmental Engineering
Graduate School of Urban Environmental Sciences
Tokyo Metropolitan University

Tokyo, Japan
September 2019
Dedicated to
The Almighty,
My Better Half,
Loving Parents
And Teachers
Doctoral Examination Committee

Prof. Akira KAWAMURA (Supervisor)
Department of Civil and Environmental Engineering
Graduate School of Urban Environmental Sciences
Tokyo Metropolitan University, Tokyo, Japan
Email: kawamura@tmu.ac.jp

Prof. Katsuhide YOKOYAMA
Department of Civil and Environmental Engineering
Graduate School of Urban Environmental Sciences
Tokyo Metropolitan University, Tokyo, Japan
Email: k-yoko@tmu.ac.jp

Assoc. Prof. Yasuhiro ARAI
Department of Civil and Environmental Engineering
Graduate School of Urban Environmental Sciences
Tokyo Metropolitan University, Tokyo, Japan
Email: y-arai@tmu.ac.jp
PREFACE

I came to Japan from India as a doctoral student on 17th September, 2016 when I received the “Tokyo Human Resources Fund for City Diplomacy” scholarship by the Tokyo Metropolitan Government, Japan under the research project entitled, “Study on guerrilla rainstorm, flood, and water pollution in megacity urban watersheds - Countermeasures against megacity urban water-related disasters bipolarized by climate change” for doing PhD at Tokyo Metropolitan University (TMU) under the guidance of Professor Akira Kawamura.

I chose Agricultural Engineering as my field of study in Kerala Agricultural University, Govt. of Kerala for B. Tech studies in 2007. During my B. Tech from 2007 to 2011, I have undergone various training programs which helped me to develop in an overall way. After graduation, I joined Indian Institute of Technology (IIT) Kharagpur as a post graduate student with the specialization of Water Management at School of Water resources. In IIT, I underwent rigorous training in various interdisciplinary subjects which helped me to broaden my views and ideas.

This dissertation is accomplished as the partial fulfilment of the requirements in my doctoral course in engineering at the Hydrology and Water Resources Laboratory of the Department of Civil and Environmental Engineering, Graduate school of Urban Environmental Sciences, Tokyo Metropolitan University from October 2016 to September 2019 under the supervision of Professor Akira Kawamura. The contents of this dissertation are based on 9 scientific articles which have been reviewed and refereed in the international journals; most parts have been presented in a number of domestic and international conferences. This thesis is the basic study on storm-runoff analysis by the different existing storage function models as well as the newly proposed ones. These storage function models were applied in different Japanese catchments to examine their effectiveness using hydrograph reproducibility and the information criteria point of view for the first time, and to evaluate their uncertainty. The results obtained from this study will be vital and indispensable for decision-making and associated flood risk reduction around the world by the development of improved rainfall-runoff models.

Padiyedath Gopalan Saritha
Tokyo Metropolitan University
September 2019
ACKNOWLEDGEMENT

Obviously, successful completion of this PhD research is not my merit alone. This study would not have been possible without the valuable support and guidance from my teachers, husband, colleagues, and friends during my doctoral study in TMU. Therefore, I would like to take this opportunity to express my heartfelt gratitude to them for their unconditional support and encouragement for the completion of this thesis.

First and foremost, I wish to express my sincere gratitude, deep sense of indebtedness and heartfelt thanks to my supervisor Professor Akira Kawamura, for his helpful and inspiring guidance, valuable suggestions, persistent encouragement and advice throughout the period of my PhD study. It has been an honour to be his PhD student. Under his great supervision and kindness, I was able to cross miles to solve a series of problems and mould me for the brighter career. His great experiences and immense knowledge will always remain an inspiration for my entire life and career. I could never have accomplished without his timely support, countless help and valuable advice at every stage of my research period. I also would like to convey my particular thanks to the Assistant Professor Hideo Amaguchi for his kindness and nice advices for my research as well as for my life during this time.

I express my sincere gratitude to Professor Katsuhide Yokoyama and Associate Professor Yasuhiro Arai for accepting to be the members of my Doctoral Examination Committee and spending valuable time to review my thesis and providing me constructive suggestions and comments which greatly helped to enhance the quality of my thesis. I also wish to thank Professor S. N. Panda, Department of Agricultural and Food Engineering, Indian Institute of Technology Kharagpur for his constant support and encouragement to get PhD admission at Tokyo Metropolitan University.

Many thanks to Mrs. Rie Kobayashi (our laboratory secretary) as well as Mrs. Yumiko Masuzaki (secretary of hydraulics laboratory) for readily providing the necessary logistical support throughout my Ph.D. course. Their kind help and valuable suggestions made my life much easier. Further, I wish to express my heartfelt gratitude to Tokyo Metropolitan Government for providing financial support during my doctoral study through Tokyo Human Resources Fund for City Diplomacy Scholarship. Special thanks to Ms. Akemi Ohira, Ms. Nakano Makiko, Ms. Mayu Abe, Ms. Kyoko Suzuki, and all others of the International Center and Graduate School Office of TMU for making my stay comfortable, which helped me to give most of my attention to the research. I am
deeply honoured to extend my acknowledgments to all the members and students of the Laboratory of Hydrology and Water resources, Department of Civil and Environmental Engineering, Tokyo Metropolitan University, particularly to Dr. Bui Thi Nuong, Ms. Jean Margaret R. Mercado, Mr. Takumi Kanazuka, Mr. Masato Otsuka, Mr. Akihiro Tonotzuka, Ms. Haruka Ota, Ms. Jiang Zisu, Mr. Hosono Hirona, Tanaka-san, Shimoji-san, Yokota-san and Thao-san for their valuable and precious supports during my doctoral course.

I wish to express special thanks to my friends Dr. Fazalurahman Kuttassery and Dr. Hasna Puthen Peediakkal for their timely help and close association during my stay in TMU. I also wish to express special gratitude to my dear friends Ms. Priyanka Valloly and Ms. Bincy A L for their encouragement and prayers.

Words cannot be expressed my indebtedness to my parents whose blessings, love and emotional support helped me in completing this work and accomplish studies successfully. I would like to thank my brother Mr. Sarath P G and sister-in-law Sreelakshmi P V for their care and love. Last but not the least, special thanks to my loving husband, Dr. Gubash Azhikodan for his care and love to me. I cannot forget his energetic support, scientific insights, valuable suggestions, and timely encouragement during my stressful and difficult moments in my doctoral study. My deepest gratitude also goes to my husband’s family for their genuine emotional care, unconditional love and support from a far distance that allowed me to persevere my study abroad.

Also, many thanks to all my dear friends and colleagues in Tokyo and to all of my friends from various nations, both inside and outside the Tokyo Metropolitan University, for their unrelenting support and encouragements. I heartily thank to all those who have contributed in one or another way for successful completion of my doctoral study.

Above all I bow my head before the Almighty whose blessings empowered and guided me to reach the destination.

Padiyedath Gopalan Saritha
Tokyo Metropolitan University
September 2019
Flood is considered as one of the severe natural disasters due to the associated flood risk and costs in both rural and urban areas. The extreme events of the high flood will always affect the nearby population and indirectly causes an enormous threat to human life, properties, etc. Therefore, the accurate prediction of the hydrograph in advance, which includes the estimation of flood peak, time to peak, volume, lag time, etc., is important for the flood mitigation in order to avoid losses. For this purpose, the rainfall-runoff models are important tools and they play a central role in flood management. Among the different conceptual lumped rainfall-runoff models, storage function (SF) models have been widely used in many parts of the world, especially in Japan, not only because of their ease of use in computation and handling but also the ease by which they express the nonlinear relationship of the rainfall-runoff process using simple equations.

The selection of appropriate models for the intended purpose is very important. Hence, there is a need for the comparative studies of rainfall-runoff models due to the existence of a variety of models to evaluate their ability to predict discharge and to provide guidelines for end-users. In addition, the predictions made using rainfall-runoff models are inherently uncertain and it is necessary to carry out parameter uncertainty analysis of a calibrated model because it is one of the major sources of uncertainty. Hence, an appropriate uncertainty consideration of the model parameters is necessary although it has been often ignored until recently. Further, there is a need for a generalized SF (GSF) model that can be applied in all the watersheds without requiring the effective rainfall as their input by incorporating all the possible inflow and outflow components and the rainfall spatial variability since it has not been considered in the SF models so far.

In light of the aforementioned discussions, this thesis aims to analyze the storm-runoff processes using the SF models with the following main objectives: (i) to establish an effective SF model from the existing conventional ones for an urban watershed in terms of hydrograph reproducibility and from an information criteria perspective; (ii) to evaluate the parameter uncertainty of the effective SF model (urban storage function (USF) model) by the bootstrap and jackknife resampling techniques; and (iii) to propose a generalized SF model for the water level and discharge prediction by considering the spatial rainfall distribution. In order to achieve these objectives, this thesis is composed of five chapters.
Chapter 1 is comprised of the background and objectives of this study. A comprehensive review of literature and a description of the scopes and methods were also presented.

Chapter 2 identifies the effective SF model from the existing conventional ones for an urban watershed in terms of hydrograph reproducibility and from an Akaike information criterion (AIC) perspective. For this purpose, the relatively new USF model and four conventional SF models of Hoshi, Prasad, Kimura, and the linear model were selected. The Shuffled Complex Evolution-University of Arizona (SCE-UA) global optimization method was used for the parameter optimization with root mean square error (RMSE) as the objective function. The results revealed that the higher values of Nash-Sutcliffe efficiency (NSE) coupled with the lower values of RMSE and other error functions indicated that the hydrograph reproducibility of USF had been the highest among the SF models for an urban watershed. Furthermore, AIC and Akaike weight (AW) were used to identify the most effective model among all those based on the information criteria perspective. The USF model received the lowest AIC score and the highest AW during most of the flood events, which indicates that it is the most parsimonious model compared to other SF models. Further, this chapter discusses the effect of lag time in Kimura’s model on hydrograph reproducibility and the results demonstrated that the use of optimum lag time in Kimura’s model could greatly improve the performance.

Chapter 3 demonstrates the bootstrap and jackknife resampling approaches for the uncertainty analysis of seven calibrated parameters of USF model, which was identified as the effective model based on the results from Chapter 2. Both the approaches were applied to the residual time series that was computed as the difference between the observed and calibrated discharge time series. The parameter uncertainty was expressed by estimating the confidence interval (CI) of the USF model parameters, and then the parameters from the highest to the lowest uncertainties were derived by utilizing two newly proposed parameter uncertainty indices. The highly uncertain parameters obtained were the same by the bootstrap and jackknife approaches even though the order of other model parameters was different. Moreover, investigations on the effect of calibrated model parameter uncertainty on model prediction revealed that the USF model was able to bracket most of the observations within the 95% CI prediction range by the bootstrap approach, whereas the jackknife method bracketed a reduced number of observations.
Chapter 4 investigated the effect of spatial distribution of rainfall over the basin in the USF model by introducing a parameter named as rainfall distribution factor ($\gamma$) and the results revealed that the introduction of parameter $\gamma$ could greatly improve the performance of USF model. Further, this chapter proposes the 9-parameter GSF model for the water level prediction from the rating curve relationship and considering the rainfall distribution factor ($\gamma$). The GSF model optimizes not only parameter $\gamma$ but also the rating curve constants $a$ and $b$ along with other model parameters which will reduce the efforts taken for the rating curve establishment of the target watersheds. The proposed GSF model was then applied to the semi-urban and rural watersheds in Japan to examine its applicability in different types of watersheds. Three other models were also applied in the watersheds for comparison with the GSF model and are (i) 8 parameter model - the GSF model without parameter $\gamma$, (ii) 7 parameter model - the GSF model with fixed values of parameters $a$ and $b$ obtained from the established rating curve by the authorities, and (iii) 6 parameter model - the GSF model without parameter $\gamma$ and with fixed values of parameters $a$ and $b$. The model performance was evaluated based on hydrograph reproducibility, AIC and AW, and the results revealed that the GSF model performed well in both the watersheds compared with the three other models, which emphasized the effect of parameter $\gamma$ in GSF model. The sensitivity of 9 parameter GSF model was also evaluated using the global sensitivity method.

Chapter 5 presents the overall conclusions and recommendations for the storm-runoff analysis by different SF models in urban and non-urban watersheds including the future research works.
PUBLICATIONS

This dissertation is mainly formulated based on nine scientific articles as the main milestones of the study which were reviewed and assessed by globally refereed journals. In addition, some parts of this work have been presented in a number of domestic as well as international conferences. The following is a list of works published by the author during the doctorate course. Some of these works are cited in the text and therefore also appear in the full bibliography as follows. (* means that the content of the paper connect directly to this dissertation.)

Peer-reviewed paper publications


**Peer-reviewed international proceeding papers**


**Domestic conference papers**

rainwater harvesting structures. 44th JSCE Kanto branch technical research presentation, Saitama University, Saitama.


TABLE OF CONTENTS

Preface .......................................................... i
Acknowledgement .............................................. ii
Abstract .......................................................... iv
Publications ..................................................... vii
Table of Contents ........................................... x
List of Figures .................................................. xv
List of Tables ................................................... xix
List of Equations ............................................. xx
List of Abbreviations ........................................ xxii
List of Symbols ............................................... xxiii

CHAPTER 1
INTRODUCTION .................................................... 1
1.1 Background .................................................. 1
1.2 Storage function (SF) models ............................... 2
1.3 Parameter uncertainty analysis of rainfall-runoff model .... 4
1.3.1 Parameter uncertainty by bootstrap method .......... 6
1.3.2 Parameter uncertainty by jackknife method ............ 7
1.4 Generalized storage function (GSF) model ................. 8
1.4.1 Generalized USF (GUSF) model for urban discharge prediction .... 9
1.4.2 GSF model for water level prediction .................. 10
1.5 Objectives, scope, and methods .......................... 10
1.6 Outline of the thesis ...................................... 12

CHAPTER 2
AN EFFECTIVE STORAGE FUNCTION MODEL FOR AN URBAN WATERSHED .......................... 15
2.1 Introduction ................................................ 15
2.2 USF and conventional SF models .................................................. 17

2.2.1 Methodology ........................................................................... 17
2.2.1.1 Conventional SF models .................................................. 17
2.2.1.2 USF model ....................................................................... 18
2.2.1.3 Parameter estimation ....................................................... 21
2.2.1.4 Performance evaluation ..................................................... 22
2.2.1.5 Uncertainty characterization ............................................. 23

2.2.2 Study area and data used .......................................................... 24

2.2.3 Results and discussion ............................................................. 26
2.2.3.1 Parameter estimation ....................................................... 26
2.2.3.2 Hydrograph reproducibility ............................................. 28
2.2.3.3 AIC aspect ................................................................. 33
2.2.3.4 Parameter uncertainty ..................................................... 34

2.3 Kimura’s model with lag time ...................................................... 37

2.3.1 Methodology ........................................................................... 37
2.3.1.1 Kimura’s model ............................................................. 37
2.3.1.2 Parameter estimation and performance evaluation .......... 39

2.3.2 Results and discussion ............................................................. 40
2.3.2.1 Parameter estimation ....................................................... 40
2.3.2.2 Effect on lag time on performance ................................. 41
2.3.2.3 Hydrograph reproducibility ............................................. 43
2.3.2.4 Storage hysteresis loop ................................................. 47
2.3.2.5 AIC aspect ................................................................. 49

2.4 Conclusions ................................................................................. 50
CHAPTER 3
PARAMETER UNCERTAINTY ANALYSIS OF USF MODEL .......... 52

3.1 Introduction .................................................................................. 52

3.2 Methodology ................................................................................ 54

3.2.1 Residual-based bootstrap approach ........................................ 54

3.2.2 Simplified jackknife approach ................................................. 58

3.2.3 Model calibration ..................................................................... 60

3.2.4 Model parameter uncertainty quantification .......................... 61

3.2.5 Model simulation uncertainty .................................................. 62

3.3 Results and discussion ................................................................. 63

3.3.1 Model calibration and performance ....................................... 63

3.3.2 Model validation ..................................................................... 68

3.3.3 Model parameter uncertainty analysis .................................... 71

3.3.3.1 Bootstrap analysis ............................................................... 71

3.3.3.2 Jackknife analysis ............................................................... 79

3.3.4 Model simulation uncertainty .................................................. 83

3.3.4.1 Bootstrap analysis ............................................................... 83

3.3.4.2 Jackknife analysis ............................................................... 87

3.3.5 Spatial variability of basin rainfall ......................................... 90

3.4 Conclusions ............................................................................... 92

CHAPTER 4
A GENERALIZED STORAGE FUNCTION MODEL ....................... 95

4.1 Introduction ............................................................................... 95

4.2 Generalized USF (GUSF) model for discharge prediction .......... 96
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.2.1</td>
<td>Methodology</td>
<td>96</td>
</tr>
<tr>
<td>4.2.1.1</td>
<td>Generalized USF (GUSF) model</td>
<td>96</td>
</tr>
<tr>
<td>4.2.1.2</td>
<td>Parameter estimation and performance evaluation</td>
<td>97</td>
</tr>
<tr>
<td>4.2.2</td>
<td>Study area and data used</td>
<td>97</td>
</tr>
<tr>
<td>4.2.3</td>
<td>Results and discussion</td>
<td>99</td>
</tr>
<tr>
<td>4.2.3.1</td>
<td>Hydrograph reproducibility and performance evaluation</td>
<td>99</td>
</tr>
<tr>
<td>4.2.3.2</td>
<td>AIC aspect</td>
<td>104</td>
</tr>
<tr>
<td>4.3</td>
<td>Generalized SF (GSF) model for water level prediction</td>
<td>105</td>
</tr>
<tr>
<td>4.3.1</td>
<td>Methodology</td>
<td>106</td>
</tr>
<tr>
<td>4.3.1.1</td>
<td>GSF model</td>
<td>106</td>
</tr>
<tr>
<td>4.3.1.2</td>
<td>Model calibration and validation</td>
<td>109</td>
</tr>
<tr>
<td>4.3.1.3</td>
<td>Performance evaluation</td>
<td>110</td>
</tr>
<tr>
<td>4.3.1.4</td>
<td>Sensitivity analysis</td>
<td>111</td>
</tr>
<tr>
<td>4.3.2</td>
<td>Study area and data used</td>
<td>112</td>
</tr>
<tr>
<td>4.3.2.1</td>
<td>Study area</td>
<td>112</td>
</tr>
<tr>
<td>4.3.2.2</td>
<td>Data used</td>
<td>115</td>
</tr>
<tr>
<td>4.3.3</td>
<td>Results and discussion</td>
<td>115</td>
</tr>
<tr>
<td>4.3.3.1</td>
<td>Model calibration</td>
<td>115</td>
</tr>
<tr>
<td>4.3.3.2</td>
<td>Hydrograph reproducibility</td>
<td>121</td>
</tr>
<tr>
<td>4.3.3.3</td>
<td>Performance evaluation</td>
<td>127</td>
</tr>
<tr>
<td>4.3.3.4</td>
<td>AIC aspect</td>
<td>132</td>
</tr>
<tr>
<td>4.3.3.5</td>
<td>Sensitivity analysis of GSF model</td>
<td>134</td>
</tr>
<tr>
<td>4.4</td>
<td>Conclusions</td>
<td>137</td>
</tr>
</tbody>
</table>
CHAPTER 5

GENERAL CONCLUSIONS AND RECOMMENDATIONS .............. 139

5.1 An effective SF model for urban watersheds and associated uncertainty analysis ................................................................. 139

5.2 A GSF model for the water level prediction ............................... 142

5.3 Recommendations for future research ...................................... 143

References .................................................................................. 145
### LIST OF FIGURES

| Fig. 2.1 | Schematic diagram of all inflow and outflow components of an urban watershed with combined sewer system. | 19 |
| Fig. 2.2 | Index map of (a) Japan, (b) Kanda river basin in Tokyo and (c) target area - upper Kanda basin at Koyo Bridge. | 24 |
| Fig. 2.3 | The estimated model parameter values for various storage function models in each event. | 27 |
| Fig. 2.4 | Reproduced hydrograph by each model for (a) Event 1; (b) Event 2; (c) Event 3; (d) Event 4; and (e) Event 5. | 30-31 |
| Fig. 2.5 | Comparison of different error evaluation functions of (a) RMSE, (b) NSE, (c) PEP, (d) PEV, (e) PETP, (f) PELT, and (g) PERC by the different storage function models. | 32 |
| Fig. 2.6 | The summary of Akaike information criterion (AIC) results, (a) corrected AICc and (b) Akaike weight (AW) values for the five events. | 34 |
| Fig. 2.7 | Model parameter uncertainty represented using two statistical indices, (a) relative error (RE) and (b) coefficient of variation (CV) (PAR represents parameter). | 35 |
| Fig. 2.8 | Event-based optimal parameters for the Kimura, 5, and 4-parameter models. | 41 |
| Fig. 2.9 | Effect of lag time on (a) RMSE, (b) NSE, (c) PEP, (d) PEV, and (e) ETP by Kimura’s model. | 42-43 |
| Fig. 2.10 | Reproduced hydrographs by each model for (a) event 1, (b) event 2, (c) event 3, (d) event 4, and (e) event 5. | 45-46 |
| Fig. 2.11 | Storage hysteresis loop reproduced by each model for (a) event 1, (b) event 2, (c) event 3, (d) event 4, and (e) event 5. | 48 |
| Fig. 3.1 | Schematic of classical bootstrap resampling method. | 54 |
| Fig. 3.2 | Flowchart of the residual-based bootstrapping method. | 57 |
| Fig. 3.3 | Schematic of classical jackknife resampling method. | 58 |
| Fig. 3.4 | Flowchart of the simplified jackknife method. | 59 |
| Fig. 3.5 | The calibrated parameters of USF model from the selected data scenarios. | 64 |
Fig. 3.6  The reproduced hydrographs by USF model for (a) Event 1; (b) Event 2; (c) Event 3; (d) Event 4; and (e) Event 5 in both data scenarios.

Fig. 3.7  The USF model validation for event 5 using the whole data-based and individual event-based parameters; (a) reproduced hydrographs, and (b) performance evaluation in each scenario.

Fig. 3.8  Scatter plots of bootstrapped parameter samples by the USF model for (a) whole data (a1-a7), (b) event 1 (b1-b7), and (c) event 2 (c1-c7), with their 95% CI in grey shading.

Fig. 3.9  The box plot of bootstrapped parameter vector (a) $k_1$, (b) $k_2$, (c) $k_3$, (d) $p_1$, (e) $p_2$, (f) $z$, and (g) $\alpha$ for both the data scenarios. The line passing through the box represents the median ($\hat{\theta}_{50}$). The red square and blue circle within the box indicate mean ($\bar{\theta}$) and calibrated parameter ($\hat{\theta}$) respectively. The written values represent the CV for each data scenario.

Fig. 3.10  Two proposed indices of (a) $IP_1$, and (b) $IP_2$ for analyzing the model parameter uncertainty.

Fig. 3.11  Scatter plots of parameter vector with block size 50 along with their 95% CI in grey shading.

Fig. 3.12  The simulation uncertainty of USF model for (a) Event 1; (b) Event 2; (c) Event 3; (d) Event 4; and (e) Event 5 using the whole data-based and individual event-based scenarios.

Fig. 3.13  The model simulation uncertainty from the bootstrap analysis for the whole data-based and individual event-based scenarios using the (a) P-factor, and the two proposed model simulation uncertainty indices of (b) $IQ_1$, and (c) $IQ_2$.

Fig. 3.14  The simulation uncertainty of USF model with block size 50 for the selected events.

Fig. 3.15  The model simulation uncertainty from the jackknife analysis for the whole data-based scenario using the P-factor, and the two proposed model simulation uncertainty indices of $IQ_1$, and $IQ_2$.

Fig. 3.16  The percentage variation of total rainfall obtained from each rain gauge with respect to the mean rainfall from all the gauges.
Fig. 4.1  Index map of Upper Kanda River basin.

Fig. 4.2  Spatial distribution of total rainfall in the upper Kanda basin during (a) event 3 and (b) event 4 (circle and square represent rain gauge and water level stations respectively).

Fig. 4.3  Reproduced hydrographs by the USF and GUSF models during calibration and validation.

Fig. 4.4  Comparison of RMSE (mm/min), NSE, PEP, and PEV by the USF and GUSF models during calibration and validation.

Fig. 4.5  The corrected AIC ($AIC_c$) values during calibration and validation.

Fig. 4.6  Schematic diagram of all inflow and outflow components of a conceptual watershed.

Fig. 4.7  Index map of (a) Japan, (b) Iga and Oto basins within the Okazaki city of Aichi prefecture, (c) Iga basin at Iga Bridge, and (d) Oto basin at Chiharazawa.

Fig. 4.8  The parameter convergence pattern of (a) GSF, (b) 8 parameter, (c) 7 parameter, and (d) 6 parameter models for the ten selected events using RMSE as the objective function during the SCE-UA application run.

Fig. 4.9  The calibrated parameters of GSF, 8, 7, and 6 parameter models for the Oto and Iga basins. ‘C’ indicates calibrated parameters from individual events and ‘V’ indicates the calibrated parameters from all the events.

Fig. 4.10 Spatial distribution of total rainfall during calibration validation events for Iga basin (a1-a3) and Oto basin (b1-b3). ‘C’ and ‘V’ indicate the calibration and validation respectively (circle and square represent rain gauge and water level stations respectively).

Fig. 4.11  The reproduced hydrographs by the models for Iga basin (a1-a5) during calibration.

Fig. 4.12  The reproduced hydrographs by the models for Oto basin (b1-b5) during calibration.
Fig. 4.13  The reproduced hydrographs by the models for Iga basin (a1-a2) during validation.

Fig. 4.14  The reproduced hydrographs by the models for Oto basin (b1-b2) during validation.

Fig. 4.15  The performance evaluation of different models during calibration and validation for Iga basin (a1-a4) and Oto basin (b1-b4). ‘C’ and ‘V’ indicate the calibration and validation respectively.

Fig. 4.16  Scatter plot of observed water level versus simulated by the models in the (i) Iga basin calibration (a1-a4) and validation (b1-b4), and (ii) Oto basin calibration (c1-c4) and validation (d1-d4).

Fig. 4.17  The summary of AIC results of corrected AIC (AICc) and Akaike weight (AW) values of the models for Iga basin (a1-a2) and Oto basin (b1-b2).

Fig. 4.18  Morris sensitivity indices for the objective function RMSE in (a) Iga basin and (b) Oto basin.
### LIST OF TABLES

<p>| Table 2.1 | Storage function models with their associated continuity equations. | 18 |
| Table 2.2 | Characteristics of target events. | 25 |
| Table 2.3 | Elapsed time taken for the calibration and evaluation of storage function models in each event. | 26 |
| Table 2.4 | Comparison of RMSE, NSE, PEP, PEV, and ETP by the SF models. | 44 |
| Table 2.5 | The summary of AIC results for the five events. | 49 |
| Table 3.1 | Description and search range of USF model parameters. | 60 |
| Table 3.2 | Performance evaluation of USF model using different statistical indicators. | 66 |
| Table 3.3 | The different statistical estimators along and parameter uncertainty indices along with the calibrated parameter vector for block size 50. | 81 |
| Table 4.1 | Characteristics of target events in Kanda basin. | 98 |
| Table 4.2 | Estimated parameters of USF and GUSF models for each event. | 99 |
| Table 4.3 | Description and search range of GSF model parameters. | 109 |
| Table 4.4 | Characteristics of the selected events for Iga and Oto basins. | 114 |
| Table 4.5 | Morris sensitivity index ($\mu^*$) and associated ranking of GSF model for RMSE in the Iga and Oto basins. | 135 |</p>
<table>
<thead>
<tr>
<th>Equation</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eq. 2.1</td>
<td>Groundwater-related loss</td>
<td>20</td>
</tr>
<tr>
<td>Eq. 2.2</td>
<td>Storm drainage</td>
<td>20</td>
</tr>
<tr>
<td>Eq. 2.3</td>
<td>Second-order ordinary differential equation of USF model</td>
<td>20</td>
</tr>
<tr>
<td>Eq. 2.4</td>
<td>Change of variables of USF model</td>
<td>20</td>
</tr>
<tr>
<td>Eq. 2.5</td>
<td>Change of variables of USF model</td>
<td>20</td>
</tr>
<tr>
<td>Eq. 2.6</td>
<td>First-order ordinary differential equation of USF model</td>
<td>20-21</td>
</tr>
<tr>
<td>Eq. 2.7</td>
<td>Akaike information criterion</td>
<td>22</td>
</tr>
<tr>
<td>Eq. 2.8</td>
<td>Corrected Akaike information criterion</td>
<td>23</td>
</tr>
<tr>
<td>Eq. 2.9</td>
<td>Akaike weight</td>
<td>23</td>
</tr>
<tr>
<td>Eq. 2.10</td>
<td>Difference in corrected Akaike information criterion</td>
<td>23</td>
</tr>
<tr>
<td>Eq. 2.11</td>
<td>Relative error</td>
<td>23</td>
</tr>
<tr>
<td>Eq. 2.12</td>
<td>Coefficient of variation</td>
<td>23</td>
</tr>
<tr>
<td>Eq. 2.13</td>
<td>Storage equation of Kimura’s SF model with lag time</td>
<td>38</td>
</tr>
<tr>
<td>Eq. 2.14</td>
<td>Continuity equation of Kimura’s SF model with lag time</td>
<td>38</td>
</tr>
<tr>
<td>Eq. 2.15</td>
<td>Modified continuity equation of Kimura’s SF model with lag time</td>
<td>38</td>
</tr>
<tr>
<td>Eq. 2.16</td>
<td>Ordinary differential equation of Kimura’s SF model with lag time</td>
<td>38</td>
</tr>
<tr>
<td>Eq. 2.17</td>
<td>Change of variable for Kimura’s model with lag time</td>
<td>38</td>
</tr>
<tr>
<td>Eq. 2.18</td>
<td>Ordinary differential equation of Kimura’s SF model with lag time</td>
<td>38-39</td>
</tr>
<tr>
<td>Eq. 2.19</td>
<td>Error in time to peak</td>
<td>39</td>
</tr>
<tr>
<td>Eq. 3.1</td>
<td>Model residual</td>
<td>56</td>
</tr>
<tr>
<td>Eq. 3.2</td>
<td>Model parameter uncertainty index</td>
<td>62</td>
</tr>
<tr>
<td>Eq. 3.3</td>
<td>Model parameter uncertainty index</td>
<td>62</td>
</tr>
<tr>
<td>Eq. 3.4</td>
<td>P-factor</td>
<td>62</td>
</tr>
<tr>
<td>Eq. 3.5</td>
<td>Model simulation uncertainty index</td>
<td>63</td>
</tr>
<tr>
<td>Eq. 3.6</td>
<td>Model simulation uncertainty index</td>
<td>63</td>
</tr>
<tr>
<td>Eq. 3.7</td>
<td>Percentage variation of total rainfall</td>
<td>90</td>
</tr>
<tr>
<td>Eq. 4.1</td>
<td>Storage equation of GUSF model</td>
<td>96</td>
</tr>
<tr>
<td>Eq. 4.2</td>
<td>Continuity equation of GUSF model</td>
<td>96</td>
</tr>
<tr>
<td>Eq. 4.3</td>
<td>Hoshi’s storage equation</td>
<td>107</td>
</tr>
<tr>
<td>Eq. 4.4</td>
<td>Rating-curve relationship</td>
<td>107</td>
</tr>
<tr>
<td>Eq. 4.5</td>
<td>Storage equation of GSF model</td>
<td>107</td>
</tr>
<tr>
<td>Eq. 4.6</td>
<td>Continuity equation of GSF model</td>
<td>107</td>
</tr>
<tr>
<td>Eq. 4.7</td>
<td>Groundwater-related loss</td>
<td>108</td>
</tr>
<tr>
<td>Eq. 4.8</td>
<td>Second-order ordinary differential equation of GSF model</td>
<td>108</td>
</tr>
<tr>
<td>Eq. 4.9</td>
<td>Change of variables of GSF model</td>
<td>108</td>
</tr>
<tr>
<td>Eq. 4.10</td>
<td>Change of variables of GSF model</td>
<td>108</td>
</tr>
<tr>
<td>Eq. 4.11</td>
<td>First-order ordinary differential equation of GSF model</td>
<td>108</td>
</tr>
<tr>
<td>Eq. 4.12</td>
<td>Elementary effect of the parameter in Morris sensitivity analysis</td>
<td>111</td>
</tr>
</tbody>
</table>
# LIST OF ABBREVIATIONS

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIC</td>
<td>Akaike information criterion</td>
</tr>
<tr>
<td>ANN</td>
<td>Artificial neural network</td>
</tr>
<tr>
<td>AW</td>
<td>Akaike weight</td>
</tr>
<tr>
<td>CI</td>
<td>Confidence interval</td>
</tr>
<tr>
<td>CV</td>
<td>Coefficient of variation</td>
</tr>
<tr>
<td>ETP</td>
<td>Error in time to peak</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographic information system</td>
</tr>
<tr>
<td>GLUE</td>
<td>Generalized likelihood uncertainty estimation</td>
</tr>
<tr>
<td>GSF</td>
<td>Generalized storage function</td>
</tr>
<tr>
<td>GUSF</td>
<td>Generalized urban storage function</td>
</tr>
<tr>
<td>iid</td>
<td>Independent and identically distributed</td>
</tr>
<tr>
<td>NSE</td>
<td>Nash-Sutcliffe efficiency</td>
</tr>
<tr>
<td>ODE</td>
<td>Ordinary differential equation</td>
</tr>
<tr>
<td>PAR</td>
<td>Parameter</td>
</tr>
<tr>
<td>PEA</td>
<td>Percentage error in area under the water level hydrograph</td>
</tr>
<tr>
<td>PELT</td>
<td>Percentage error in lag time</td>
</tr>
<tr>
<td>PEP</td>
<td>Percentage error in peak discharge</td>
</tr>
<tr>
<td>PERC</td>
<td>Percentage error in runoff coefficient</td>
</tr>
<tr>
<td>PETP</td>
<td>Percentage error in time to peak discharge</td>
</tr>
<tr>
<td>PEV</td>
<td>Percentage error in volume</td>
</tr>
<tr>
<td>RE</td>
<td>Relative error</td>
</tr>
<tr>
<td>RKG</td>
<td>Runge-Kutta-Gill</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root mean square error</td>
</tr>
<tr>
<td>SA</td>
<td>Sensitivity analysis</td>
</tr>
<tr>
<td>SCE-UA</td>
<td>Shuffled Complex Evolution-University of Arizona</td>
</tr>
<tr>
<td>SF</td>
<td>Storage function</td>
</tr>
<tr>
<td>SMPT</td>
<td>Soil moisture parameter tank</td>
</tr>
<tr>
<td>SUFI</td>
<td>Sequential uncertainty fitting</td>
</tr>
<tr>
<td>SWAT</td>
<td>Soil &amp; water assessment tool</td>
</tr>
<tr>
<td>TMG</td>
<td>Tokyo Metropolitan Government</td>
</tr>
<tr>
<td>USF</td>
<td>Urban storage function</td>
</tr>
<tr>
<td>WMO</td>
<td>World Meteorological Organization</td>
</tr>
</tbody>
</table>
LIST OF SYMBOLS

\( \gamma \)  
Rainfall distribution factor

\( a \)  
Rating curve constant

\( b \)  
Rating curve constant

\( s \)  
Storage

\( Q \)  
Observed river discharge

\( t \)  
Time

\( k_1 \)  
Model parameter

\( k_2 \)  
Model parameter

\( p_1 \)  
Model parameter

\( p_2 \)  
Model parameter

\( R \)  
Rainfall

\( I \)  
Inflows from other basins

\( E \)  
Evapotranspiration

\( q_R \)  
Storm drainage from the basin through the combined sewer system

\( O \)  
Water intake from the basin

\( q_I \)  
Groundwater-related loss

\( q_w \)  
Domestic sewage

\( k_3 \)  
Model parameter

\( z \)  
Model parameter

\( \alpha \)  
Model parameter

\( Q_0 \)  
Initial river discharge before the rain starts

\( q_{\text{max}} \)  
Sewer maximum carrying capacity

\( Q_d \)  
Direct runoff

\( T_l \)  
Lag time

\( R_e \)  
Effective rainfall

\( C \)  
Number of complexes in SCE-UA method

\( r \)  
Number of populations in each complex of SCE-UA method

\( k \)  
Number of model parameters to be estimated

\( \mathcal{L} \)  
Likelihood

\( \hat{\theta} \)  
Maximum likelihood estimator

\( y \)  
Number of observations
\( n \) Sample size

\( AIC_c \) Corrected AIC

\( AW_i \) Akaike weight of \( i^{th} \) model

\( \Delta AIC_{c,i} \) Difference in corrected AIC for \( i^{th} \) model

\( AIC_{c,i} \) corrected AIC for the \( i^{th} \) model

\( AIC_{c,min} \) Minimum corrected AIC among the models

\( M \) Number of models

\( RE_{i,p} \) Relative error for the \( i^{th} \) model and \( p^{th} \) parameter

\( CV_{i,p} \) Coefficient of variation for the \( i^{th} \) model and \( p^{th} \) parameter

\( N \) Number of target events

\( P_{i,j} \) Estimated parameter value for the \( i^{th} \) model and \( j^{th} \) event

\( \bar{P}_i \) Average parameter value from \( N \) events

\( \sigma_{i,p} \) Standard deviation for the \( i^{th} \) model and the \( p^{th} \) parameter value

\( R_{60} \) 60-minute maximum rainfall

\( B \) Number of bootstrap samples

\( X \) Input data set

\( \theta \) Parameter vector

\( \varepsilon \) True model residual

\( \hat{\theta} \) Calibrated parameter vector

\( \hat{Q} \) Calibrated river discharge

\( \hat{\varepsilon} \) Calibrated model residual

\( \hat{\varepsilon}^b \) Bootstrapped model residual

\( Q^b \) Bootstrapped discharge series

\( \hat{\theta}^b \) Bootstrapped parameter vector

\( \bar{Q}^b \) Simulated discharge series from bootstrapping

\( d \) Number of block in jackknife resampling

\( g \) Length of block in jackknife resampling

\( \hat{\theta}^j_d \) Jackknifed parameter vector

\( \hat{Q}^j_d \) Simulated discharge series from jackknifing

\( \theta \) Parameter mean

\( \sigma_{\theta} \) Parameter standard deviation

\( IP_1 \) Model parameter uncertainty index
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$IP_2$</td>
<td>Model parameter uncertainty index</td>
</tr>
<tr>
<td>$n_{CI}$</td>
<td>Observed discharge within the 95% CI.</td>
</tr>
<tr>
<td>$IQ_1$</td>
<td>Model simulation uncertainty index</td>
</tr>
<tr>
<td>$IQ_2$</td>
<td>Model simulation uncertainty index</td>
</tr>
<tr>
<td>$\hat{\theta}_{50}$</td>
<td>Parameter median</td>
</tr>
<tr>
<td>$TR_i$</td>
<td>Total rainfall from each gauge</td>
</tr>
<tr>
<td>$\bar{TR}$</td>
<td>Mean rainfall from all the gauges</td>
</tr>
<tr>
<td>$\beta$</td>
<td>Rating curve constant</td>
</tr>
<tr>
<td>$H$</td>
<td>Water level</td>
</tr>
<tr>
<td>$d_i$</td>
<td>Elementary effect of the $i^{th}$ parameter</td>
</tr>
<tr>
<td>$\Delta$</td>
<td>Magnitude of step in Morris sensitivity analysis</td>
</tr>
<tr>
<td>$p$</td>
<td>Number of levels in Morris sensitivity analysis</td>
</tr>
<tr>
<td>$f(\theta)$</td>
<td>Target function value for the parameter vector</td>
</tr>
<tr>
<td>$r$</td>
<td>Number of repetitions in elementary effect calculation</td>
</tr>
<tr>
<td>$\mu$</td>
<td>Morris sensitivity indices</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Morris sensitivity indices</td>
</tr>
<tr>
<td>$\mu^*$</td>
<td>Modified Morris sensitivity indices</td>
</tr>
<tr>
<td>$R^2$</td>
<td>Coefficient of determination</td>
</tr>
<tr>
<td>$R_{av}$</td>
<td>Basin average rainfall</td>
</tr>
<tr>
<td>$t_{po}$</td>
<td>Observed time to peak discharge</td>
</tr>
<tr>
<td>$t_{pc}$</td>
<td>Computed time to peak discharge</td>
</tr>
</tbody>
</table>
CHAPTER 1

INTRODUCTION

1.1 Background

Flood is considered as one of the severe natural disasters due to the associated flood risk and costs in both rural and urban areas (Carrera et al., 2015; Leskens et al., 2014). The extreme events of the high flood will always affect the nearby population and indirectly causes an enormous threat to human life, properties, different crops, etc. (Ruslan et al., 2017) due to the disruption of economic activity and overall have a negative impact in the watersheds (Balica et al., 2013). Flood mitigation is one of the water management strategies that can control the demolishing impact of the floods (Bubeck et al., 2012). However, the accurate prediction of the hydrograph in advance, which includes the estimation of flood peak, time to peak, volume, lag time, etc., is important for the flood mitigation in order to avoid losses due to floodplain inundation. Further, estimation of flood peaks is also required for the design of bridges, culverts, waterways, spillways for dams, and estimation of scour at a hydraulic structure (Sahoo and Saritha, 2015). For this purpose, the rainfall-runoff models are important tools and they play a central role in flood management (Padiyedath et al., 2018a).

There is no universally accepted rainfall-runoff model classification as of now and there exist different ways of classifications depending on the criteria of interest (Dawdy, 1969; Singh, 1995; Sivakumar, 2017; Snyder and Stall, 1965). The selection of appropriate models for the intended purpose is very important. According to Sivakumar (2017), based on simplicity and convenience, the models can be grouped into two categories, namely; physical models and abstract models. The physical models can represent the processes of a watershed in a physically realistic manner on a reduced size such as open channel hydrologic model of the river, the hydraulic model of dam spillway, etc. The abstract model is the representation of the system using mathematical equations, which links the input to the output, and it is also called as a mathematical model (Sivakumar, 2017). The abstract model can be further divided into empirical models, theoretical models, and conceptual models (Dooge, 1977). The empirical models extract information only from the existing data without considering the hydrological characteristics and highly depends on the boundary conditions. Unit hydrograph, rational
method, least square method etc. are the examples of this method (Devi et al., 2015; Sivakumar, 2017). The theoretical model is based on physical laws governing the hydrological process and it includes MIKESHE, Soil & Water Assessment Tool (SWAT), etc. (Abbott et al., 1986). The conceptual model is an intermediary between the empirical and theoretical models. Generally, conceptual models consider physical laws but in highly simplified form. The examples of conceptual models include tank model (Sugawara, 1974) and the models based on the spatially lumped form of continuity equation and the storage-discharge relationship (Dooge, 1959; Nash, 1958; Sivakumar, 2017).

The rainfall-runoff models can also be divided as a function of their process description (lumped and distributed), time variability (event-based, continuous time, and large time-scale), and technique of solution (numerical, analog, and analytical) (Amaguchi et al., 2012; Singh, 1995; Singh and Woolhiser, 2002). Most of the conceptual rainfall-runoff models have been concerned with lumping up the dominant sub-watershed processes that contribute to the overall watershed response (Boyle et al., 2001). The lumped models are easy to use, as they generally do not account for the spatial distribution of the input compared to the distributed models even though spatially lumped models also exist (Carpenter and Georgakakos, 2006). Among the different conceptual lumped rainfall-runoff models, storage function (SF) models have been widely used in many parts of the world, especially in Japan, not only because of their ease of use in computation and handling but also the ease by which they express the nonlinear relationship of the rainfall-runoff process using simple equations (Kawamura et al., 2004).

1.2 Storage function (SF) models

Extensive studies have been conducted using SF models in order to analyze the rainfall-runoff transformation process. Kimura (1961) proposed the first SF model in Japan with two parameters and delay time. The model was originally developed for the calculation of flood flow resulted from the effective rainfall by dividing the basin into pervious and impervious areas (Kimura, 1961). The storage equation of Kimura is a monovalent function of discharge. However, the bivalency was achieved by the introduction of lag time in the continuity equation and attained the storage-discharge hysteresis loop. Additionally, the incorporated lag time skillfully addresses the hydrograph lagging by delaying the runoff as a function of effective rainfall. This nonlinear lumped model is still widely used in Japan for flood prediction. Later,
Laurenson (1964) developed a procedure to reproduce the surface runoff hydrograph of a catchment from the effective rainfall using a different two-parameter SF model and tested the method in South Creek, Australia. Subsequently, Prasad (1967) proposed a three-parameter SF model by assuming the storage as a bivalent function of discharge by the introduction of an additional parameter in the storage equation itself, rather than in the continuity equation, which handled the loop shape of the storage-discharge relationship. The model also presented an additional term for the representation of unsteady flow effects that is observed in natural channels compared to that of Kimura’s model. He considered the relationship between the effective rainfall and surface runoff in the model. Soon after, Kuribayashi and Sadamichi (1969) evaluated the characteristics of the kinematic wave and Kimura’s SF model parameters. They compared the characteristics of both models and developed theoretical relationships under an assumption of constant rainfall. Later, Hoshihata (1972) examined the applicability of the SF model as a distributed model. He described a practical method for the estimation of the SF model parameters using the watershed slope but had insufficient data to conclude the results. Mein et al. (1974) extended the work of Laurenson (1965) by developing a nonlinear method for estimating surface runoff hydrographs by representing the basin as a series of conceptual reservoirs. Aoki et al. (1976) compared hydrograph estimates for a channel using the SF model and kinematic wave model and related their parameters. Subsequently, Hoshi and Yamaoka (1982) added another parameter and improved the robustness of SF model. Nagai et al. (1982) examined the physical significance of the SF model parameters obtained by applying a mathematical optimization technique. Thereafter, Sugiyama et al. (1997) theoretically analyzed the SF model parameters by comparing the SF and kinematic wave models and then evaluated SF model characteristics (Sugiyama et al., 1999).

However, all the aforementioned models require effective rainfall as their input for the prediction of direct runoff. Hence, they involve the separation of baseflow and effective rainfall components from total discharge and total rainfall, respectively. There was no adequate method of objectively quantifying effective rainfall after deducing losses until recently (Perumal and Sahoo, 2007). In addition, numerous baseflow separation techniques are currently in use and thereby the baseflow separation will be a subjective process (Padiyedath et al., 2017a). This, subsequently, may further affect the value of parameters to be estimated and their relative stability. Later, in order to overcome these
problems, Baba et al. (1999) introduced an SF model with the loss mechanism that uses the observed rainfall, and total runoff directly and applied to a mountainous river basin in Hokkaido, Japan. The incorporated loss mechanisms (infiltration and all other outflow components) avoided the need for effective rainfall estimation and baseflow separation. The use of the SF model of Baba for the prediction of runoff in urban areas may be difficult, because urban areas differ completely from mountainous areas in terms of their imperviousness, absence of vegetation, presence of sewer systems, etc. Therefore, Takasaki et al. (2009) developed a new urban SF (USF) model considering the urban runoff process and compared with Baba’s SF model. It uses the observed rainfall and runoff directly, without effective rainfall estimation and baseflow separation for flood prediction. The model considers all possible inflow and outflow components, including groundwater inflow as an outflow from the basin. Later, Park et al. (2012) evaluated the parameter characteristics of Kimura’s SF model for the application in ungauged basins by comparing the model with kinematic wave model. However, all the studies in the literature have mainly focused on the theoretical significance of the parameters involved and the modification of existing models.

1.3 Parameter uncertainty analysis of rainfall-runoff model

The predictions made using rainfall-runoff models are inherently uncertain. As the rainfall-runoff models are being increasingly used for the runoff simulation, it is very vital that these models should undergo vigorous calibration and uncertainty analysis. The uncertainties in the modeling mainly arise from parameter uncertainties, measurement errors associated with the input data, and from model structure errors arising from the aggregation of spatially distributed watershed processes into a relatively simple runoff model (Sivakumar and Berndtsson, 2010). Generally, the effectiveness of a model in providing a good prediction of the hydrological processes is mainly determined by its parameter values (Jeremiah et al., 2012). The input data is often contaminated by measurement errors and this inevitably leads to uncertain parameter estimates. As a result, the rainfall-runoff model simulations are far from being perfect, in other words, there always exists a disparity between the model simulation and the corresponding observed data due to this uncertain parameter values (Shrestha, 2009). Therefore, the model parameter uncertainty has received a prime recognition over other sources of uncertainties in the field of hydrological modeling. The recent studies on hydrological model uncertainties mostly refer to the identification of parameter uncertainty (Uhlenbrook et
al., 1999) or parameter calibration (Ajami et al., 2004) and their impacts on the model simulation results (Freer et al., 1996; Kuczera and Parent, 1998).

Traditionally, model parameters have been quantified from watershed properties (Nandakumar and Mein, 1997) or theoretically analyzed by comparing with similar models (Li et al., 2010). However, since the introduction of computer-intensive statistics, the parameters are being estimated by calibrating the models against observed data (Abbott et al., 1986; Refsgaard et al., 1992) even though it increases the efforts and costs taken for the data measurements required for calibration and validation. Although the optimization context typically assumes that the calibrated parameters represent time-invariant properties of the catchment, they are influenced by factors such as quantity and quality of input data, model error, correlation between the parameters, etc. (Duan et al., 1992). This will lead the parameter estimates to deviate from their underlying true values (Ebtehaj et al., 2010) thus leading to a great level of uncertainty of parameters, and cannot fully characterize the actual processes. However, these parameters often have no measurable reference in nature (Bellprat, 2013). Therefore, the major concern that arises is that what confidence bounds can be placed on the calibrated parameters, given the different sources of uncertainty is mainly arising from observational and model parameterization errors and how do these uncertainties affect the hydrologic simulations (Ebtehaj et al., 2010). Moreover, the high number of parameters included in some rainfall-runoff models will also increase the uncertainty (Brocca et al., 2011). Obviously, this parameter uncertainty further contributes to model simulation uncertainties, but to what extent is unknown. Hence, its quantitative evaluation is critical in reducing the uncertainty of these simulations.

Any analysis with a calibrated model must include parameter uncertainty because calibration without uncertainty is meaningless and misleading (Abbaspour, 2015). Hence, an appropriate uncertainty consideration of the model parameters is necessary although it has been much ignored until recently. Recent researchers have paid more attention to these uncertainties and many uncertainty analysis techniques have been developed and applied to different catchments in the past decades (Yang et al., 2008). Most of these techniques rely on either parametric methods or Bayesian methods (Gallagher and Doherty, 2007; Kuczera, 1988; Selle and Hannah, 2010; Yang et al., 2008). The most traditional parametric methods used for the assessment of model parameter uncertainty are the linear analysis (first-order approximation) by providing a rough confidence
interval (CI) of parameters (Kuczera, 1988), nonlinear constrained maximization or minimization, etc. (Gallagher and Doherty, 2007). However, in the parametric method, the structure of the model is specified a priori and the number and nature of the parameters are generally fixed in advance, and there is a little flexibility (Sivakumar, 2017). Since the advances in computer technology, the Monte Carlo approaches with a Bayesian inference have become popular due to their ability to handle nonlinearity and interdependency of parameters in complex hydrological models (Li et al., 2010). The other methods based on Bayesian approaches are Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Binley, 1992; Hornberger and Spear, 1981), Sequential Uncertainty Fitting algorithm (SUFI) (Abbaspour et al., 1997, 1999), etc. Still, the Bayesian technique requires the form specification of the error distribution for response variables (Selle and Hannah, 2010). Hence, the nonparametric method can be used over the above methods as they make no prior assumptions on the model structure and thus are more flexible. There exists several nonparametric approaches in which the bootstrap and jackknife resampling methods have received considerable attention due to their ability to provide confidence interval in many settings (Hollander and Wolfe, 1973).

1.3.1 Parameter uncertainty by bootstrap method

The bootstrap method, a nonparametric technique, has been developed by Efron (1979) for random resampling of the original data set to develop replicate data sets from which the underlying distribution of the statistics of interest such as mean, variation, correlation, etc. can be estimated (Sivakumar, 2017). This resampling technique has applications in diverse fields like hydrology, groundwater hydrology, air pollution modeling, toxicology, etc. (Dixon, 2006), where it has been successfully used in hydrological modeling to design storms from exceedance series, to develop artificial neural network (ANN) model, to estimate the sampling variability of reconstructed runoff, etc. (Jeong and Kim, 2005; Sun et al., 2013; Zucchini and Adamson, 1989) by utilizing non-time series data. However, the outcome from the rainfall-runoff models is the time-series hydrograph, and hence the time series application of the bootstrap method becomes necessary. Sophisticated approaches have been developed for this purpose and has been extensively used for the trend analysis of temperature and streamflow time series, generation of synthetic streamflow sequences that are used in simulation studies, forecasting of low flow frequency, uncertainty assessment of water quality trends, etc. (Hirsch et al., 2015; Lall and Sharma, 1996; Önöz and Bayazit, 2012; Sonali and Nagesh
Kumar, 2013; Srinivas and Srinivasan, 2005; Tasker and Dunne, 1997). However, use of the bootstrap technique for model parameter uncertainty analysis by employing the time series data appears to be quite narrow until recently and very limited studies have been conducted to quantify the calibrated parameter uncertainty of rainfall-runoff models using this technique.

Ebtehaj et al. (2010) introduced a nonparametric block bootstrapping approach coupled with global optimization to estimate the parameter uncertainty resulting from uncertainty in the forcing data and evaluate its impacts on the resulting streamflow simulations. Later, Selle and Hannah (2010) demonstrated a model based bootstrap and compared the results with the block bootstrap approach for the parameter uncertainty of abc hydrological model and a conceptual salt load model. The bootstrap approach also seems to have been used for the analysis of parameter uncertainty of SWAT model (Li et al., 2010; Zhang et al., 2014). Further, Brigode et al. (2014, 2015) analyzed the effect of different rainfall-runoff calibration periods and information contained in the calibration period on extreme flood estimations using the block bootstrap method. The uncertainty studies conducted using the SWAT model for different catchments reported that the parameter uncertainty and its effect on model simulation uncertainty vary from catchment to catchment even for the same model. Therefore, there is a need to carry out such studies in different types of watersheds worldwide under varying agro-climatic conditions with different rainfall-runoff models.

1.3.2 Parameter uncertainty by jackknife method

Quenouille (1949) introduced the jackknife approach, one of the nonparametric technique, for resampling the original data to develop replicate samples and to find the distribution of a statistics such as bias, standard deviation, etc. Subsequently, Tukey (1958) used the jackknife method to provide an estimate of the variance of the statistic. The delete-1 jackknife, in its simplest form, evaluates the statistics of interest by leaving out each observation at a time from the sample set. It has been used to solve many problems in various fields such as hydrology and soil science (Donnelly-Makoweccki and Moore, 1999; Gaume et al., 2007; Lilly et al., 2008), environment and finance (Gomes et al., 2008), etc. in which it has been successfully used in hydrological modeling for the frequency analysis of extreme events, estimation of the sampling variability of reconstructed runoff, identification of dynamic models, etc. (Duchesne and MacGregor, 2001; Sun et al., 2013; Takara, 2009) by utilizing the non-time series data. However, the
use of jackknife for time series data was limited because the classical jackknife method assumes that the data set is independent and identically distributed (iid) (Efron, 1982). Therefore, the direct resampling is not feasible for a time series data that exhibits strong temporal correlation, and the dependence cannot be preserved (Li et al., 2010).

The outcome from the rainfall-runoff models is hydrograph time series data, and hence the time series application of jackknife method is necessary. In order to overcome the problem of dependence of time series, the delete-d jackknife approach has been developed in which a block of observation is deleted instead of single observation at a time in order to preserve the serial dependence in the time series (Shao and Wu, 1989) and later this approach has been used for many applications. However, the use of jackknife technique for the parameter uncertainty analysis by employing the time series data appears to be very narrow until recently. Only one study has been conducted to quantify the uncertainty arising from the parameter calibration of rainfall-runoff models in ungauged catchments using this technique so far. In the reported study, the parameter uncertainty was estimated using the jackknife procedure in which a re-calibration was carried out multiple times for each gauged catchment, leaving out a year of record on each pass (Jones and Kay, 2007). However, the main objective of the study was to provide a mechanism for the estimation of uncertainty bounds of generalized flood frequency curves for ungauged catchments using two conceptual rainfall-runoff models and not the parameter uncertainty. Therefore, it is essential to employ this technique for the assessment of parameter uncertainty and its subsequent effect on the simulation uncertainty of rainfall-runoff models as a primary objective.

1.4 Generalised storage function (GSF) model

Generally, most of the conventional SF models incorporated the runoff coefficient in order to account for the loss components in the basin. In addition, the rainfall is spatially averaged over the basin and a basin average rainfall is considered in the SF models so far. However, in actual condition, there will be spatial variability in rainfall across a catchment, which is not captured when undertaking the lumped catchment modeling. This spatial variability will be quite high even in small watersheds based on the meteorological factors (Yonese et al., 2017). In addition, there might be problems with the location of the rain gauge in terms of capturing a representative rainfall corresponding to each rainfall event, especially for catchments with high rainfall gradients (Vaze et al., 2012). Therefore, the use of basin average rainfall will further result in either underestimation or
overestimation of storm runoff based on the meteorological factors as well as the location of rainfall occurrence (Yonese et al., 2018). For example, if a localized rainfall with high intensity is occurring near the watershed outlet, the outlet will receive an immediate high magnitude response without any significant losses compared with a delayed and diminished outlet response resulted from the upstream rainfall. Vaze et al. (2011) analyzed the effect of different rainfall data sets on the calibration and simulation of conceptual rainfall-runoff models and concluded that considerable improvement can be obtained in the modelled runoff with the better spatial representation of rainfall. Moreover, it is often assumed that the rainfall-runoff models developed for the runoff analysis can be applied in all the watersheds irrespective of its nature (McPherson and Schneider, 1974) even though it is not the case. The rural watersheds will experience significant infiltration loss, and other losses like depression storage, interception, etc. compared with an urban watershed and therefore, the rainfall-runoff model should be able to account for these losses in both the watersheds.

Hence, there is a need for a generalized SF (GSF) model that can be applied in all the watersheds without requiring the effective rainfall as their input by incorporating all the possible inflow and outflow components. The rainfall spatial variability has not been considered in the SF models so far and the developed GSF model is able to take care of the spatial distribution of rainfall in the basin.

1.4.1 Generalized USF (GUSF) model for urban discharge prediction

USF model, being the lumped model, considers a basin average rainfall and this will further result in the underestimation or overestimation of storm runoff based on the meteorological factors as well as the location of rainfall occurrence. For example, the occurrence of high intensity localized rainfall near the watershed outlet will results in an immediate high magnitude response at the outlet without any significant losses. This effect will be profound in small urban watersheds due to the relatively short time of concentration, presence of sewer system, and high percentage of impervious surfaces. So far, the rainfall spatial variability has not been considered in the SF models and thereby an attempt should be made to account for the spatial distribution of rainfall in the urban watersheds for the discharge prediction. This can be achieved by incorporating the rainfall distribution factor, $\gamma$ in the existing USF model and this slightly modified USF model is termed as generalised USF (GUSF) model hereinafter, which will be able to take care the rainfall spatial variability observed in the watersheds.
1.4.2 GSF model for water level prediction

All the existing SF models require discharge data for their calibration and subsequent runoff analysis so far. This observed river discharge is generally obtained from water level observations made at a gauging station, which are further converted to the flow estimates using a well-defined and stable rating curve (Vaze et al., 2012). However, there will be uncertainties in the converted discharge data resulting from errors in rating curves derived from stream gauging operations (Bates and Townley, 1988) as well as due to extrapolation outside the limits of the rating curve (Vaze et al., 2012). There are several studies that analyzed the uncertainties involved in the discharge estimation from the rating curve (Domeneghetti et al., 2012; Westerberg et al., 2011; Wolfs and Willems, 2014). In addition, data for a much longer period is needed to establish a stable rating curve, which is practically impossible for ungauged and partially gauged watersheds, and it is difficult to update from time to time. The discharge estimated from the erroneous information of rating curve will further contribute to uncertainties in the model prediction (Bates and Townley, 1988). The direct use of observed water level for the model development will reduce the uncertainties in the model prediction. In addition, from the disaster point of view, the prediction of water level information is often sufficient to make an early warning about the flooding and to carry out control and evacuation activities compared with the uncertain discharge predictions. However, an efficient and effective water level prediction system is still lacking. Therefore, a precise technique for flood water level prediction and monitoring as an alarming system should be developed to prevent future disasters. The GSF model predicts the water level using the rating curve relationship by considering the spatial distribution of rainfall over the basin and incorporating all the possible inflow and outflow components. The spatial distribution of rainfall in the basin was also considered in the GSF model by introducing the parameter called rainfall distribution factor, hereafter termed as $\gamma$.

1.5 Objectives, scope, and methods

In light of the aforementioned discussions, this study aims to analyze the storm runoff processes using the storage function models. The main objectives of this study are as follows:

1) Establish an effective SF model from the existing conventional ones for an urban watershed in terms of hydrograph reproducibility and from an Akaike information
criterion (AIC) perspective in order to evaluate the ability of models to predict discharge and to provide information and guidelines for end-users. For this purpose, we have selected the relatively new USF model and four conventional SF models of Hoshi, Prasad, Kimura without lag time, and the linear model in order to conduct the performance evaluation.

2) Incorporate and analyze the effect of lag time in the conventional Kimura’s SF model on hydrograph reproducibility and compared with Prasad’s SF model for an urban watershed in terms of error functions, storage hysteresis loop, and AIC perspective by directly coupling the observed rainfall to observed discharge for an urban watershed. This was carried out to examine whether there is an improvement in performance or not in the Kimura’s SF model by the inclusion of lag time.

3) Evaluation of the uncertainty of optimal parameter estimates of USF model, which arises due to uncertainties in the input data, by the residual-based bootstrap resampling technique in an urban watershed to reduce the model prediction uncertainties resulting from the parameter uncertainty. The bootstrap approach was applied to both the individual flood events and the whole events in order to demonstrate the impact of different available data scenarios on the uncertainty behavior of calibrated parameters using two types of proposed indices.

4) Proposal of a simplified jackknife method for the parameter uncertainty analysis and its application using a case study with the USF model in an urban watershed in order to cope with the block length selection since the selection of block length is very critical for time series in delete-d jackknife method and each block should be effectively independent for the application.

5) Proposal of a GSF model for the water level prediction from the rating curve relationship and considering the spatial distribution of rainfall over the basin by introducing a parameter named as rainfall distribution factor ($\gamma$). The GSF model optimizes not only parameter $\gamma$ but also the rating curve constants along with other model parameters, which will reduce the efforts taken for the rating curve establishment of the target watersheds.

6) Modification of the existing USF model for the discharge prediction in urban watersheds by the incorporation of rainfall distribution factor to account for the spatial variability in basin rainfall.
1.6 Outline of the thesis

This thesis is composed of five chapters.

Chapter 1 comprises of the background, motivation, and objectives of this study. A comprehensive review of literature and a description of the scopes and methods were also presented.

Chapter 2 identifies the effective SF model from the existing conventional ones for an urban watershed in terms of hydrograph reproducibility and from an AIC perspective. For this purpose, we have selected the relatively new USF model and four conventional SF models of Hoshi, Prasad, Kimura without lag time, and the linear model in order to conduct the performance evaluation. The Shuffled Complex Evolution-University of Arizona (SCE-UA) global optimization method was used for the parameter optimization of each model with root mean square error (RMSE) as the objective function. The reproducibility of the hydrograph was evaluated using the performance evaluation criteria of RMSE, Nash-Sutcliffe efficiency (NSE), and other error functions of peak, volume, time to peak, lag time, and runoff coefficient. The results revealed that the higher values of NSE coupled with the lower values of RMSE and other error functions indicated that the hydrograph reproducibility of USF had been the highest among the SF models. Furthermore, AIC and Akaike weight (AW) were used to identify the most effective model among all those based on the information criteria perspective. The USF model received the lowest AIC score and the highest AW during most of the events, which indicates that it is the most parsimonious model compared to the other SF models. Moreover, uncertainty characterization of the SF model parameters was also conducted to analyze the effect of each parameter on model performance. Further, this chapter discussed the effect of lag time in Kimura’s model on hydrograph reproducibility and compared with Prasad’s SF model. The analysis of the effect of lag time on hydrograph reproducibility revealed that the use of optimum lag time in Kimura’s model could greatly improve the performance. Further, the Kimura’s SF model with optimum lag time exhibited higher hydrograph reproducibility associated with lowest error evaluation criteria and lowest AIC values in the single-peak events that makes it the superior model for single-peak events. Concurrently, Prasad’s model depicted better performance in terms of reproducibility and AIC aspect during the multi-peak events, which indicates that it is the parsimonious model for multi-peak events.
Chapter 3 demonstrates the bootstrap and jackknife resampling approaches associated with the SCE-UA global optimization algorithm for the analysis of calibrated parameter uncertainty and its subsequent effect on the model simulation of the urban-specific USF rainfall-runoff model. Both the approaches were applied to the residual time series that was computed as the difference between the observed and calibrated discharge time series. The parameter uncertainty was expressed by estimating the confidence interval (CI) of the USF model parameters obtained from both bootstrap and jackknife methods, and then the parameters from the highest to the lowest uncertainties were derived by utilizing two newly proposed parameter uncertainty indices, which can make the best use of CI. The highly uncertain parameters obtained were the same by the bootstrap and jackknife approaches even though the order of other model parameters was different. Moreover, investigations on the effect of calibrated model parameter uncertainty on model prediction revealed that the USF model was able to bracket most of the observations within the 95% CI prediction range by the bootstrap approach, whereas the jackknife method bracketed a reduced number of observations.

Chapter 4 investigated the effect of spatial distribution of rainfall over the basin in the USF model by introducing a parameter named as rainfall distribution factor (\(\gamma\)) and the results revealed that the introduction of parameter \(\gamma\) could greatly improve the performance of USF model. Further, this chapter proposes the 9-parameter GSF model for the water level prediction from the rating curve relationship and considering the rainfall distribution factor (\(\gamma\)). The GSF model optimizes not only parameter \(\gamma\) but also the rating curve constants \(a\) and \(b\) along with other model parameters which will reduce the efforts taken for the rating curve establishment of the target watersheds. The proposed GSF model was then applied to the semi-urban and rural watersheds in Japan to examine its applicability in different types of watersheds. Three other models were also applied in the watersheds for comparison with the GSF model and are (i) 8 parameter model - the GSF model without parameter \(\gamma\), (ii) 7 parameter model - the GSF model with fixed values of parameters \(a\) and \(b\) obtained from the established rating curve by the authorities, and (iii) 6 parameter model - the GSF model without parameter \(\gamma\) and with fixed values of parameters \(a\) and \(b\). The model performance was evaluated based on hydrograph reproducibility, AIC and AW, and the results revealed that the GSF model performed well in both the watersheds compared with the three other models, which emphasized the
effect of parameter $\gamma$ in GSF model. The sensitivity of 9 parameter GSF model was also evaluated using the global sensitivity method.

Chapter 5 presents the overall conclusions and recommendations for the storm-runoff analysis by different SF models in urban and non-urban watersheds including the future research works.
CHAPTER 2

AN EFFECTIVE STORAGE FUNCTION MODEL FOR AN URBAN WATERSHED

2.1 Introduction

Flooding is a crucial issue in both rural and urban areas, but the severity level of floods is greater in urban areas because most of the population is concentrated near floodplains (Mason et al., 2007). Urban areas are characterized by high population, concentrated human activities, presence of sewer systems, and impervious surfaces (Zoppou, 2001) in which the latter two features will accelerate the rainfall-runoff transformation process, and flood flows are therefore higher and more rapid than is the case in rural catchments (Hollis, 1975). These flash floods cause damage to human life, properties, different crops, etc. and have a negative impact (Padiyedath et al., 2017b; Sahoo and Saritha, 2015) in urban watersheds. Therefore, it is very important to detect urban floods compared to those in rural areas because of the increased risks and costs associated with them (Mason et al., 2012). The modeling of the rainfall-runoff transformation process in an urban watershed is essential not only for flash flood estimation but also for flood control by the drainage optimization using the pumping systems. Flood mitigation is one of the water management strategies that can control the excessive damage caused by floods (Bubeck et al., 2012). Hence, the accurate prediction of the hydrograph in advance, which includes the estimation of flood peak, time to peak, volume, lag time, etc., is important in order to avoid losses due to floodplain inundation. With the increasing population and urbanization, prediction of the urban flash flood is becoming an important problem to mitigate their impacts. For this purpose, the rainfall-runoff models are important tools and they play a central role, especially in urban watersheds.

Among the different lumped rainfall-runoff models, the SF models have been widely used in many parts of the world not only due to its easiness in computation and handling, but also due to the ease of expressing the nonlinear relationship of the rainfall-runoff process with simple equations. Enormous studies have been conducted using SF models in order to analyze the rainfall-runoff transformation process. There was a need for the comparative studies of rainfall-runoff models due to the existence of a variety of models which was identified quite early by the World Meteorological Organization (WMO,
in order to evaluate the ability of models to predict discharge and to provide information and guidelines for end-users on the use of such models with regard to specific conditions and accuracy requirements. In addition, the comparative assessments of models serve to highlight strengths and weaknesses of modeling approaches of various complexity (Perrin et al., 2001). The inferences of comparative assessments may be different from study to study based on the calibration methodology, model structure, study area, and the model performance evaluation criteria. There are several studies, which compared the performance of different rainfall-runoff models. For instance, Michaud and Sorooshian (1994) compared the discharge simulation accuracy of three models such as a complex distributed model, a simple distributed model, and a simple lumped model using RMSE and average bias as the evaluation criteria. Subsequently, Refsgaard and Knudsen (1996) inter-compared the lumped conceptual, distributed physically based and intermediate models using evaluation criteria of NSE and other index based on flow duration curve. Later, Perrin et al. (2001) examined the role of complexity in hydrological models by relating the number of optimized parameters with their model performance using four different criteria in 19 models whose number of parameters ranges from three to nine. He concluded that very simple models can achieve a level of performance almost as high as models with more parameters, and the complexity alone cannot guarantee good and reliable performances. This is because; the over-parameterization will add complexity and sometimes face the problem of equifinality (Beven, 1993) during calibration. Therefore, it is essential to address this issue through assessing the performance of different rainfall-runoff models with different complexity to identify an effective one for urban watersheds that have a promising future scope.

Despite the progress in the aforementioned direction, none of the studies has evaluated the various SF models not only in terms of the prediction accuracy but also in terms of the information criteria point of view, as far as the authors know. Specifically, there are no studies that describe the performance evaluation of different SF models for an urban area including the USF model. Hence, this study aims to identify an effective SF model, among those selected, for an urban watershed in terms of hydrograph reproducibility and from an AIC perspective. For this purpose, we have selected the relatively new USF model and four conventional SF models of Hoshi, Prasad, Kimura, and the linear model in order to conduct the performance evaluation. In addition, the effect of lag time in
Kimura’s model on hydrograph reproducibility was analyzed. The Kanda River basin, a typical small- to medium-sized urban watershed in Tokyo was selected as the target basin and the five SF models were applied to five selected flood events. In order to assess the performance in terms of the reproducibility of the hydrograph, we first formulated the SF models with optimal parameters identified using the SCE-UA global optimization method (Duan et al., 1992; Duan et al., 1993). The RMSE was chosen as the objective function for optimization. These SF models with optimal parameters were further assessed for reproducibility of the hydrograph with minimum RMSE and maximum NSE and other error functions of peak, volume, time to peak, lag time, and runoff coefficient. In addition, for the first time in SF model research, the authors have utilized AIC and AW to identify the most effective SF model for an urban watershed based on the information criteria perspective (Akaike, 1998).

2.2 USF and conventional SF models

2.2.1 Methodology

2.2.1.1 Conventional SF models

SF models are flood-event-based lumped models used as short-term models for simulating a few or individual flood events. They are characterized by the relationship between storage and discharge. They have different degrees of simplification that affect the input-output transformation (Takasao and Takara, 1988). The four conventional SF models are linear, Kimura, Prasad, and Hoshi models, and are shown in Table 2.1 with their associated continuity equations where $s$ is the storage (mm), $Q$ is the observed river discharge (mm/min), $t$ is the time (min), and $k_1, k_2, p_1, p_2$ are model parameters.

Among the models, Hoshi’s model has been found to be superior in terms of an additional parameter $p_2$, which was quantified by numerical experiments and can well define the flow characteristics based on kinematic wave theory (Hoshi and Yamaoka, 1982). Some simplifications of Hoshi’s storage model can lead to Prasad’s storage model (Prasad, 1967). If $p_2 = 1$ in Hoshi’s model, we obtain Prasad’s storage model. In a similar fashion, if we set $k_2 = 0$ in Prasad’s model, the model can be transformed into Kimura’s model (Kimura, 1961). Furthermore, the most simplified linear model can be obtained by maintaining $p_1 = 1$ in Kimura’s model. For the comparison, the authors used Kimura’s SF model with one storage tank, which is widely used as a special case of Kimura’s original model with the delay time (third parameter) equal to zero (Takasao and
Because delay time is a function of effective rainfall and basin characteristics, its estimation becomes a difficult process especially for small watersheds where small stream channels are not printed on a map (Sugiyama et al., 1997). Also, the linear model considered herein is used to check how efficiently a model can reproduce the hydrograph with a limited number of parameters.

2.2.1.2 USF model

In order to develop an SF model for an urban watershed without the separation of effective rainfall and baseflow components from total rainfall and discharge respectively, it is essential to consider all inflow and outflow components of the watershed. Fig. 2.1 shows the schematic diagram of all the possible inflow and outflow components of an urban watershed with the combined sewer system. We are considering the combined sewer system because many older cities in different parts of the world continue to operate combined sewers with a high installed rate instead of the separate system due to the high cost involved (Metcalf and Eddy, 1972; US EPA, 1999). The model is a lumped one based on the relationship between the rainfall over the basin and the runoff at the outlet point. The runoff at the outlet point is the river discharge although both pluvial and fluvial floods occur within the basin, which have a delayed effect in the river discharge at the outlet point. During light rain, only the pluvial flood occurs but finally discharging to the river and contributing to the river discharge. During heavy rain, both pluvial and fluvial floods

<table>
<thead>
<tr>
<th>No.</th>
<th>Models</th>
<th>Storage equation</th>
<th>Continuity equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Linear</td>
<td>( s = k_1 Q )</td>
<td>( \frac{ds}{dt} = R + I - E - O - Q - q_t )</td>
</tr>
<tr>
<td>2</td>
<td>Kimura</td>
<td>( s = k_1 (Q)^{p_1} )</td>
<td>( \frac{ds}{dt} = R + I - E - O - Q - q_t )</td>
</tr>
<tr>
<td>3</td>
<td>Prasad</td>
<td>( s = k_1 (Q)^{p_1} + k_2 \frac{dQ}{dt} )</td>
<td>( \frac{ds}{dt} = R + I - E - O - Q - q_t )</td>
</tr>
<tr>
<td>4</td>
<td>Hoshi</td>
<td>( s = k_1 (Q)^{p_1} + k_2 \frac{d}{dt} (Q)^{p_2} )</td>
<td>( \frac{ds}{dt} = R + I - E - O - Q - q_t )</td>
</tr>
<tr>
<td>5</td>
<td>USF</td>
<td>( s = k_1 (Q + q_R)^{p_1} + k_2 \frac{d}{dt} (Q + q_R)^{p_2} )</td>
<td>( \frac{ds}{dt} = R + I - E - O - (Q + q_R) - q_t )</td>
</tr>
</tbody>
</table>
occur and the fluvial flood causes more damage than the pluvial flood by overflowing the river. Therefore, the USF model measures the combined effect of both the floods at the outlet point. The basin storage is mainly composed of river storage, surface and subsurface storage, and the sewer system storage. The storage has been considered as just one independent cell for the entire basin. There is no other inflows from other basins but an outflow from the basin to the treatment plant through the combined sewer system rather than discharging into the river as lateral inflow. The inflow components in Fig. 2.1 are represented by rainfall $R$ (mm/min) and urban-specific and groundwater inflows from other basins $I$ (mm/min). Urban-specific inflows include leakage from water distribution pipes, irrigational flow, etc. The outflow components are constituted by the river discharge $Q$ (mm/min); evapotranspiration $E$ (mm/min); storm drainage from the basin through the combined sewer system $q_R$ (mm/min); water intake from the basin for intended purposes such as water supply, agricultural needs, etc. $O$ (mm/min), and groundwater-related loss $q_I$ (mm/min). In addition, domestic sewage $q_w$ has also been depicted in Fig. 2.1 even though it does not contribute to the watershed storage $s$ (mm).

![Fig. 2.1. Schematic diagram of all inflow and outflow components of an urban watershed with combined sewer system.](image)

$E$: Evapotranspiration  
$R$: Rainfall  
$I$: Urban specific and groundwater inflows from other basins  
$Q$: Water intake from basin  
$q_R$: Storm drainage from the basin through combined sewer system  
$q_w$: Domestic sewage  
$q_I$: Ground water related loss  
$q_l$: Infiltration hole height  
$q_R$: River discharge  
$s$: Storage  
$O$: Water intake from basin
The USF model is the empirical representation of Hoshi’s SF model shown in Table 2.1 in which the river discharge \( Q \) is replaced by the discharge including the storm drainage \( Q + q_R \). Combining the expression of storage for USF model with the associated continuity equation given in Table 2.1 yields the nonlinear expression of the USF model (Takasaki et al., 2009). Groundwater-related loss \( q_l \) was defined by considering the infiltration hole height \( z \) and is given by the following (Takasaki et al., 2009):

\[
q_l = \begin{cases} 
  k_3(s - z) & (s \geq z) \\
  0 & (s < z)
\end{cases}
\]  

(2.1)

where \( k_3 \) and \( z \) are the parameters. The expression for storm drainage \( q_R \) from the combined sewer system discharged out of the basin is developed by assuming a linear relationship between total discharge \( Q + q_R \) and the storm drainage \( q_R \) immediately after the rainfall. The \( q_R \) is defined (Takasaki et al., 2009) as follows:

\[
q_R = \begin{cases} 
  \alpha(Q + q_R - Q_0) & \alpha(Q + q_R - Q_0) < q_{R\text{max}} \\
  q_{R\text{max}} & \alpha(Q + q_R - Q_0) \geq q_{R\text{max}}
\end{cases}
\]  

(2.2)

where \( \alpha \) is the slope of the linear relationship between total discharge \( Q + q_R \) and the drainage \( q_R \); and \( Q_0 \) is the initial river discharge just before the rain starts (Takasaki et al., 2009). The maximum volume of \( q_R \) cannot exceed the sewer maximum carrying capacity \( q_{R\text{max}} \). Substituting the storage equation into the continuity equation will lead to a second-order ordinary differential equation (ODE) as follows:

\[
k_2 \frac{d^2}{dt^2} (Q + q_R)^{p_2} = -k_1 \frac{d}{dt} (Q + q_R)^{p_1} + R + I - E - O - (Q + q_R) - q_l
\]

(2.3)

In order to solve the second-order ODE, the change of variables is performed as follows:

\[
x_1 = (Q + q_R)^{p_2}
\]

(2.4)

\[
x_2 = \frac{dx_1}{dt} = \frac{d}{dt} \{(Q + q_R)^{p_2}\}
\]

(2.5)

Substituting Eq. (2.1) into Eq. (2.3) and performing the change of variables will lead to the emergence of two first-order ODEs concerning two conditions as shown in Eq. (2.1). When \( s \geq z \), the first-order ODE is as follows:

\[
\frac{dx_2}{dt} = \frac{(k_1)}{(k_2)} \left( \frac{p_1}{p_2} \right) x_1^{(p_1/p_2 - 1)} x_2 - \left( \frac{1}{k_2} \right) x_1^{(1/p_2)} - \left( \frac{k_1 k_3}{k_2} \right) x_1^{(p_1/p_2)} - k_3 x_2 + \\
\left( \frac{1}{k_2} \right) (R + I - E - O + k_3 z)
\]

(2.6a)
In the case of \( s < z \), the first-order ODE concerning the same processes are given by the following:

\[
\frac{dx_2}{dt} = -\left(\frac{k_1}{k_2}\right) \left(\frac{p_1}{p_2}\right) x_1^{(p_1/p_2-1)} x_2 - \left(\frac{1}{k_2}\right) x_1^{(1/p_2)} + \left(\frac{1}{k_2}\right) (R + I - E - O) \quad (2.6b)
\]

By solving the two, simultaneous, non-linear ODEs of \( \frac{dx_1}{dt} \) (Eq. 2.5) and \( \frac{dx_2}{dt} \) (Eq. 2.6) numerically, we obtain the total discharge \( Q + q_R \). In order to solve the two first-order simultaneous ODEs, we used the Runge-Kutta-Gill (RKG) method. The river discharge \( Q \) is obtained as the solution after subtracting the \( q_R \), which is calculated using Eq. (2.2), from the total discharge.

The USF model is a seven-parameter model with parameters \( k_1, k_2, k_3, p_1, p_2, z, \alpha \) used in the rainfall-runoff modeling. Generally, the conventional Hoshi SF is a four-parameter model with parameters \( k_1, k_2, p_1, p_2 \) used for the transformation of effective rainfall into direct runoff. However, the separation techniques involved result in uncertainties and erroneous estimation of runoff. Hence, in order to incorporate the loss related to groundwater \( q_l \) and to consider the observed discharge as a whole in urban watersheds, we added the term \( q_l \) (Eq. 2.1) with the addition of two more parameters \( k_3 \) and \( z \) and modified the framework. Therefore, now Hoshi’s SF model can be designated as a 6-parameter model. In a similar way, the Prasad, Kimura and Linear models were transformed into 5, 4, and 3-parameter models, respectively. In this chapter, the USF, Hoshi, Prasad, Kimura, and the Linear models will be the 7, 6, 5, 4, and 3 parameter models, respectively.

2.2.1.3 Parameter estimation

The performance of a model highly depends on how well the model is calibrated. There are chances for the existence of multiple optima (more than one solution) due to the non-linear structural characteristics of SF models. In order to overcome this problem, the SCE-UA method proposed by Duan et al. (1992; 1993), which will identify the global optimum parameters associated with a given calibration dataset, was used to identify the optimal parameters of all the aforementioned models. It is a well-known, global optimization strategy developed for effective and efficient optimization for calibrating the watershed models. The SCE-UA method has been found to be a useful technique for complex parameter identification problems in hydrologic modeling (Canfield and Lopes, 2004; Canfield et al., 2002; Eckhardt and Arnold, 2001; Kawamura et al., 2004). This
method is based on the synthesis of four concepts: competitive evolution, controlled random search, simplex method, and complex shuffling. The algorithmic parameters of SCE-UA were selected as per the recommendations of Duan et al. (1993). The population is partitioned into several complexes, each of which is permitted to evolve independently. The number of complexes, \( C \), was set equal to 20 and the number of populations in each complex, \( r = 2k + 1 \), where \( k \) is the number of parameters to be estimated. The objective function to be minimized using the SCE-UA method was selected as the RMSE between the observed and computed using the estimated parameters. The search range of parameters for SCE-UA was set as, \( k_1 (10\text{~}500) \), \( k_2 (100\text{~}5000) \), \( k_3 (0.001\text{~}0.05) \), \( p_1 (0.1\text{~}1) \), \( p_2 (0.1\text{~}1) \), \( z (1\text{~}50) \), and \( \alpha (0.1\text{~}1) \) (Takasaki et al., 2009).

2.2.1.4 Performance evaluation

The river discharge computed for each event using the different SF models was compared in order to assess the reproducibility of the observed hydrographs using eight performance evaluation criteria.

1. RMSE
2. NSE (Nash and Sutcliffe, 1970; ASCE, 1993)
3. Percentage error in peak discharge (PEP):
   \[
   \text{PEP} = \left[ 1 - \frac{\text{computed peak discharge}}{\text{observed peak discharge}} \right] \times 100
   \]
4. Percentage error in volume (PEV):
   \[
   \text{PEV} = \left[ 1 - \frac{\text{computed volume of discharge}}{\text{observed volume of discharge}} \right] \times 100
   \]
5. Percentage error in time to peak discharge (PETP):
   \[
   \text{PETP} = \left[ 1 - \frac{\text{computed time to peak}}{\text{observed time to peak}} \right] \times 100
   \]
6. Percentage error in lag time (PELT):
   \[
   \text{PELT} = \left[ 1 - \frac{\text{computed lag time}}{\text{observed lag time}} \right] \times 100
   \]
7. Percentage error in runoff coefficient (PERC):
   \[
   \text{PERC} = \left[ 1 - \frac{\text{computed runoff coefficient}}{\text{observed runoff coefficient}} \right] \times 100; \text{ and}
   \]

Further, AIC was also used in order to identify the most effective model by comparing the different models for each event. The most effective model is then the model with the lowest AIC score and is given by the following expression (Akaike, 1981; Akaike, 1998),

\[
AIC = 2k - 2\log(L(\hat{\theta}|y))
\] (2.7)
where $k$ is the number of parameters to be estimated and $\log(\mathcal{L}(\hat{\theta}|y))$ is the log likelihood at its maximum likelihood estimator $\hat{\theta}$ based on $y$ observations. Later, this concept was refined to correct for small data samples (Hurvich and Tsai, 1989) as follows:

$$AIC_c = AIC + \frac{2k(k+1)}{n-k-1}$$

(2.8)

where $n$ is the sample size. A better way of interpreting the $AIC_c$ score is to normalize the relative likelihood values as AW. The weight of all models summed together equals one and the model with the highest AW is considered to be the most effective. The AW is considered as the weight of evidence that the model $i$ is the best-approximating model for the given data and candidate models. The AW for the $i^{th}$ model ($AW_i$) is as follows:

$$AW_i = \frac{\exp(-0.5\Delta AIC_{c,i})}{\sum_{m=1}^{M} \exp(-0.5\Delta AIC_{c,m})}$$

(2.9)

where the $\Delta AIC_{c,i}$ is calculated as follows:

$$\Delta AIC_{c,i} = AIC_{c,i} + AIC_{c,min}$$

(2.10)

where $AIC_{c,i}$ is the individual $AIC_c$ score for the $i^{th}$ model, $AIC_{c,min}$ is the minimum $AIC_{c,i}$ score among $M$ models, and $M$ is the number of models.

2.2.1.5 Uncertainty Characterization

For the target watershed, optimal parameter sets were obtained for each event using all the models. However, the obtained parameter values were different for each event corresponding to each model. The variability in the model parameters induced due to the spatial averaging of rainfall received at different gauging points is termed as the parameter uncertainty (Chaubey et al., 1999) and is quantitatively assessed using relative error (RE), and coefficient of variation (CV). The different errors for the $i^{th}$ model and $p^{th}$ parameter are as follows:

$$RE_{i,p} = \frac{\sum_{j=1}^{N} |P_{i,j} - \overline{P}_i|}{\overline{P}_i}$$

(2.11)

$$CV_{i,p} = \frac{\sigma_{i,p}}{\overline{P}_i} \times 100$$

(2.12)

where $N$ is the number of target events, $P_{i,j}$ is the estimated parameter value for the $i^{th}$ model and $j^{th}$ event, $\overline{P}_i$ is the average parameter value from all the events, and $\sigma_{i,p}$ is the standard deviation for the $i^{th}$ model and the $p^{th}$ parameter value.
2.2.2 Study area and data used

The selected urban watershed for the particular study was the upper Kanda River basin and is shown in Fig. 2.2. The different SF models were applied in the target basin, having an area of 7.7 km² at Koyo Bridge, in order to determine the effective model. The Kanda River basin lies between latitudes 35.70° N and 35.64° N and longitudes 139.56° E and 139.64° E in Tokyo, Japan, with an urbanization rate of more than 95%. The source of the river is the Inokashira pond and it joins the Zenpukuji River and flows east (Ando and Takahasi, 1997). The drainage pattern follows the combined sewer system and the sewer installed population rate is 100%. The main flow path length of the river, sewer density of pipes having a diameter greater than 25 cm, and the average slope of the watershed are 6.017 km, 22.76 km⁻¹, and 0.025 radians respectively. The computed time of concentration of surface runoff from the upstream reaches to the watershed outlet was

![Fig. 2.2. Index map of (a) Japan, (b) Kanda River basin in Tokyo and (c) target area - upper Kanda basin at Koyo Bridge.](image-url)
about 30 min. The impervious area percentage was precisely estimated as 68% using the urban landscape geographic information system (GIS) delineation (Koga et al., 2016) that further reduced the water retention capacity of the basin significantly. There is a wide variety of land cover features with different impermeable properties within all land use classifications (Koga et al., 2016).

The smaller time of concentration indicated that the river discharge will occur immediately after the rainfall within a short period and it is desirable to use hydrological data at very short time intervals for the rainfall-runoff analysis. Therefore, the rainfall and water level data were collected at one-minute intervals from the Bureau of Construction, Tokyo Metropolitan Government (TMG), from 2003–2006 for the present study. The average rainfall of the basin was determined using the Thiessen polygon method from the eight rain gauges scattered over the basin as shown in Fig. 2.2. Five target events were selected from the data, whose 60-minute maximum rainfall ($R_{60}$) is greater than 30 mm and is capable of producing flash floods. Table 2.2 shows the characteristics of the five selected rainfall events. The inflow component $I$ in the continuity equation was fixed at 0.0012 mm/min based on the annual report of the Bureau of Construction, TMG. The water intake $O$ from the basin and evapotranspiration $E$ were set at 0 as there is no intake from the target basin and the evapotranspiration during heavy rainfall is insignificant. The maximum storm drainage, $q_{R_{max}}$ was estimated as 0.033 mm/min using Manning’s equation.

<table>
<thead>
<tr>
<th>Event No.</th>
<th>Event date</th>
<th>$R_{60}$ (mm/h)</th>
<th>Total R (mm)</th>
<th>Climatic factors</th>
<th>Number of peaks</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>13-10-2003</td>
<td>53.9</td>
<td>57.5</td>
<td>Intensive localized storm</td>
<td>Single-peak</td>
</tr>
<tr>
<td>2</td>
<td>25-06-2003</td>
<td>42.6</td>
<td>46.2</td>
<td>Frontal rainfall</td>
<td>Single-peak</td>
</tr>
<tr>
<td>3</td>
<td>8–10/10/2004</td>
<td>42.0</td>
<td>261.1</td>
<td>Typhoon</td>
<td>Multi-peak</td>
</tr>
<tr>
<td>4</td>
<td>11-09-2006</td>
<td>32.7</td>
<td>37.9</td>
<td>Frontal rainfall</td>
<td>Single-peak</td>
</tr>
<tr>
<td>5</td>
<td>15-07-2006</td>
<td>31.5</td>
<td>31.5</td>
<td>Frontal rainfall</td>
<td>Single-peak</td>
</tr>
</tbody>
</table>
2.2.3 Results and discussion

2.2.3.1 Parameter estimation

The SCE-UA method was applied for parameter estimation of the five SF models for the five selected flood events in the target watershed with RMSE as the objective function. The model parameters are estimated by calibration using the average watershed rainfall and the observed river discharge. The convergence of parameters was also checked and it was found that the parameters converged before the 50th generation in each SCE-UA application run. The total population generated was different from model-to-model based on the number of parameters in each model. The best parameter set among the total population at the 50th generation with the minimum RMSE was used for further hydrograph reproduction. Table 2.3 shows the elapsed time taken for calibration of models using SCE-UA and the computational time of each model for each event using the estimated parameters. All the model simulations carried out in this chapter were run on Windows 10 with Intel Core i7-6700 CPU as the processor and 16GB RAM. The parameter calibration and evaluation were conducted on MATLAB. It is clear from the table that the USF has taken the longest time for computation because it has the most number of parameters. On the other hand, the 3-parameter model has received the least time for simulations.

Table 2.3. Elapsed time taken for the calibration and evaluation of storage function models in each event.

<table>
<thead>
<tr>
<th>Model</th>
<th>Event 1</th>
<th>Event 2</th>
<th>Event 3</th>
<th>Event 4</th>
<th>Event 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>USF (sec)</td>
<td>Calibration</td>
<td>665.12</td>
<td>653.99</td>
<td>2923.85</td>
<td>869.76</td>
</tr>
<tr>
<td></td>
<td>Evaluation</td>
<td>0.57</td>
<td>0.56</td>
<td>1.44</td>
<td>0.73</td>
</tr>
<tr>
<td>Hoshi (sec)</td>
<td>Calibration</td>
<td>592.46</td>
<td>547.38</td>
<td>2570.06</td>
<td>703.16</td>
</tr>
<tr>
<td></td>
<td>Evaluation</td>
<td>0.4</td>
<td>0.39</td>
<td>1.24</td>
<td>0.46</td>
</tr>
<tr>
<td>Prasad (sec)</td>
<td>Calibration</td>
<td>452.54</td>
<td>412.8</td>
<td>1916.46</td>
<td>627.52</td>
</tr>
<tr>
<td></td>
<td>Evaluation</td>
<td>0.36</td>
<td>0.33</td>
<td>1.08</td>
<td>0.42</td>
</tr>
<tr>
<td>Kimura (sec)</td>
<td>Calibration</td>
<td>103.51</td>
<td>95.93</td>
<td>422.18</td>
<td>121.47</td>
</tr>
<tr>
<td></td>
<td>Evaluation</td>
<td>0.28</td>
<td>0.26</td>
<td>0.88</td>
<td>0.31</td>
</tr>
<tr>
<td>Linear (sec)</td>
<td>Calibration</td>
<td>29.75</td>
<td>27.86</td>
<td>124.65</td>
<td>36.92</td>
</tr>
<tr>
<td></td>
<td>Evaluation</td>
<td>0.26</td>
<td>0.23</td>
<td>0.66</td>
<td>0.26</td>
</tr>
</tbody>
</table>
Fig. 2.3 shows the estimated model parameters for each selected event and SF model. Figs. 2.3(a), (b), and (c) show the $k_1, k_3, z$ parameters, respectively, and these are associated with all of the five models. The $k_1$ values are quite close for all the models except for the 3-parameter model during events 4 and 5. Parameter $k_3$ was found to be
similar for the USF (7-parameter) and 6-parameter models during all the events even though it varies among events. The $k_3$ value for the other models was also found to be similar and they were close to zero. The $z$ parameter for the USF, 6, and 5-parameter models varies among events, while the 4 and 3-parameter models have quite similar values close to zero during all the events. Fig. 2.3(d) exhibits parameter $p_1$ that is common for all the models except the 3-parameter model. The $p_1$ values are sufficiently close for the 6, 5, and 4-parameter models during all the events. However, the USF model has the highest $p_1$ value among all the models even though the value is closer to the other models during events 1 and 3. Fig. 2.3(e) demonstrates parameter $k_2$ that is present in the USF, 6, and 5-parameter models, while Fig. 2.3(f) shows the parameter $p_2$, which forms a part of the USF and 6-parameter models only. We observed a high level of agreement between the USF and 6-parameter models in the $k_2$ value from Fig. 2.3(e). On the other hand, the 5-parameter model shows small disparities in the values as compared to those of the USF and 6-parameter models. However, the parameter fluctuates substantially during all the events for all the models. The parameter values of $p_2$ in Fig. 2.3(f) for the USF and 6-parameter models are identical during all the events although it varies among the events. Fig. 2.3(g) depicts parameter $\alpha$, which is associated with the USF model only. The $\alpha$ values were found to be consistent during all the events for the USF model.

It is evident from the above discussion that the USF and 6-parameter model parameters values are identical in all the events except for the parameters $z$ and $p_1$ in events 2, 4, and 5. During these events, the $z$ and $p_1$ parameters of both the models lie farther from each other, and the 6-parameter model lies close to the values of 5-parameter model. Generally, during the parameter estimation, each model attempts to either reduce or increase each parameter in association with the other parameters based on their model structure in order to get the best combination, which will lead to the better performance. Therefore, this could be a reason for the differences in values of parameters $z$ and $p_1$ in association with other parameters in USF and other models during events 2, 4, and 5, whose climatic factor is frontal rainfall as shown in Table 2.2. The effect of parameter uncertainty and variability based on the model structure are discussed in more detail in section 2.2.3.4.

2.2.3.2 Hydrograph reproducibility

The SF models with these identified parameters were used to estimate river discharge in order to evaluate hydrograph reproducibility from the observed rainfall as input. Fig.
2.4 shows the reproduced hydrograph using the different SF models with the parameters shown in Fig. 2.3. In Fig. 2.4, the x-axis and y-axis increments are different from event to event. It can be seen from Fig. 2.4 that the 7-parameter USF model nearly overlaps with the observed river discharge and precisely reproduces the shape of the observed hydrograph. It is also capable of accurate reproduction of the peak during all the events even though it shows slight deviations during events 4 and 5. During events 4 and 5, it was most close to the observed peak compared with the peaks estimated by other SF models. Therefore, the USF model can most exactly reproduce the shape of the observed hydrograph as well as the peak discharge compared to that of the other SF models irrespective of the number of peaks. Even though the 6-parameter model shows a slight deviation in the reproduced hydrograph on the rising and recession limbs during all the events, the model accurately reproduces the peak discharge, which is slightly less than that estimated by the USF model. The model does not preserve the shape of the hydrograph particularly well in the multi-peak event 3 although it estimates the peak accurately. The 5-parameter model underestimated the peak discharge during all the events except for event 1. The model failed to reproduce not only the shape of the hydrograph but also the peak, particularly in the multi-peak event. Both the 4 and 3-parameter models, especially the 3-parameter model, were unable to reproduce the observed hydrograph. They underestimated and early estimated the peak discharge during all the events. The models failed to conserve the shape as well as the peak discharge regardless of the number of peaks.

Fig. 2.5 shows the values of various error functions, i.e. RMSE, NSE, PEP, PEV, PETP, PELT, and PERC, as described in section 2.2.1.4, for the five events using the five models. From Fig. 2.5(a) and (b), we can see that the USF model generates the lowest RMSE, close to zero, and highest NSE, close to 100%, among the five SF models, followed by the 6, 5, 4, and 3-parameter models during all the events. It is evident that the model with a large number of parameters will have the lowest RMSE and highest NSE, which further reveals that the SCE-UA method has successfully identified the optimal parameters for each model during each event. The low RMSE and high NSE can be interpreted as high hydrograph reproducibility. However, the 4 and 3-parameter models have high RMSE and low NSE values as compared to those of the other models. This is because of the absence of parameters that describe the loop effect between storage and discharge during the rising and recession limbs. Fig. 2.5(c) depicts that the PEP
(a) Discharge (mm/min) vs. Time (min) for 12:00, 14:00, 16:00, 18:00, 20:00.

(b) Discharge (mm/min) vs. Time (min) for 10:00, 12:00, 14:00, 16:00, 18:00.

(c) Discharge (mm/min) vs. Time (min) for 12:00, 18:00, 00:00, 06:00, 12:00, 18:00, 00:00.

Graphs show the observed discharge (Q-observed) along with modeled discharges using USF, 6-Parameter, 5-Parameter, 4-Parameter, and 3-Parameter models.
estimated using the USF and 6-parameter models are very low and not greater than 10% during any of the events, even though the 6-parameter model shows PEP>10% during event 5. Both the models estimated a PEP close to zero during the first three events, while they slightly underestimated (positive PEP) the peak during events 4 and 5. In contrast, the 5, 4 and 3-parameter models largely vary in their PEP values and always underestimate the peak discharge. Like the PEP, the USF and 6-parameter models show the best performance in PEV and PETP values as shown in Fig. 2.5(d) and (e) respectively, which is close to zero as compared to that of the other models. Simultaneously, the 5, 4
and 3-parameter models generate higher values of PEV and PETP. They overestimated the volume and early estimated the peak.

Fig. 2.5(f) demonstrates the PELT generated by different models for the selected events. The USF model has values of either zero or close to zero immediately followed by the 6 and 5-parameter models respectively. The 4 and 3-parameter models have similar
PELT values among themselves and are far from those of the other SF model values. Fig. 2.5(g) additionally shows the PERC and we can see that the PERC value of the USF, 6, and 5-parameter models are very close to zero except for the 5-parameter model during event 2 and 6-parameter model during event 5. The high PERC value of the 5-parameter model during event 2 indicates a low volume of runoff estimated by the model as well as high PEV as shown in Fig. 2.5(d). In the same way, the negative PERC values generated by the 6-parameter model during event 5 can be interpreted as a high volume of runoff estimated by the model. The 4 and 3-parameter models exhibit greater discrepancies compared to those of the other models during all events.

The higher values of NSE coupled with the lower values of RMSE, PEP, PEV, PETP, PELP, and PERC for the USF model indicate that the hydrograph reproducibility of the USF model is the highest among the SF models. The 6-parameter model was also found to be good for urban discharge estimation just after the USF model. The 5-parameter model can be used as a substitute for the USF and 6-parameter models in urban rainfall-runoff transformation process with little deviation to some extent. However, the 4, and 3-parameter models were found to be inappropriate for hydrograph reproducibility.

2.2.3.3 AIC aspect

In addition to hydrograph reproducibility, AIC aspect was also used in order to determine the effectiveness of the models for each selected event. Fig. 2.6(a) shows the $AIC_C$ values (Eq. 2.8) for each model during each event. It can be seen from the figure that the 6-parameter model has the lowest $AIC_C$ during event 1 and event 2. However, the USF had the lowest $AIC_C$ during events 3, 4 and 5. Even though the USF model did not receive the lowest $AIC_C$ during the first two events, it was very close to the lowest value of the 6-parameter model. There is nearly no support for 4 and 3-parameter models from Fig. 2.6(a) because they generate a far higher $AIC_C$ score, which indicates the necessity of more parameters in order to describe the storage characteristics of the urban watershed more accurately. The exclusion of the delay time parameter in Kimura’s 4-parameter model could also be a reason for this high $AIC_C$ score. From Fig. 2.6(a), it is not easy to clearly distinguish the difference between the $AIC_C$ values of the USF, 6, and 5-parameter models. Hence, we analyzed the $AIC_C$ values using an associated statistic known as AW (Eq. 2.9) to depict the differences distinctly. As a general rule of thumb, the AW of the candidate models during each event should be higher than 10% of the highest AW of that event (Royall, 1997) so that we can easily exclude models with a weight lower than 10%
of the highest AW model. Based on this rule, we can exclude the 4 and 3-parameter models.

Fig. 2.6(b) shows the AW for each event using the different SF models. The weight exhibits an opposite trend to that of the $AICC$ values and the model with the highest weight is the best (Hurvich and Tsai, 1989). Like the $AICC$ score, the 6-parameter model received the highest weights during events 1 and 2. During the remaining events, the USF model has the highest weight followed by the 6-parameter model. Even though the 6-parameter is followed by the USF model, the difference between the AW values of these models is quite large, significantly greater for events 3 and 5. Therefore, the USF model is much more effective than the 6-parameter model during such multi-peak event 3 and single-peak event 5 based on the AW values. During event 1, the 6-parameter model was followed by the USF model and during event 2, it was followed by the 5-parameter model. The difference in AW values between the 6-parameter and USF models are not as great as compared to that during events 3 and 5. Consequently, the USF model can be more suitable for multi-peak events as compared to the other models as per the AIC aspect.

### 2.2.3.4 Parameter uncertainty

Fig. 2.7 shows the parameter variability of five SF models represented by two statistical indices (Eqs. 2.11 and 2.12). The seven symbols in the figure represent the different parameters of each SF model. Fig. 2.7(a) demonstrates the RE values of each parameter and which are entirely different for each model. The RE of parameter $k_1$, which...
is used to represent the physical watershed characteristics such as watershed area, land use, etc., is small compared to that of the other parameters for all the SF models, except for the 3-parameter model in which it is the parameter with the highest RE. The parameters \( k_3 \) and \( z \) are used to depict the groundwater-related loss. From Fig. 2.7(a), we can see that the RE of parameter \( k_3 \) is quite high in all models and the parameter \( z \) received the highest RE for the USF and 5-parameter models. The high RE of these two parameters plays an important role in hydrograph reproducibility of the SF models. The RE of \( z \) in the 4, and 3-parameter models is very low and the models are least affected by this parameter. The \( p_1 \) parameter is controlled by the flow regime (Sugiyama et al., 1997). It has higher RE values in the 6, 5, and 4-parameter models. It was found to be one among other parameters with a low RE in the USF model. The parameter \( k_2 \) is a complicated function of several variables that can affect the wedge storage as well as the storage-discharge relationship (Prasad, 1967). This parameter was included only in the USF, 6, and 5-parameter models and had a medium level of RE values. The parameter \( p_2 \) is incorporated in the USF and 6-parameter models and had quite high RE values in both models. The parameter \( \alpha \) is associated only with the USF model to represent the effect of storm drainage and is that with the least variability in the USF model.
Fig. 2.7(b) shows the CV values for the estimated parameters. CV is the numerical representation of variability in data. The parameter pattern in CV values is quite similar to that in RE values, even though it shows slight deviations. The observed deviations are (i) the parameter order changed for some models and (ii) the CV values of parameters were more closely located or sometimes overlapped. The parameter \( z \) had higher variability in its values for the USF and 5-parameter models. On the other hand, \( p_2 \) was more uncertain in nature for the 6-parameter model. \( k_3 \) and \( k_1 \) are the parameters with the highest CV value for the 4 and 3-parameter models, respectively.

In general, a higher variability in rainfall resulted in a higher variability in the parameters. A larger variation in rainfall values within a single event will result in a higher variation in all estimated parameters. The parameter estimates for each event may be quite inconsistent and this uncertainty in the model parameters can be attributed to the spatial variability in rainfall, change in watershed characteristics, etc.

It cannot be argued that the better performance of USF model over the other four models is essentially due to the additional parameter \( \alpha \). It is not because of just one additional parameter, but a combination of all the parameters. If the number of parameters was the criteria for model performance, the 3-parameter model should have comparable performance at least with the 4-parameter model. However, the 4-parameter model exhibits substantial improvement in performance compared with the 3-parameter model as shown in Fig. 2.5. The addition of parameter \( p_1 \) transformed the linear storage model into a non-linear SF model and improved its structure. However, the 4 and 3-parameter models depicted a non-linear and linear monovalent storage-discharge relationship respectively. On the other hand, the USF, 6, and 5-parameter models considered the looped storage-discharge relationship and hence asserted that the inclusion of loop effect can considerably enhance the performance. The 6-parameter model revealed an improved performance than the 5-parameter model even though both the model take care of the loop effect. This can be attributed to the representation of non-linear unsteady flow in 6-parameter model while the 5-parameter model constituted only the linear unsteady flow effects. Therefore, it can be deduced that the introduction of non-linear wedge storage can additionally increase the model performance. The difference in performance between the USF and 6-parameter models can be ascribed to the effect of storm drainage diverting to the treatment plant through the combined sewer system instead of going to the river in the USF model. According to the above discussion, it was noted that the models with a
different number of optimized parameters produced quite different results, especially for 4 and 3-parameter models with a difference of one parameter each. This strengthens the argument raised by Gan et al. (1997), in which the structure of the model is of critical importance for the model performance rather than the number of optimized parameters. In addition, the effectiveness of a model cannot be defined in terms of the individual additional parameters alone but should be considered as a combination of parameters that describe different watershed and flow attributes.

Steefel and Van Cappellen (1998) commented that an effective model is determined based on its simplicity relative to its performance for a given number of observations. Nevertheless, the simple 4 and 3-parameter models were not capable of reproducing the observed hydrographs and could not demonstrate an equivalent performance of that produced by the other SF models. Therefore, simplicity alone cannot be used as a valid criterion for how effective a model is. Perrin et al. (2001) suggested that the number of free parameters might be restricted between three and five in lumped rainfall-runoff models. However, even the 5-parameter model failed to exactly reproduce the hydrograph and peak. Therefore, the number of free parameters from three to five is not sufficient to clearly represent urban discharge at least in this particular study.

2.3 Kimura’s model with lag time

The results from the USF and conventional models simulation exhibited that the Kimura’s model without lag time failed to outperform in the flood prediction in comparison with the other SF models. Therefore, to know about the effect of lag time in Kimura’s model, the Kimura’s model with lag time was analyzed for its ability to reproduce the shape of the hydrograph as well as the hysteresis loop.

2.3.1 Methodology

2.3.1.1 Kimura’s model

It is very important to analyze the effect of lag time in Kimura’s model in terms of its ability to simulate the discharge and hence we analyzed the effect of lag time on Kimura’s model and made an attempt to understand whether the Kimura’s model without lag time can exhibit a comparable performance with Kimura’s model with lag time. Also, in order to check how effective the Kimura’s model with lag time, we compared the model with another 3-parameter SF model of Prasad. We used the Kimura's SF model with one
storage tank for the pervious area which is widely used as a special case of Kimura’s original model and is given as (Kimura, 1961),

\[ s(t) = k_1 Q_d^{p_1}(t) \]  \hspace{1cm} (2.13)

where \( s(t) \): storage at time \( t \) (mm), \( Q_d(t) \): direct runoff at time \( t \) (mm/min), and \( k_1, p_1 \): model parameters. Kimura introduced the bivalence of storage by the inclusion of lag time in the continuity equation and is as follows:

\[ \frac{ds(t)}{dt} = R_e(t - T_l) - Q_d(t) \] \hspace{1cm} (2.14)

where \( T_l \): lag time, \( R_e \): effective rainfall at time \( t-T_l \). The above continuity equation (2.14) requires the estimation of effective rainfall and baseflow separation for the evaluation of direct runoff, which is a subjective process. Therefore, in order to avoid the separation process, we used the same continuity equation of Kimura given in Table 2.1 with lag time instead of Eq. (2.14) and is given as:

\[ \frac{ds(t)}{dt} = R(t - T_l) - E(t - T_l) + I(t) - O(t) - q_l(t) - Q(t) \] \hspace{1cm} (2.15)

where \( R \): observed rainfall at time \( t-T_l \) (mm/min), \( E \): evapotranspiration at time \( t-T_l \) (mm/min), \( I \): urban specific and groundwater inflows from other basins at time \( t \) (mm/min), \( O \): water intake from the basin at time \( t \) (mm/min), \( q_l \): groundwater related loss at time \( t \) (mm/min), \( Q \): observed river discharge at time \( t \) (mm/min). The loss to groundwater \( (q_l) \) was already defined by Eq. (2.1). Substituting the storage equation of Kimura (Table 2.1) into Eq. (2.15) will lead to a first-order ordinary differential equation (ODE) as follows:

\[ k_1 \frac{dQ_d^{p_1}(t)}{dt} = R(t - T_l) - E(t - T_l) + I(t) - O(t) - q_l(t) - Q(t) \] \hspace{1cm} (2.16)

In order to solve this first-order ODE, the change of variable is performed as follows:

\[ x_1 = Q_d^{p_1}(t) \] \hspace{1cm} (2.17)

Substituting Eq. (2.1) into Eq. (2.16) and performing the change of variables will lead to the emergence of two first-order ODEs concerning two conditions as shown in Eq. (2.1). When \( s \geq z \), the first-order ODE is as follows:

\[ \frac{dx_1}{dt} = -k_3 x_1 - \left( \frac{1}{k_3} \right) \frac{1}{x_1^{p_1}} + \left( \frac{1}{k_1} \right) \left( R(t - T_l) - E(t - T_l) + I(t) - O(t) + k_3 z \right) \] \hspace{1cm} (2.18a)

In the case of \( s < z \), the first-order ODE concerning the same processes are given as,
\[
\frac{dx_1}{dt} = -\left(\frac{1}{k_1}\right)x_1^{p_1} + \left(\frac{1}{k_1}\right)(R(t - T_l) - E(t - T_l) + I(t) - O(t)) \tag{2.18b}
\]

By solving the non-linear ODE of (2.18a) and (2.18b) numerically using the RKG method, we obtain the total discharge \( Q \).

The conventional Kimura’s and Prasad’s SF models are three parameter models with parameters \( k_1, p_1, T_l \) and \( k_1, p_1, k_2 \) respectively. However, these 3-parameter models are transformed into 5-parameter models by the addition of two more parameters \( k_3 \) and \( z \) to each model in order to consider the observed discharge as a whole as explained in section 2.2.1.2. In order to analyze the effect of lag time, the same Kimura’s model was considered with the lag time equal to zero which is referred to as 4-parameter model hereinafter in this chapter. The Kimura’s model with optimized lag time was mentioned as Kimura’s model for the comparison with the 5-parameter (Prasad) model.

2.3.1.2 Parameter estimation and performance evaluation

The SCE-UA method proposed by Duan et al. (1992; 1993) was used to identify the optimal parameters of all the three models. The search range of parameters for SCE-UA was set as, \( k_1 (10-500), k_2(100-5000), k_3 (0.001-0.05), p_1 (0.1-1), z (1-50) \), and \( T_l (0-25) \). The hydrograph reproducibility of models with the observed one was assessed using the RMSE, NSE, and other error functions of percentage error in peak (PEP), percentage error in volume (PEV) and error in time to peak (ETP). The ETP is defined as,

\[
ETP = t_{po} - t_{pc} \tag{2.19}
\]

where \( t_{po} \): observed time to peak discharge (min), \( t_{pc} \): computed time to peak discharge (min).

The lag time in Kimura’s model is the lag between the peak rainfall and discharge and have a significant influence on the hydrograph reproducibility by delaying the runoff. Hence, it is important to assess the effect of lag time on the hydrograph reproducibility by Kimura’s model. To this purpose, lag times ranging from 0 to 25 min was considered and analyzed the associated changes in different hydrograph reproducibility characteristics such as RMSE, NSE, PEP, PEV, and ETP for each event. Then, the hydrograph reproducibility by the Kimura’s model was compared with the Prasad’s model for further performance evaluation. Additionally, AIC was also used in order to identify the best model for each event.

The target basin is the upper Kanda River basin with an area of about 7.7 km\(^2\) at Koyo
Bridge as shown in Fig. 2.2. The rainfall and water level data at one-minute interval was collected from the Tokyo Metropolitan Government (TMG) during 2003-2006 for the study. Five target events were selected from the data, whose 60-minute maximum rainfall ($R_{60}$) is greater than 30 mm, for the application of SF models and are shown in Table 2.2. The rainfall data from the eight rain gauges were used to compute the catchment average rainfall by using the Thiessen polygon method. The inflow component $I$ was fixed at 0.0012 mm/min based on the business annual report of the TMG. The other outflow components $O$ and $E$ were set at zero.

### 2.3.2 Results and discussion

#### 2.3.2.1 Parameter estimation

The event-based optimal parameters of Kimura’s model with lag time were estimated using the SCE-UA optimization method and are shown in Fig. 2.8 along with the 4 and 5-parameter models. Fig. 2.8(a), (b), (c), and (d) show the parameters $k_1, p_1, k_3,$ and $z$ respectively, and these are associated with all the three considered models. Fig. 2.8(a) shows that the Kimura’s model has the lowest and quite similar $k_1$ values compared with other models among all the events except event 5. The other two models, 5 and 4-parameter models, have quite near values of $k_1$ and they come closer to the values of Kimura’s model during events 3 and 5. Fig. 2.8(b) shows that the $p_1$ values of Kimura’s model are highly fluctuating among the events and are far higher than other model parameter values. However, the $p_1$ value of all the three models meets at event 3, which is a multi-peak event. The other two models have alike $p_1$ values and are consistent with the events. The parameter $k_3$ exhibits the similar pattern of $p_1$ and all the model parameters coincide at event 3 as shown in Fig. 2.8(c). Kimura’s model has higher values of $k_3$ compared with other models that are relatively stable. It can be clearly seen from Fig. 2.8(d) that there is a gradual increase in the values of parameter $z$ in 5-parameter model from event 2 onwards, in contrast to the consistent values of $z$ in Kimura’s model. The 4-parameter model was also able to generate $z$ values analogous to Kimura’s model except for event 1. The parameter $k_2$ depicted in Fig. 2.8(e) is present only in 5-parameter model and it ranges between 300 and 1000. The parameter, $T_l$ depends on the hyetograph and is varying from event to event as shown in Fig. 2.8(f). The observed maximum and minimum $T_l$ are 20 and 10 min respectively and conclusively we can say that the watershed response to a rainfall event is 16 min on an average. This shorter lag time depicts that the watershed can generate floods immediately after the rainfall.
The effect of lag time ($T_l$) in Kimura’s model was analyzed using the performance evaluation criteria of RMSE, NSE, PEP, PEV, and ETP for each event and are shown in Fig. 2.9. The values corresponding to $T_l=0$ represent the 4-parameter Kimura’s model without lag time and the values at optimized lag time represent Kimura’s model and are tabulated in Table 2.4. It can be envisaged from Fig. 2.9(a) that the RMSE have high
value at $T_l=0$. It starts decreasing with increase in $T_l$ until it reaches the minimum RMSE values at optimum $T_l$. Once it reaches the minimum RMSE, it begins to increase with further increase in $T_l$. The NSE also followed the same pattern of RMSE as shown in Fig. 2.9(b), but obviously in the opposite direction. Apart from RMSE and NSE, the PEP exhibited a different trend with changes in $T_l$ as shown in Fig. 2.9(c). It starts to decrease with increase in $T_l$ and the PEP values close to zero was obtained before reaching the optimum $T_l$ in all the events. The changes in PEV values with changes in $T_l$ of the model are shown in Fig. 2.9(d) and are similar to the trend in PEP values. The minimum PEV value adjacent to zero was observed at a different $T_l$ rather than the optimized value except for event 5. Generally, with the increase in $T_l$, the underestimated peak discharge progressively moved to overestimation and the overestimated volume gradually changed.
to underestimation. Fig. 2.9(e) shows that the ETP gradually advances from early to late prediction with the increase in $T_l$ and approaches zero at a particular lag time rather than the optimum one. The results revealed that the lag time has a higher impact on the hydrograph reproducibility characteristics. Hence, the estimation of optimum lag time, which gives the best combination of evaluation criteria, is essential to achieve a better performance.

2.3.2.3 Hydrograph reproducibility

Further, the hydrograph reproducibility in terms of the error functions by the three models (Kimura without lag time, Kimura with optimized lag time, and Prasad) for each event are shown in Table 2.4 which include RMSE, NSE, PEP, PEV, and ETP. Additionally, Fig. 2.10 shows the visual representation of hydrograph reproducibility of the five selected events by the models. From Table 2.4, we can see that 4-parameter model received highest RMSE and least NSE in all the events, which further reveals its low hydrograph reproducibility. It is evident from the table that the model always underestimated peak discharge (positive PEP) and overestimated the volume (negative PEV) with an early peak prediction (positive ETP) in all the events. It is also clear from
Table 2.4. Comparison of RMSE, NSE, PEP, PEV, and ETP by the SF models.

<table>
<thead>
<tr>
<th>Event No.</th>
<th>Model</th>
<th>RMSE (mm/min)</th>
<th>NSE (%)</th>
<th>PEP (%)</th>
<th>PEV (%)</th>
<th>ETP (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4-parameter (T_l=0)</td>
<td>0.051</td>
<td>89.6</td>
<td>6.4</td>
<td>-9.4</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Kimura (T_l=16)</td>
<td>0.012</td>
<td>99.4</td>
<td>3.2</td>
<td>0.3</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>5-parameter</td>
<td>0.016</td>
<td>98.9</td>
<td>-0.5</td>
<td>-1.2</td>
<td>-1</td>
</tr>
<tr>
<td>2</td>
<td>4-parameter (T_l=0)</td>
<td>0.048</td>
<td>74.5</td>
<td>19.9</td>
<td>-12.8</td>
<td>13</td>
</tr>
<tr>
<td></td>
<td>Kimura (T_l=16)</td>
<td>0.012</td>
<td>98.5</td>
<td>-11.6</td>
<td>0.4</td>
<td>-2</td>
</tr>
<tr>
<td></td>
<td>5-parameter</td>
<td>0.014</td>
<td>97.8</td>
<td>7.9</td>
<td>1.6</td>
<td>-4</td>
</tr>
<tr>
<td>3</td>
<td>4-parameter (T_l=0)</td>
<td>0.025</td>
<td>92.9</td>
<td>9.1</td>
<td>-1.7</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>Kimura (T_l=10)</td>
<td>0.015</td>
<td>97.4</td>
<td>-8.0</td>
<td>1.0</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>5-parameter</td>
<td>0.013</td>
<td>98.1</td>
<td>3.2</td>
<td>0.4</td>
<td>-5</td>
</tr>
<tr>
<td>4</td>
<td>4-parameter (T_l=0)</td>
<td>0.032</td>
<td>53.1</td>
<td>42.8</td>
<td>-7.3</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Kimura (T_l=20)</td>
<td>0.004</td>
<td>99.1</td>
<td>-7.2</td>
<td>2.1</td>
<td>-1</td>
</tr>
<tr>
<td></td>
<td>5-parameter</td>
<td>0.017</td>
<td>86.0</td>
<td>26.0</td>
<td>4.1</td>
<td>-2</td>
</tr>
<tr>
<td>5</td>
<td>4-parameter (T_l=0)</td>
<td>0.031</td>
<td>56.8</td>
<td>40.6</td>
<td>-11.6</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>Kimura (T_l=20)</td>
<td>0.002</td>
<td>99.8</td>
<td>-1.4</td>
<td>0.01</td>
<td>-1</td>
</tr>
<tr>
<td></td>
<td>5-parameter</td>
<td>0.017</td>
<td>86.9</td>
<td>28.0</td>
<td>0.9</td>
<td>-3</td>
</tr>
</tbody>
</table>

Fig. 2.10 that the 4-parameter model considerably underestimated the peak discharge with a highly deviated recession limb and lags behind the observed hydrograph with an early estimated peak. However, the introduction of lag time in Kimura’s model drastically changed the RMSE to the least and NSE to the highest values except for event 3, a multi-peak event, as shown in Table 2.4. Also, the model started to slightly overestimate the peak discharge with a late peak prediction which was very close to the observed time to peak except for event 1. The model was able to reproduce the volume, which was close to the observed volume even though it was consistently underestimated very slightly. It can also be envisaged from Fig. 2.10 that the Kimura’s model slightly overestimated the peak discharge in all the events except for event 1 even though it fits well with the rising and recession limbs. Therefore, the results exhibited that the introduction of lag time in Kimura’s model greatly improved its reproducibility.
Fig. 2.10. Reproduced hydrographs by each model for (a) event 1, (b) event 2, (c) event 3, (d) event 4, and (e) event 5.

On the contrary, the 5-parameter Prasad’s model has the lowest RMSE and highest NSE for event 3 and having comparable RMSE and NSE values with Kimura’s model during the rest of the events. The 5-parameter model gives best PEP values in events 1, 2, and 3 among all the models as shown in Table 2.4 even though it considerably underestimated the peak discharge during events 4 and 5 that is evident from Fig. 2.10. Therefore, the 5-parameter model can be considered as the good model in estimating the peak discharge for the single as well as multi-peak events compared with Kimura’s model. The model was also able to reproduce the shape of the hydrograph in events 1, 2, and 3 although it depicted a deviated rising limb in the events 4 and 5 as shown in Fig. 2.10. It is noticeable from the table that the 5-parameter model received low PEV values close to
zero throughout all the events. However, the model has the least PEV value only during event 3, which further revealed that the model is good for the volume estimation of multi-peak events over the Kimura’s model. On the other hand, Kimura’s model was superior to 5-parameter model in the volume estimation of single-peak events. The ETP values exhibited in Table 2.4 revealed that the Kimura’s model is good in estimating the time to peak discharge compared with 5-parameter model during all the events, especially in multi-peak events. This is because of the presence of lag time in Kimura’s model, which can delay the time to peak discharge based on the rainfall.

The above results demonstrated that Kimura’s model has high hydrograph reproducibility during the single-peak events. This can be attributed to the effect of incorporated lag time on the runoff response of the basin. The consideration of single lag time for the multiple peaks in a multi-peak event may be insufficient to achieve a higher reproducibility. Therefore, the 5-parameter model can be contemplated as the good model for reproducibility of multi-peak events. Additionally, hydrograph characteristics of 4-parameter model revealed that the model is not appropriate for both single and multi-peak events, which additionally showed the relevance of lag time in Kimura’s SF model.

2.3.2.4 Storage hysteresis loop

Furthermore, the storage hysteresis loop effect was analyzed by computing the storage estimated by the models. Fig. 2.11 shows the storage hysteresis loops reproduced by the models for all the events. The continuity Eq. (2.15) was used to compute the storage which requires the estimation of the outflow component \( q_t \), that represents the groundwater related loss. However, the quantification of \( q_t \) further needs two parameters \( k_3 \) and \( z \) as shown in Eq. (2.1) which is not known for the actual watershed. Consequently, we have computed the storage estimated by the models and compared the storage loops among the models. It can be envisaged from Fig. 2.11 that the 4-parameter model generated a bivalent storage loop and the storage is increasing with an increase in discharge. After the inflection point, the loop changed the direction and the storage started to decrease. We can see from Fig. 2.11(a), (b), (d), and (e) that the model generated single loops during the single-peak events, while the produced loop had a complicated shape with multiple loops in multi-peak event 3 as shown in Fig. 2.11(c). However, it is clear from Fig. 2.11 that the storage loop produced by Kimura’s model was very narrow and become close to a monovalent storage-discharge relationship in all the events even though the model has multiple loops during event 3. The narrow loop was arisen due to the
Fig. 2.11. Storage hysteresis loop reproduced by each model for (a) event 1, (b) event 2, (c) event 3, (d) event 4, and (e) event 5.
incorporation of the lag time, which was 16, 16, 10, 20, and 20 min during events 1, 2, 3, 4, and 5 respectively as shown in Fig. 2.8(f). The storage estimated by the model was very low compared with the 4-parameter model. On the other hand, 5-parameter model exhibited a clear bivalent storage-discharge relationship as shown in Fig. 2.11. The storage by the 5-parameter model during the rising limb portion was close to that of 4-parameter model while the storage during recession limb portion was lower than the 4-parameter model in all events except for event 5. This difference in the storage loop behavior between the models during event 5 can be possibly ascribed to the higher $z$ value of the model as shown in Fig. 2.8(d). The estimated storage by the 5-parameter model was far higher with a relatively wide loop when compared with the storage loop of Kimura’s model.

2.3.2.5 AIC aspect

The best model for each selected event was determined by using the AIC aspect and are shown in Table 2.5. The best model is the one with the lowest AIC score. The results show that the 4-parameter model could not succeed to achieve lower AIC values in any of the events and was far higher compared with other model values. The addition of lag time parameter in the Kimura’s model substantially reduced the AIC values and made it comparable with the 5-parameter Prasad’s model values during all the events. The Kimura’s model with optimized lag time has the lowest AIC values in events 1, 4, and 5, which are single-peak events. Concurrently, 5-parameter model received lowest AIC

Table 2.5. The summary of AIC results for the five events.

<table>
<thead>
<tr>
<th>Event No.</th>
<th>Model</th>
<th>Kimura without $T_l$</th>
<th>Kimura</th>
<th>Prasad</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>AIC</td>
<td>552.0</td>
<td>389.4</td>
<td>395.2</td>
</tr>
<tr>
<td></td>
<td>AICc</td>
<td>552.1</td>
<td>389.6</td>
<td>395.3</td>
</tr>
<tr>
<td>2</td>
<td>AIC</td>
<td>1103.0</td>
<td>859.3</td>
<td>854.7</td>
</tr>
<tr>
<td></td>
<td>AICc</td>
<td>1103.2</td>
<td>859.4</td>
<td>854.8</td>
</tr>
<tr>
<td>3</td>
<td>AIC</td>
<td>4128.1</td>
<td>3877.6</td>
<td>3842.4</td>
</tr>
<tr>
<td></td>
<td>AICc</td>
<td>4128.2</td>
<td>3877.6</td>
<td>3842.4</td>
</tr>
<tr>
<td>4</td>
<td>AIC</td>
<td>2802.2</td>
<td>2240.3</td>
<td>2299.5</td>
</tr>
<tr>
<td></td>
<td>AICc</td>
<td>2802.3</td>
<td>2240.4</td>
<td>2299.6</td>
</tr>
<tr>
<td>5</td>
<td>AIC</td>
<td>1729.9</td>
<td>1398.2</td>
<td>1444.6</td>
</tr>
<tr>
<td></td>
<td>AICc</td>
<td>1730.0</td>
<td>1398.3</td>
<td>1444.7</td>
</tr>
</tbody>
</table>
values in events 2 and 3 in which event 3 is a multi-peak event. The AICc values computed for each event was almost equal to the AIC values, which indicate that the dataset used is long enough to consider for the AIC analysis (Hurvich and Tsai, 1989). The AIC values highly depend on the number of parameters to be optimized and it is evident that the models with the same number of parameters may have almost the same AIC values. However, the Kimura and 5-parameter models have the same number of optimized parameters and yet the Kimura’s model received lowest AIC values during most of the single-peak events, which make it the best model for the single-peak events compared with 5-parameter model. This higher performance exhibited by Kimura’s model can be attributed to the presence of lag time parameter, which can effectively constitute the hydrograph lagging. On the other hand, the 5-parameter model received the lowest AIC value during the multi-peak event, which makes it suitable for multi-peak events. The higher AIC score generated by 4-parameter model specifies that the incorporation of lag time is indispensable in order to achieve better performance in urban watersheds.

2.4 Conclusions

Firstly, the USF and other four conventional models with optimal parameters identified using the SCE-UA method were applied to five flood events in an urban watershed in Tokyo to evaluate performance with minimum RMSE. Initially, the models were assessed for their hydrograph reproducibility using the seven error functions of RMSE, NSE, PEP, PEV, PETP, PELT, and PERC. The results revealed that the USF model had the lowest RMSE (high NSE) among all the models for all the events, which implies that the SCE-UA method successfully identified the optimal parameters. The lower values of PEP, PEV, PETP, PELT, and PERC of the USF model further indicate that the hydrograph reproducibility of USF model is the highest among the studied SF models. In addition, the summary of AIC results shows that the USF received the highest AW during most of the events compared to that of the other SF models, which makes it the most effective model. The other SF models have lower AW scores, indicating the necessity of the addition of more parameters that describe the storage characteristics of an urban watershed. In conclusion, the USF model can be considered as the best model for not only hydrograph reproducibility but also the most parsimonious based on the AIC perspective during most of the flood events in an urban watershed, when compared to the conventional models, if the optimal parameters are successfully identified for the events.
The uncertainty characteristics reveal that it is necessary to investigate the aspect of uncertainty of the parameters in more detail to identify the key parameters of runoff response in an urban basin.

The results also exhibited that the 4-parameter Kimura’s model without lag time failed to outperform in the flood prediction in comparison with the other SF models. Further, we analyzed the effect of lag time in Kimura’s model (5-parameter) on hydrograph reproducibility and compared with 5-parameter Prasad’s SF model. The Kimura’s SF model with optimum lag time exhibited higher hydrograph reproducibility associated with lowest error evaluation criteria and lowest AIC values in the single-peak events, which makes it the superior model for single-peak events. Concurrently, the 5-parameter model depicted better performance in terms of reproducibility and AIC aspect during the multi-peak events, which indicates that it is the parsimonious model for multi-peak events. The inability of Kimura’s model to truly reproduce the observed hydrograph of multi-peak events can be ascribed to the consideration of single lag time for the multiple peaks in the model, which makes the model parsimonious only for the single-peak events. The differences in performance between the Kimura’s model with and without lag time can be attributed to the differences in the values of lag time parameter. Therefore, the results revealed that the inclusion of optimized lag time can considerably enhance the performance of Kimura’s model and its incorporation is inevitable.

The validation process of the models is very crucial with an ultimate goal of producing an accurate and credible model and it involves parameter uncertainty. However, in this chapter, we are mainly concerned with the calibration of the selected SF models and their associated performance. Chapter 3 will cover the detailed uncertainty analysis of USF model parameters and their relative stability.
CHAPTER 3
PARAMETER UNCERTAINTY ANALYSIS OF USF MODEL

3.1 Introduction

Urban watersheds are defined as the watersheds in which the urban areas occupy most of the basin from upstream to downstream and are under constant development in terms of buildings, roads, other infrastructures, etc. (Kawamura, 2018). The modeling of urban watershed processes is complicated due to the increasing complexities of the urban hydrologic system, that can be attributed to urbanization, rapid population growth, model scale, etc. (McPherson and Schneider, 1974). Generally, in rural watersheds, the percentage impervious areas as well as the installed sewer system density is either very low or absent. They will undergo slow and steady changes of hydrologic and hydraulic characteristics and the corresponding flood risk will be moderate due to the relatively low population and settlements it accommodates. In contrast to rural watersheds, the urban watersheds face constant and drastic changes in terms of increase in impervious land cover and graded land surfaces, expansion of existing sewer systems, frequent occurrence of high intensity rainfall due to the heat island phenomena, leakage from the water distribution system, increased flood and inundation risk, increase in human settlement and associated activities, removal of vegetation and natural storage, etc. (Amaguchi et al., 2012). These changes alter the runoff process significantly and accelerate the rainfall-runoff transformation process, which could lead to higher and rapid flood flows (Hollis, 1975). Therefore, it is very important to detect these urban flood flows, as they are associated with increased risks and costs (Mason et al., 2012). For this purpose, the rainfall-runoff models are important tools and they play a central role in urban watersheds (Padiyedath et al., 2018a).

The predictions made using rainfall-runoff models are inherently uncertain and the three major sources of uncertainties are data uncertainty, model structure uncertainty, and parameter uncertainty (Bates and Townley, 1988; Sivakumar and Berndtsson, 2010). The model parameter uncertainty has received a prime recognition over other sources of uncertainties in the field of hydrological modeling and recent studies on hydrological model uncertainties mostly refer to the identification of parameter uncertainty (Uhlenbrook et al., 1999) or parameter calibration (Ajami et al., 2004). This parameter
uncertainty will further contribute to model simulation uncertainties (Freer et al., 1996) and hence its quantitative evaluation is critical in reducing the uncertainty of these simulations. Among the different techniques available for the parameter uncertainty analysis, the nonparametric method has gained popularity over other methods as they make no prior assumptions on the model structure and thus are more flexible. The bootstrap method (Efron, 1979) and the jackknife method (Quenouille, 1949) are the nonparametric techniques, developed for random resampling of the original data set to develop replicate data sets from which the underlying distribution of the statistics of interest such as mean, variation, correlation, etc. can be estimated (Sivakumar, 2017). This resampling techniques has applications in diverse fields like hydrology, groundwater hydrology, air pollution modeling, toxicology, etc. (Dixon, 2006). However, use of these techniques for model parameter uncertainty analysis by employing the time series data appears to be quite narrow until recently and very limited studies have been conducted to quantify the calibrated parameter uncertainty of rainfall-runoff models.

The rainfall-runoff modeling and the associated uncertainty studies are highly dependent on the nature of the study area as well as the model being used (Mockler, et al., 2016). Therefore, there is a need to carry out such studies in different types of watersheds worldwide under varying agro-climatic conditions with different rainfall-runoff models. The model parameter uncertainty studies have been mainly conducted in large watersheds with different types of land use classes. To the best of our knowledge, no studies on parameter uncertainty analysis of urban-specific rainfall-runoff models using the bootstrap and jackknife approaches have been reported for urban watersheds. It is often assumed, incorrectly, that the rainfall-runoff models developed for river basin hydrologic analysis can be transferred more or less intact to the urban basins (McPherson and Schneider, 1974). Generally, urban areas have been drained by underground sewer systems that were specially designed to remove storm water as rapidly as possible. In order to accurately predict floods, it is essential to consider this flow component. The USF model (Takasaki et al., 2009) is an urban-specific conceptual model, which considers outflow from the combined sewer systems along with other inflow and outflow components. The performance of different SF models have already been evaluated and it was found that the USF model performs better as compared to conventional SF models for a typical small to medium sized urban watershed in Tokyo, Japan (Padiyedath et al., 2018a; Padiyedath et al., 2018b) and has potential applications in urban watersheds.
Therefore, it is essential to address the parameter uncertainty issues associated with this model in order to reduce its effects on the model simulation uncertainty.

In light of the aforementioned discussions, it is apparent that very few studies have been conducted for model parameter uncertainty analysis using the bootstrap and jackknife methods. Among these, none of the studies have been carried out in urban watersheds, particularly using the USF model (Takasaki et al., 2009), a relatively new SF model specially developed for urban watersheds where combined sewer systems are in use. Hence, an attempt has been made to explore the use of bootstrap and jackknife resampling methods to evaluate the uncertainty of optimal parameter estimates that arise due to uncertainties in the input data using a case study in the upper Kanda river basin, a typical small to medium sized urban watershed in Tokyo, Japan. Previous studies on model parameter uncertainty analysis were conducted using the all available data instead of individual flood events since the hydrologists were mainly interested in the estimation of catchment hydrological variables such as peak flow, flood volume, etc. with utmost accuracy and reliability. The flood-runoff analysis in urban watersheds is generally event-based due to the relevance of flash flood peak estimation and short time of concentration. Therefore, the bootstrap approach was applied in this study to both the individual flood events and the whole events in order to demonstrate the impact of different available data scenarios on the uncertainty behavior of calibrated parameters whereas the jackknife approach was applied only to the whole events. Additionally, two types of new indices have been proposed for the detailed analysis of uncertainty involved in the model parameters and model simulations.

3.2 Methodology

3.2.1 Residual-based bootstrap approach

The classical idea behind the bootstrap method is the resampling and extraction of $B$ samples from the original sample with an unknown distribution having a size of $n$ as shown in Fig. 3.1. This method makes no assumptions concerning the distribution of data or model being used. The $B$ bootstrap samples can provide the best knowledge regarding the underlying true distribution of the sample. However, the use of bootstrap for time series data was limited because the classical bootstrap technique assumes that the data set is independent and identically distributed ($iid$) (Efron, 1982), which means each data of the data set will be mutually independent and selected from the same population.
Generally, the time series data sets are highly dependent in nature and it is quite unreasonable to perform classical bootstrapping as it destroys the original dependency structure of the time series. In order to overcome the problem of dependence of time series, the bootstrap method can be extended either as a block bootstrap (Davison and Hinkley, 1997; Künsch, 1989), in which the time series is divided into different blocks and these blocks are resampled instead of the individual data value or as a model based bootstrap (Lahiri, 2003; Selle and Hannah, 2010), which adopts a specific time-series form of dependence. In Selle and Hannah (2010), they considered a first-order autoregressive model in order to consider the dependence of model error rather than assuming it is independent. However, a modification of this approach, which can be simpler to apply in practice, is to construct the bootstrap samples as fitted values plus residuals, where the residuals are sampled with replacement from the observed distribution of residuals. This method is known as the resampling of residuals (Shalizi, 2016; Shao and Tu, 1995) (hereinafter residual-based bootstrap).

The residual-based bootstrap approach was used to generate sample estimates of the hydrologic model parameters corresponding to the calibrated data set and to quantify the associated uncertainties. In this method, first we calibrate the model, and then simulate by resampling residuals to that estimate and adding them back to the fitted values (Shalizi, 2016). This surrogate data set is then re-analyzed like a new data set. By repeating the procedure $B$ times, bootstrapped time series are generated and the hydrologic model is then calibrated using each bootstrapped time series, to arrive at bootstrapped estimates of the calibrated parameter sets. These estimates are further used for the confidence interval analysis of the model parameter estimators. The procedure for the residual-based
bootstrap, explained by Stine (1985) and others (Shalizi, 2016; Shao and Tu, 1995), is described as follows.

Consider the original data set \( \{ X(t), Q(t) \} \); where \( X(t) \) is the input data at time \( t \), \( Q(t) \) is the observed discharge data at time \( t \), and \( t \) is the time from \( 1, ..., n \) where \( n \) is the data length. The observed discharge can be written as a function, \( Q(t) = F(X, \theta) + \epsilon(t) \) where \( X = X(1), ..., X(t) \), \( \theta \) is the parameter vector \( \theta_1, ..., \theta_k \) with \( k \) being the number of model parameters, and \( \epsilon(t) \) is the model residuals. Initially, the model was calibrated using the SCE-UA method to obtain the calibrated parameter vector \( \hat{\theta} \) which was further used along with the input data to compute the model calibrated discharge data, \( \hat{Q}(t) = F(X, \hat{\theta}) \), which can be demonstrated as \( Q(t) = F(X, \hat{\theta}) + \hat{\epsilon}(t) \). Thereafter, the model residuals can be expressed using the following equation.

\[
\hat{\epsilon}(t) = Q(t) - \hat{Q}(t) = Q(t) - F(X, \hat{\theta}) \tag{3.1}
\]

The model residuals, \( \hat{\epsilon}(t) \), were assumed to be iid for \( t = 1, ..., n \), which is the only assumption made for the bootstrapping (Stine, 1985). Julian and Gardner (2014) examined the effect of land cover on runoff patterns and the results revealed that increases in urbanization caused a decrease in long-term hydrologic memory. In urban watersheds, the impervious surfaces decrease water storage, which is the predominant factor that affecting long-term hydrologic memory, and the runoff became flashier (Julian and Gardner, 2014). This flash flood decreases the watershed hydrologic memory. Therefore, the resulting model residuals of urban watersheds can be assumed to hold low memory due to the quick runoff response resulted from the increased percent of impervious surfaces. Further, the detailed residual-based bootstrapping procedure is outlined in Fig. 3.2 and briefed below:

(1) Bootstrap resampling of the residual time series \( \hat{\epsilon}(t) \) with replacement to form new bootstrapped residual series, \( \hat{\epsilon}^b(t) \), where \( b = 1, ..., B \).

(2) Add the new bootstrapped residual series, \( \hat{\epsilon}^b(t) \) to the calibrated discharge data \( \hat{Q}(t) \) to form the bootstrapped discharge series as \( Q^b(t) = \hat{Q}(t) + \hat{\epsilon}^b(t) \). This bootstrapped discharge series will form the replication of the observed discharge series.

(3) Calibrate the bootstrapped discharge series, \( Q^b(t) \) with input data set, \( X \) and obtain the \( b \)th bootstrapped parameter vector \( \hat{\theta}^b \) using SCE-UA method and the associated simulated discharge series \( \hat{Q}^b(t) = F(X, \hat{\theta}^b) \). By this way, the model can be re-fitted
to each bootstrapped discharge series, $Q^b(t)$ yielding ‘bootstrap estimates’ of model parameters.

(4) Derive the ordered bootstrap estimates $\hat{\theta}^b = \hat{\theta}^b(1), ..., \hat{\theta}^b(k)$ obtained after the bootstrap resampling method. Then, the 95% CI for $\hat{\theta}^b$ was estimated from the ordered bootstrap samples.

The essential idea of this bootstrap approach is that the pseudo replicate samples (bootstrap samples) drawn at random with replacement from the data can be used to furnish information about the uncertainty of quantities estimated from the data (Selle and Hannah, 2010). The precision of a bootstrap estimate depends on the number of times the original data set is randomly resampled (i.e., how many bootstrap replicates). The bootstrap estimate converges to a consistent range of values as the number of resamples

![Flowchart](image)

Fig. 3.2. Flowchart of the residual-based bootstrapping method.
become large by the law of large numbers (Meyer et al., 1986). Efron and Tibshirani (1993) suggested that the number of bootstrap samples should be at least 1000. Therefore, all the computations performed in the bootstrap analysis were based on 1000 bootstrap replicates ($B = 1000$) from which the confidence intervals for the original corresponding parameter estimates can be calculated. This method has asymptotic convergence properties which means that by increasing the number of simulated bootstrapped time series, estimation error will be reduced (Ebtehaj, 2010). Two data scenarios were used to perform the residual-based bootstrapping in order to identify the parameter fluctuation under the varying conditions of available data scenarios whose detailed descriptions are given in section 3.2.3.

### 3.2.2 Simplified jackknife approach

Jackknife is a resampling technique, which is less dependent on model assumptions and does not need the theoretical formula required by the traditional approaches (Shao and Tu, 1995). The method requires the recalculation of parameters using the resampling method to provide a specified number of evaluations of the parameters (Cover and Unny, 1986). However, the jackknife requires repeatedly computing the statistic by deleting each observation at a time as shown in Fig. 3.3, which may be computationally intensive for large data samples (Mousavi et al., 2011). An idea for computational saving is to use the delete-d jackknife by dividing the $n$ data points into $d$ blocks of length $g$ ($n = dg$) and compute the statistics of interest by deleting each block (Shao and Tu, 1995) rather than deleting each observation at a time. When the length of block $d$ is large, the blocks will be approximately independent and the serial correlation between the blocks is overcome in the case of time-series data (Jones and Kay, 2007). However, the block length selection is still a challenging task and therefore a simplified jackknife method is demonstrated in

![Fig. 3.3. Schematic of classical jackknife resampling method.](image-url)
this chapter in which the existing delete-d jackknife method has been modified in order to overcome the problems associated with the block length selection.

Consider the original data set \{X(t), Q(t)\}; where \(X(t)\) is the input data, and \(Q(t)\) is the observed discharge data. After the model calibration, the model residuals, \(\hat{e}(t)\) were computed as explained in section 3.2.1. These model residuals, \(\hat{e}(t)\), were assumed to be iid for \(t = 1, \ldots, n\), which is the only assumption made for the proposed jackknife method. The detailed jackknife procedure is outlined in Fig. 3.4 and briefed below:

1. Divide the model residual series into \(d\) blocks of length \(g\). Then leave out the first block of residual data set and add the remaining jackknifed residual series to the calibrated discharge series, \(Q_1^j(t) = Q(t) + \hat{e}_1^j\).

2. Calibrate the jackknifed discharge series \(Q_1^j(t)\) with input data set, \(X\) and obtain the jackknifed parameter vector \(\hat{\theta}_1^j\) and the associated simulated discharge series, \(\hat{Q}_1^j(t) = F(X, \hat{\theta}_1^j)\).

Fig. 3.4. Flowchart of the simplified jackknife method.
3. Repeat steps (1) and (2) by deleting each block and obtain the jackknifed parameter vector, $\hat{\theta}_d^j$ and associated simulated discharge series, $\hat{Q}_d^j(t)$. In the present study, the residual data series is divided into a block length of 50 for the jackknife analysis ($g = 50$).

4. Derive the ordered jackknife estimates, $\hat{\theta}_d^j = \hat{\theta}_d^j(1), ..., \hat{\theta}_d^j(k)$ and then estimate the 95% CI for $\hat{\theta}_d^j$ from the ordered jackknife samples.

In the present context, jackknife resampling has been applied to the model residuals rather than applying to the observed discharge series data. Here, we are leaving out the model residuals only, and keeping other inflow and outflow components and thereby considering their effect over the subsequent data blocks during the calibration process. Only the whole data-based scenario described in section 3.2.3 is used to perform the jackknife method.

### 3.2.3 Model calibration

The SCE-UA method proposed by Duan et al. (1992) was used to calibrate the USF model. It is a well-known global optimization strategy developed for effective and efficient optimization for calibrating the watershed models by optimizing a single objective function for up to 16 parameters (Duan et al., 1992; Green and Van Griensven, 2008). This method combines a simplex method with the concept of controlled random search for the competitive evolution of the population with complex shuffling. The algorithmic parameters of SCE-UA method were selected as per the recommendations of Duan et al. (1993). In the first step of the method, it generates an initial population as the

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
<th>Search range</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k_1$</td>
<td>Physical watershed characteristics (Sugiyama et al., 1997)</td>
<td>[10, 500]</td>
</tr>
<tr>
<td>$k_2$</td>
<td>Loop relationship between the storage and discharge (Prasad, 1967)</td>
<td>[100, 5000]</td>
</tr>
<tr>
<td>$k_3$</td>
<td>Groundwater related loss</td>
<td>[0.001, 0.05]</td>
</tr>
<tr>
<td>$p_1$</td>
<td>Index of flow regime (Sugiyama et al., 1997)</td>
<td>[0.1, 1]</td>
</tr>
<tr>
<td>$p_2$</td>
<td>Non-linear unsteady flow effects (Hoshi &amp; Yamaoka, 1982)</td>
<td>[0.1, 1]</td>
</tr>
<tr>
<td>$z$</td>
<td>Infiltration hole height</td>
<td>[0, 50]</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Effect of storm drainage diverted to the treatment plant</td>
<td>[0.1, 1]</td>
</tr>
</tbody>
</table>
first generation by random sampling from the feasible parameter space, which was defined by setting the lower and upper search range for \( k \) number of parameters to be optimized. From the second generation onwards, this population is partitioned into several complexes, each of which is permitted to evolve independently. Size of the population produced in each generation was decided based on the number of parameters in the target model. The objective function to be minimized using the SCE-UA method was selected as the RMSE. Common use in hydrological modeling and simplicity were the reasons for the selection of RMSE as the objective function (Ebtehaj et al., 2010; WMO, 1992). The calibrated parameters are functionally dependent on the length and properties of the calibration data. The seven parameters of USF model are shown in Table 3.1 with their descriptions and search range used in the SCE-UA parameter optimization method (Padiyedath et al., 2018a; Takasaki et al., 2009). A narrow search range will constrain the parameters and the calibrated parameters will not reflect the actual watershed characteristics. Therefore, a wide search range was defined, instead of a narrow one by considering the possible physical minimum and maximum parameter values.

In addition, the model calibration was conducted using two data scenarios of: (i) whole data-based scenario where all the available events were used for the model calibration, and (ii) individual event-based scenario where individual flood events were used.

3.2.4 Model parameter uncertainty quantification

The performance of hydrological models is significantly affected by the calibrated parameter uncertainty. The parameter uncertainty is generally expressed by estimating the CI of the parameters. However, the CI gives the uncertainty range of each parameter from which it is difficult to identify the parameter with the highest and least uncertainty due to the different ranges of parameter values. Therefore, it is necessary to propose certain indices, which can interpret the CI of parameters with different ranges and clearly differentiate them based on their contribution to the uncertainty. Therefore, in addition to the CI of parameters, we have computed different statistical estimators of the mean (\( \bar{\theta} \)), standard deviation (\( \sigma_\theta \)), and coefficient of variation (CV) of the bootstrapped and jackknifed parameter sets. Further, in addition to these statistical estimators, two indices were proposed for assessing the uncertainty of model parameters (model parameter uncertainty indices), which can elucidate the CI in a better way. Here, the indices are considering the individual parameters rather than the parameter vector in order to derive
the parameters from the highest to the lowest uncertainty (Selle and Hannah, 2010). The first index, $IP_1$, utilizes the width of the CI and hence the parameter with a small index value will be less uncertain as compared with other parameters. The second index, $IP_2$, compares the median value from the confidence region with the calibrated parameter vector $\hat{\theta}$ and it should be minimum for the stability of the parameters. These two indices were implemented to quantify the parameter uncertainty derived using the bootstrap analysis. The model parameter uncertainty indices are given as,

$$IP_1(i) = \left(\frac{\hat{\theta}_{97.5}(i) - \hat{\theta}_{2.5}(i)}{\hat{\theta}(i)}\right) \times 100$$ (3.2)

$$IP_2(i) = \left(\frac{\hat{\theta}(i) - \hat{\theta}_{50}(i)}{\hat{\theta}(i)}\right) \times 100$$ (3.3)

where $\hat{\theta}_{97.5}$ is the 97.5th percentile; $\hat{\theta}_{2.5}$ is the 2.5th percentile; and $\hat{\theta}_{50}$ is the 50th percentile (median) for the $i^{th}$ parameter obtained from bootstrapping. $\hat{\theta}$ is the calibrated parameter.

### 3.2.5 Model simulation uncertainty

The model simulation uncertainty is referred to as the uncertainty of simulated discharge, which occurs due to the calibrated parameter uncertainty, and is illustrated as the 95% CI of the simulated discharge series by the model. This 95% CI should envelope most of the observations and at the same time; it is desirable to have a narrow envelope (Swain and Patra, 2017). $P$-factor is a statistical term used for the assessment of model simulation uncertainty and is calculated as the percentage of original discharge data at each time step that lies within the 95% CI (Yang et al., 2008). The value of the $P$-factor ranges between 0 and 100% and the goodness of model simulation uncertainty is judged based on the closeness of $P$-factor to 100% (i.e., all observations bracketed within the 95% CI). The $P$-factor is computed as follows:

$$P\text{-factor} = \left(\frac{n_{CI}}{n}\right) \times 100$$ (3.4)

where $n_{CI}$ is the number of original observed discharge values at each time step that are bracketed within the 95% CI. The $P$-factor is used here to analyze the simulation uncertainty derived from both the bootstrap and jackknife methods. In addition to the $P$-factor, two other indices have been proposed for assessing the uncertainty of model-simulated discharge (model simulation uncertainty indices) derived from both the
methods by utilizing the 95% CI similar to the model parameter uncertainty indices. The model simulation uncertainty indices are given below.

\[ IQ_1 = \frac{1}{n} \sum_{t=1}^{n} \left( \frac{\hat{Q}_{97.5}(t) - \hat{Q}_{2.5}(t)}{Q(t)} \right) \times 100 \]  
\[ IQ_2 = \frac{1}{n} \sum_{t=1}^{n} \left( \frac{Q(t) - \hat{Q}_{50}(t)}{Q(t)} \right) \times 100 \]  

where \( \hat{Q}_{97.5}(t) \), \( \hat{Q}_{2.5}(t) \), and \( \hat{Q}_{50}(t) \) are the 97.5%, 2.5%, and 50% levels of the cumulative distribution of the model simulated discharge series respectively. \( Q(t) \) is the observed discharge data.

3.3 Results and discussion

The USF model was applied to the selected flood events of the upper Kanda river basin, a typical small to medium-sized urban watershed in Tokyo as shown in Fig. 2.2 for the uncertainty analysis. Five target events were selected from the data, whose 60-minute maximum rainfall (\( R_{60} \)) is greater than 30 mm, for the application of SF models and are shown in Table 2.2.

3.3.1 Model calibration and performance

The SCE-UA optimization method was applied for calibrating the USF model in the target watershed with RMSE as the objective function for both the data scenarios discussed in section 3.2.3. In the whole data-based scenario, all the selected events were considered for model calibration and a single set of parameters was derived from all the events. On the other hand, in the individual event-based scenario, each event was considered for model calibration. The convergence of parameters was checked and the parameters were found to converge before the 50\(^{th} \) generation in each SCE-UA application run. Thereafter, the best parameter set, \( \hat{\theta} \), among the population at the 50\(^{th} \) generation with a minimum RMSE value was used for the estimation of calibrated discharge series. Fig. 3.5 shows the calibrated model parameters using both the data scenarios in which the whole data-based parameters are represented by a red line and the individual event-based parameters are depicted by the solid blue symbol. It is clear from Fig. 3.5(a) and (g) that the individual event-based parameters \( k_1 \) and \( \alpha \) are identical in all the events and are similar to the whole data-based parameter values. Also, the parameters \( k_2 \) and \( p_1 \), as shown in Fig. 3.5(b) and (d), respectively, have similar values in the data scenarios even though they exhibit slight variations between events. However, the
Fig. 3.5. The calibrated parameters of USF model from the selected data scenarios.
remaining individual event-based parameters $k_3, p_2,$ and $z$ are varying significantly between events and are similar to the whole data-based parameters only during certain events. The parameters $k_3$ and $z$ represent the loss to the groundwater (Takasaki et al., 2009). The $z$ values close to zero indicate a high rate of recession and higher $z$ values represent a higher river flow at the outlet point instead of contributing to the groundwater. The higher value of $z$ in event 1 can be attributed to its meteorological factor, which is an intensive localized storm, as shown in Table 2.2. Parameter $p_2$ portrays the change in storage during the rising and recession limbs of a hydrograph based on the type of rainfall event (Hoshi and Yamaoka, 1982). The higher $p_2$ values exhibited during events 1 and 3, as shown in Fig. 3.5(e), may be possibly due to differences in meteorological factors from other events.

The results confirm that the parameters $k_3, p_2,$ and $z$ will have a prominent effect in the estimation of discharge due to their high variability. In addition, the meteorological factors can significantly affect parameter values during the model calibration. It is evident from Fig. 3.5 that the whole data-based parameters closely resemble parameters of event 3, which is a multi-peak event, with the largest number of observations compared with other events. This further indicates that the events with a large number of observations have a great impact on the whole data-based model calibration as compared to events with less number of observations. However, the considered data sets are not sufficient to generalize the above discussions despite providing a brief description of parameter uncertainty. Therefore, in order to have an elaborative idea of calibrated parameter uncertainty, the bootstrap and jackknife approaches were employed for generating samples, which could be further, utilized for conducting the uncertainty analysis.

Thereafter, the model performance on estimating discharge using the whole data-based and individual event-based parameters was analyzed. Table 3.2 presents the detailed performance evaluation using the statistical indicators of RMSE, NSE, percentage error in peak (PEP), and percentage error in volume (PEV) (Padiyedath et al., 2018a). Additionally, Fig. 3.6 provides a visual representation of the hydrograph reproduced by the model for both the data scenarios. It is apparent from Table 3.2 that the model with individual event-based parameters has lower values of RMSE and higher values of NSE in all the events as compared to the whole data-based parameters which further reveals better model performance in simulating individual flood events using the event-based parameters. It is evident from the table that the PEP values estimated by the
model using the individual event-based parameters were very low (close to zero) compared to that from the whole data-based parameters, even though the model exhibited a higher PEP value during event 1, and was not greater than 10% during any of the events. Fig. 3.6 also shows that the model was able to reproduce the peak discharge with utmost accuracy using the individual event-based parameters. On the other hand, the model with whole data-based parameters exhibited remarkable anomaly in the reproduction of peak values, especially in events 4 and 5. Likewise the PEP, USF model shows the best performance in PEV values using the individual event-based parameters as shown in Table 3.2 which is close to zero as compared to that of the whole data-based parameters.

The results further confirmed that the difference between the values of statistical indicators shown in Table 3.2 for the considered data scenarios is quite large and significantly greater for events 4 and 5. It can also be envisaged from Fig. 3.6 that the calibrated discharge using the individual event-based parameters by USF model nearly overlaps with the observed river discharge and reproduces the shape of the observed hydrograph with only slight variations. On the contrary, the model with whole data-based parameters deviated significantly while reproducing the shape of the hydrograph. Therefore, the results indicates that the individual event-based parameters can exactly reproduce the shape of the observed hydrograph as well as the peak discharge by significantly reducing the RMSE by 50% compared to that of the whole data-based parameters during the calibration. Hence, it is necessary to consider the calibration based

---

**Table 3.2. Performance evaluation of USF model using different statistical indicators (WD –Whole data; IE-Individual event).**

<table>
<thead>
<tr>
<th>Statistical index</th>
<th>RMSE (mm/min)</th>
<th>NSE (%)</th>
<th>PEP (%)</th>
<th>PEV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WD</td>
<td>IE</td>
<td>WD</td>
<td>IE</td>
</tr>
<tr>
<td>Event 1</td>
<td>0.013</td>
<td>0.006</td>
<td>99.16</td>
<td>99.86</td>
</tr>
<tr>
<td>Event 2</td>
<td>0.010</td>
<td>0.004</td>
<td>98.76</td>
<td>99.83</td>
</tr>
<tr>
<td>Event 3</td>
<td>0.010</td>
<td>0.009</td>
<td>98.41</td>
<td>98.62</td>
</tr>
<tr>
<td>Event 4</td>
<td>0.012</td>
<td>0.006</td>
<td>92.91</td>
<td>98.25</td>
</tr>
<tr>
<td>Event 5</td>
<td>0.014</td>
<td>0.005</td>
<td>91.14</td>
<td>98.88</td>
</tr>
</tbody>
</table>
Rainfall (mm/min)
Discharge (mm/min)
Time (min)

(a) $Q_{\text{observed}}$  $Q_{W \text{ calibrated}}$  $Q_{I \text{ calibrated}}$

(b) $Q_{\text{observed}}$  $Q_{W \text{ calibrated}}$  $Q_{I \text{ calibrated}}$

(c) $Q_{\text{observed}}$  $Q_{W \text{ calibrated}}$  $Q_{I \text{ calibrated}}$
on individual flood events for the parameter uncertainty analysis rather than considering the whole data based calibration alone.

3.3.2 Model validation

The performance of a model derived from the calibration data set is insufficient evidence for its satisfactory performance since no simulation model is intended merely to show how well it fits the data used for its development. Thus, the data used for model calibration...
validation should be different as those used for calibration but must represent a situation similar to that for which the data are to be generated (Klemeš, 1986). Therefore, in order to test the operational performance of the model, the observed events are split into two segments in which the first segment is comprised of events 1 to 4 and event 5 forms the second segment. The first segment was used for the calibration whereas the second segment was used for the validation purpose. The calibrated parameters obtained from the whole data-based scenario as well as the individual event-based scenario were used to validate event 5 in order to evaluate its operational adequacy. Fig. 3.7(a) shows the model validation in event 5 using the parameter sets obtained from both the scenarios. It is clear from Fig. 3.7(a) that the discharge simulated using the calibrated parameters of events 1 and 2 have highly deviated from the observed discharge. On the other hand, simulated discharge using the parameters of whole data-based analysis and events 3 and 4 from the individual event-based analysis were close to the observed discharge. However, it is not easy to clearly portray the difference between the simulated discharge hydrographs of these three cases from Fig. 3.7(a). Hence, we evaluated the performance from these cases using the same performance evaluation criteria of RMSE, NSE, PEP, and PEV that used during the calibration and is shown in Fig. 3.7(b). The left y-axis of Fig. 3.7(b) represents RMSE and NSE, while the right y-axis depicts the PEP and PEV. It can be envisaged from the figure that the event 4 generated the lowest RMSE and highest NSE in reproducing the hydrograph of event 5, which was immediately followed by event 3, whole data-based validation, and event 2 respectively. Event 1 exhibited the least performance during validation. In the same way, the PEP and PEV values were also close to zero in the case of event 4 and the rest of the cases exhibited varying values of PEV and PEV. The highest performance of calibrated parameters of event 4 in validation could be possibly due to their same meteorological factor with an almost equal amount of total rainfall as shown in Table 2.2. Further comparison on model performance during calibration and validation revealed that the RMSE and NSE values were satisfactory in validation compared with the values in calibration (Table 3.2), except for event 1 from the individual event-based scenario. Event 3 and whole data-based validation performed equally in validation in terms of RMSE and other performance evaluation criteria, similar to that exhibited in calibration (Table 3.2), which further supported the result that the events with a large number of observations have domination on the whole data-based model calibration.
The validation results revealed that the model can be implemented for operational use in the context of flood forecasting. However, there arises a question that which calibration approach is the most performant, subject to validation. Based on the above discussions, it is recommended that the model should be calibrated using a large number of flood events having the same meteorological factor and those calibrated parameters can be used for flood forecasting under the assumption that the hydrological conditions under which the model is going to be used will be similar to those under calibration. An alternative approach would be to use individual event-based parameters for calibration.

Fig. 3.7. The USF model validation for event 5 using the whole data-based and individual event-based parameters; (a) reproduced hydrographs (Ev represents event), and (b) performance evaluation in each scenario.

The validation results revealed that the model can be implemented for operational use in the context of flood forecasting. However, there arises a question that which calibration approach is the most performant, subject to validation. Based on the above discussions, it is recommended that the model should be calibrated using a large number of flood events having the same meteorological factor and those calibrated parameters can be used for flood forecasting under the assumption that the hydrological conditions under which the model is going to be used will be similar to those under calibration. An alternative approach would be to use individual event-based parameters for calibration.
approach in this situation is to calibrate the model to all available flood events by assuming that the meteorological and hydrological conditions are the same for all the events. These calibration techniques will provide a minimum standard for operational validation of the model. However, it needs more such calibrations at different sub-periods including more flood events to arrive at a conclusion. Moreover, Moore et al. (2007) suggest that in many situations it is hard for the lumped conceptual models to outperform in operational use for flood forecasting. Therefore, it is recommended that further work is undertaken on alternative formulations which will describe the operational adequacy of the model.

3.3.3 Model parameter uncertainty analysis

3.3.3.1 Bootstrap analysis

The calibration parameter uncertainty analysis was conducted using the five available flood events even though only four events were considered during the validation in section 3.3.2. The computed model residual series (Eq. 3.1) was used to perform the resampling process for 1000 times by employing the residual-based bootstrap approach. Then, associated bootstrapped discharge series were generated by adding 1000 bootstrapped residual series to the calibrated discharge series as described in section 3.2.1. These bootstrapped discharge series, $\hat{Q}^b(t)$, were used to obtain the $b^{th}$ bootstrapped parameter vector, $\hat{\theta}^b$ of the USF model for both the whole data-based and individual event-based scenarios. Fig. 3.8 shows the scatter plots of the bootstrapped parameter vectors with their 95% CI in grey shading. The search range shown in Table 3.1 is illustrated as the left y-axis and the percentage contribution of 95% CI to the search range is depicted on the right y-axis of Fig. 3.8.

It is apparent from Fig. 3.8(a1)-(f1) that the $k_1$ values lie close to the lower limit of the search range and converged to a reduced range between 20 and 70 in all the cases. The 95% CI of parameter $k_1$ have a comparable width in all the cases and constitute about 1-5% of the search range, which is quite narrow. The scatter plot of parameter $k_2$ was narrow as well as close to the lower search range with values clustered around 500 to 2000, as shown in Fig. 3.8(a2)-(f2). Similarly, the 95% CI of $k_2$ was also narrow for the whole data-based parameter and was quite similar with the values of events 1 and 3. As compared to this pattern, the CI was relatively wide during the rest of the events. The parameter $k_3$ has a widespread pattern as compared to parameters $k_1$ and $k_2$, as shown in
(a) Whole Data

(b) Event 1

(a1)

(a2)

(a3)

(a4)

(a5)

(a6)

(a7)

(b1)

(b2)

(b3)

(b4)

(b5)

(b6)

(b7)

Bootstrap run, j

Bootstrap run, j
Fig. 3.8. Scatter plots of bootstrapped parameter samples by the USF model for (d) event 3 (d1-d7), (e) event 4 (e1-e7), and (f) event 5 (f1-f7) with their 95% CI in grey shading.
Fig. 3.8(a3)-(f3). The 95% CI of $k_3$ was wide and its contribution to the search range was high, except for event 3 and the whole data-based scenario. There is a well-spread pattern for parameter $p_1$ from 0.1 to 1 within the search range whereas most of the $p_2$ values accumulated near the lower search range between 0.1 and 0.7, as shown in Fig. 3.8(a4)-(f4) and (a5)-(f5), respectively. The 95% CI of these parameters are wide as compared to $k_1$ and $k_2$ with a high percentage contribution to the search range. It is evident from Fig. 3(a6)-(f6) that most of the z values are gathered near the lower limit of the search range and the 95% CI is relatively wide. Parameter $\alpha$ demonstrated a very widespread pattern with values close to the upper search range, as depicted in Fig. 3.8(a7)-(f7). The 95% CI of $\alpha$ was wide in all the scenarios and constituted about 25-50% of the search range. It can be envisaged from Fig. 3 that the scatter plot of whole data-based parameters is similar to the parameter pattern exhibited in event 3, which further strengthens the argument that the events with a large number of observations have domination on the whole data-based model calibration. Even though a wide search range was considered, certain parameters converged to a very narrow range. On the other hand, some parameters showed a widespread pattern from the lower to the upper limit of search range. This could be a reflection of the equifinality concept (Beven and Freer, 2001) and reconsideration of this search range could enhance the performance of the model in cases where parameter values accumulate on the search range boundaries. Additionally, a larger number of bootstrap resamples can lead to a narrow 95% CI due to the convergence of parameters as observed in the study of Selle and Hannah (2010).

Fig. 3.9 shows the statistical representation of Fig. 3.8 in terms of the box-whisker plot of 1000 bootstrapped parameter vectors for both the data scenarios in which the bottom and the top lines of the boxes show the 25th and 75th percentiles, respectively and the line passing through the box represents the median ($\bar{\theta}_{50}$). The whiskers extend to the 2.5th and the 97.5th percentiles and the highest and lowest observations are plotted as asterisks. Additionally, Fig. 3.9 represents the mean ($\bar{\theta}$ as the blue square) and CV (values at the top) of the bootstrapped parameter vectors along with the calibrated parameter values ($\hat{\theta}$ as the red circle). Detailed descriptions of the plot are given in the figure caption. It is clear from Fig. 3.9(a) and (b) that the bootstrap estimates of $\bar{\theta}_{50}$ and $\bar{\theta}$ of parameters $k_1$ and $k_2$ have similar values and are very close to the calibrated $\hat{\theta}$ values in all the events. However, the parameter $k_3$ exhibited differences in the $\bar{\theta}$ values during event 1, as depicted in Fig. 3.9(c). It is apparent from Fig. 3.9(d) that the $\bar{\theta}_{50}$ and $\bar{\theta}$ values of $p_1$
Fig. 3.9. The box plot of bootstrapped parameter vector (a) $k_1$, (b) $k_2$, (c) $k_3$, (d) $p_1$, (e) $p_2$, (f) $z$, and (g) $\alpha$ for both the data scenarios. The line passing through the box represents the median ($\hat{\theta}_{50}$). The red circle and blue square within the box indicate calibrated parameter ($\hat{\theta}$) and mean ($\hat{\theta}$) respectively. The written values represent the CV for each data scenario.
are similar except for event 4 whereas the $\bar{\theta}$ and $\tilde{\theta}$ values are identical except for events 4 and 5. On the other hand, the $\bar{\theta}_{50}$, $\bar{\theta}$, and $\tilde{\theta}$ values of parameter $p_2$ were close enough except for event 5, as shown in Fig. 3.9(e). Similar to the parameter $p_2$, the $\bar{\theta}_{50}$, $\bar{\theta}$, and $\tilde{\theta}$ values of parameter $z$ in Fig. 3.9(f) were identical, except in event 1. Subsequently, the $\bar{\theta}$ values of $\alpha$ exhibited minor discrepancy only in event 5 as compared to the $\bar{\theta}_{50}$ and $\tilde{\theta}$ values, as illustrated in Fig. 3.9(g). Overall, the $\bar{\theta}$ values were in accordance with the $\bar{\theta}_{50}$ and $\tilde{\theta}$ values in most of the cases even though the $\bar{\theta}$ values show minor deviations. The CV values also varied between scenarios, as shown in Fig. 3.9. During the whole data-based analysis, the highest CV value of around 133% was observed for parameter $z$ and the least CV value was noted for parameter $k_2$. Further, the parameters were ordered based on their CV values as follows: $z > \alpha > k_3 > p_1 > p_2 > k_1 > k_2$. However, for the individual event-based analysis, during event 1, the highest CV value was exhibited by the parameter $k_3$ which was followed by parameter $z$. The order of parameters based on CV values are $k_3 > z > p_1 > \alpha > p_2 > k_2 > k_1$. The same order for event 2 was $p_2 > k_3 > z > p_1 > k_2 > \alpha > k_1$. During events 3 and 4, based on the CV values, the parameter $z$ had the highest uncertainty. On the contrary, parameters $p_2$ and $z$ had very high CV values as compared to other parameters during event 5. Therefore, the results reveal that the parameter with the highest and lowest uncertainty varies from case to case. However, $z$ and $k_1$ were the parameters with the highest and lowest uncertainty respectively based on their CV values in most of the cases.

Selle and Hannah (2010) identified the parameter with the highest uncertainty of a conceptual salt load model using the CV value as the only index. However, in this chapter, two proposed indices were computed, in addition to the CV, for objectively assessing the parameter uncertainty derived by the bootstrap method in order to have a clear understanding of the 95% CI as well as the median values of the parameters, as shown in Fig. 3.10. In this figure, the $IP_1$ and $IP_2$ index values of parameter $z$ for the whole data-based scenario is represented at the figure boundaries with their values. Since the $\bar{\theta}$ value of parameter $z$ was very close to zero in the whole data-based scenario, as shown in Fig. 3.5(f), the calculated $IP_1$ and $IP_2$ values of $z$ were very high and represented at the boundaries. It is evident from Fig. 3.10(a) that the parameter $z$ has the highest value of $IP_1$ during events 3 and 4 and also in the whole data-based case, which further indicates that $z$ had the highest uncertainty in most of the considered scenarios based on $IP_1$. This higher $IP_1$ value of $z$ can be interpreted as its wide 95% CI and calibrated parameter
values close to zero during these scenarios. However, the parameter $p_2$ demonstrated a higher value of $IP_1$ during events 2 and 5, which could also be attributed to its very wide 95% CI as compared to other parameters, as shown in Fig. 3.8(c5) and (f5) while parameter $p_1$ has the highest $IP_1$ value during event 1. The parameters $k_2$ and $k_1$ demonstrated the lowest uncertainty from the cases whose 95% CI was very narrow as compared to the rest of the parameters. The remaining parameters showed a different order of $IP_1$ values in the considered scenarios, based on their 95% CI width and the calibrated parameter values. The high uncertainty, in terms of $IP_2$, was exhibited by the parameter $z$ in all the cases except for event 3, as illustrated in Fig. 3.10(b). During event 3, all the parameters exhibited a small magnitude of uncertainty and were comparable to each other, even though the $IP_1$ portrayed $z$ as the most uncertain parameter in event 3, which can be further interpreted as the very similar median and calibrated values of parameters. Also, for a narrow CI, the median and calibrated parameter values will come closer and further the $IP_2$ values will approach zero. The parameter $z$ exhibited negative $IP_2$ values with a high magnitude in the whole data-based scenario and event 4, significantly high in the whole data-based scenario, and these high magnitude negative $IP_2$ values indicate that the bootstrap median values are much higher than the calibrated parameters. The results revealed the difference in both the calculated indices, $IP_1$ and $IP_2$, is because both represent different aspects of uncertainty analysis.

The parameter $z$ represents the infiltration hole height in the USF model (Takasaki et al., 2009), which depends upon characteristics like basin storage and rainfall intensity, and will vary greatly from event to event with the highest uncertainty. Additionally, the optimum value of $z$ estimated from the model calibration is close to zero with a very wide range of bootstrapped parameter values, as shown in Fig. 3.8(a6)-(f6) which also makes it the most uncertain parameter. The parameter with higher uncertainty after $z$ varied from case to case. However, based on the $IP_1$ and $IP_2$ values, $p_1$, $p_2$, $\alpha$, $k_3$, and $k_2$ had higher uncertainty values after parameter $z$ for most of the cases. The 95% CI of these parameters are relatively wide which can be transformed into higher index values. The parameter $k_1$ exhibited the least uncertainty. One of the reasons for this could be the fact that parameter $k_1$ describes features of the watershed (Sugiyama et al., 1997) and there is a very low chance of a change in watershed features within a short span. This further indicated that parameter $k_1$ remains reasonably stable under varying input data scenarios. In addition, the equifinality concept can also derive parameter uncertainty by generating
non-unique parameter sets during the calibration process and there will be a lot of different parameter combinations that lead to multiple optimal solutions (Beven and Freer, 2001; Yang et al., 2008). However, this parameter uncertainty can be overcome to some extent by using global searching techniques during calibration.

### 3.3.3.2 Jackknife analysis

The computed model residual series (Eq. 3.1) was used to perform the jackknife approach by employing a block length of 50 under the whole data-based scenario and

---

Fig. 3.10. Two proposed indices of (a) $IP_1$, and (b) $IP_2$ for analyzing the model parameter uncertainty.
generated the associated jackknifed discharge series as described in section 3.2.2. These discharge series were calibrated to obtain the jackknifed parameter vector, \( \tilde{\theta}_d \) of USF model. Fig. 3.11 shows the scatter plots of these parameter vectors with their uncertainty range in grey shading. The uncertainty range of these parameters was estimated by computing the 95% CI. It is apparent from Fig. 3.11 that the jackknifed parameters are converged to a very narrow range with a slightly wide 95% CI. This wide uncertainty range can be attributed to the presence of several outlier values obtained after jackknifing. Most of the parameter values, such as \( k_1, k_2, k_3, \) and \( z \), were lying close to the lower limit of the search range used during the calibration, whereas the parameters \( p_1, p_2, \) and \( \alpha \)

![Fig. 3.11. Scatter plots of parameter vector with block size 50 along with their 95% CI in grey shading.](image-url)
exhibited a widespread pattern within the search range. It was also noted that the parameter values were converged to a very narrow range after the uncertainty analysis compared with the wide search range (Table 3.1) used during the calibration process, indicating that the proposed jackknife approach is feasible for the parameter uncertainty analysis. The approach not only converges the parameter values to a narrow range but also provides a future reference of the search range for parameter calibration of the target model.

The 95% CI gives the uncertainty range of each parameter from which it is difficult to identify the parameter with the highest and least uncertainty due to the different ranges of parameter values. Therefore, after obtaining the uncertainty range of each parameter, we computed different statistical estimators of the mean ($\bar{\theta}$), standard deviation ($\sigma_\theta$), and coefficient of variation (CV) along with the calibrated parameter vector ($\hat{\theta}$) and are shown in Table 3.3. It is clear from Table 3.3 that the jackknife estimate of mean for all the parameters are close to the calibrated parameter values in the selected block size of 50. The standard deviation values obtained from the jackknife analysis were almost similar and relatively small. The highest CV value was observed for parameter $z$, which was around 455%. It was followed by the parameters $k_3$ and $p_2$ whose CV values were about 44% and 20% respectively. The remaining parameters exhibited CV values of less than 20% and the least CV value was noted for parameter $p_1$. Further, the parameters were ordered based on their CV values and the order of parameters is as follows: $z > k_3 >$

Table 3.3. The different statistical estimators along and parameter uncertainty indices along with the calibrated parameter vector for block size 50.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Calibrated Parameter, $\hat{\theta}$</th>
<th>Mean, $\bar{\theta}$</th>
<th>$\sigma_\theta$</th>
<th>CV</th>
<th>$IP_1$</th>
<th>$IP_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k_1$</td>
<td>43.47</td>
<td>42.40</td>
<td>4.28</td>
<td>10.10</td>
<td>45.65</td>
<td>-2.49</td>
</tr>
<tr>
<td>$k_2$</td>
<td>619.90</td>
<td>629.69</td>
<td>46.80</td>
<td>7.43</td>
<td>38.83</td>
<td>1.55</td>
</tr>
<tr>
<td>$k_3$</td>
<td>0.0052</td>
<td>0.0058</td>
<td>0.0026</td>
<td>43.99</td>
<td>189.94</td>
<td>10.91</td>
</tr>
<tr>
<td>$p_1$</td>
<td>0.41</td>
<td>0.35</td>
<td>0.03</td>
<td>6.05</td>
<td>28.62</td>
<td>0.97</td>
</tr>
<tr>
<td>$p_2$</td>
<td>0.33</td>
<td>0.21</td>
<td>0.07</td>
<td>19.76</td>
<td>94.55</td>
<td>4.59</td>
</tr>
<tr>
<td>$z$</td>
<td>0</td>
<td>0.44</td>
<td>0.95</td>
<td>454.51</td>
<td>1778.06</td>
<td>100</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.42</td>
<td>0.35</td>
<td>0.06</td>
<td>14.22</td>
<td>65.02</td>
<td>3.44</td>
</tr>
</tbody>
</table>
The results revealed that the highest uncertainty was demonstrated by parameter $z$, which was 10 times higher in magnitude compared with the next uncertain parameter $k_3$, whereas the parameter $p_1$ was the one with the least uncertainty based on their CV values.

Further, the parameter uncertainty was evaluated by computing the two proposed uncertainty indices in order to have a clear understanding of the 95% CI as well as the median values of the parameters as shown in Table 3.3. It is clear from the table that the parameter $z$ has the highest value of $IP_1$ in the whole data-based case, which further indicates that $z$ had the highest uncertainty compared with other parameters based on $IP_1$. This higher $IP_1$ value of $z$ can be interpreted as its wide 95% CI and calibrated parameter values close to zero likewise in the bootstrap analysis. Parameter $k_3$ exhibited the second highest $IP_1$ value even though it was very small compared with parameter $z$. The remaining parameters demonstrated an index value of less than 100 and the uncertainty was relatively low. The high uncertainty, in terms of $IP_2$, was also exhibited by the parameter $z$ as shown in Table 3.3. The value of $IP_2$ was 100 for parameter $z$ and the remaining parameters showed $IP_2$ values less than or equal to 10. This small $IP_2$ values obtained for the parameters, except for $z$, can be further interpreted as the very similar median and calibrated values of parameters. Also, for a narrow CI, the median and calibrated parameter values will come closer and further the $IP_2$ values will approach zero. The parameter $k_1$ exhibited negative $IP_2$ value and these negative values indicate that the jackknife median values are much higher than the calibrated parameters. The results revealed that the highly uncertain parameters obtained were the same by the bootstrap and jackknife approaches even though the order of other model parameters was different in whole data-based scenario.

Most of the time, the optimum value of $z$ estimated from the jackknife analysis by SCE-UA method is the lower limit of search range as shown in Fig. 3.11. A slight deviation from zero to a higher value can cause high uncertainty of this parameter. The parameter with higher uncertainty after $z$ is $k_3$ which is associated with $z$ to depict the groundwater related loss as shown in Eq. (2.1) and there is a chance of high correlation between these two parameters which will lead to high uncertainty in $k_3$ values after $z$. The parameter $p_1$ received the least uncertainty, which can be attributed to its characteristics that control the flow regime (Sugiyama et al., 1997), and is reasonably stable under the changing input data scenarios. Moreover, the simulated discharge is least
affected by the parameters $p_1, k_2, k_1, \alpha$ and are highly sensitive with a small change in parameters $z, k_3, \text{and} p_2$.

3.3.4 Model simulation uncertainty

3.3.4.1 Bootstrap analysis

The uncertainty in model simulation due to the calibrated parameter uncertainty was estimated by computing the 95% CI of the 1000 simulated discharge series generated by the bootstrap approach for the whole data-based and the individual event-based scenarios. Fig. 3.12 shows the lower and the upper limits of the 95% CI of simulated discharge (prediction range) for each event from both the whole data-based and the individual event-based scenarios. It is desirable to have a narrow range and Fig. 3.12(a) shows that the prediction range from the whole data-based parameters at the peak flows of event 1 is wider than the range simulated from the individual event-based parameters. However, the width of the prediction range at low flows was almost identical for event 1 from both the scenarios. Fig. 3.12(b) shows that the prediction range was unable to capture the observed values during the flood peak of the whole data-based scenario, whereas the prediction range of individual event-based scenario was able to bracket a large amount of the observed values, including the flood peaks. The prediction range of the whole data-based scenario illustrated in Fig. 3.12(c), included the highest flood peak value with a wide prediction range. On the other hand, the prediction range of the individual event-based scenario was very narrow, was close to the observed peak flows, and hence was not able to capture the flood peaks. During events 4 and 5 from the whole data-based parameters, most of the flood peak values were falling inside the prediction range even though the low flows were not well captured as shown in Fig. 3.12(d) and (e). Concurrently, the prediction range of the individual event based scenario was able to capture almost all the flows, except the peak value during events 4 and 5. Overall, the whole data-based scenario captured the observed discharge with a very wide prediction range whereas the individual event-based scenario bracketed observations within a very narrow prediction range. Also, as can be seen from Fig. 3.12, that the prediction range is very narrow at the low flows for both the scenarios. Hence, it can be concluded that the model simulates peak discharge with higher uncertainty as compared to low flows. High uncertainty in the model simulation during flood peaks can be attributed to the influence of low flows as they may have dominated the parameter estimation process due to their greater numbers as compared to the peak flow (Gallagher and Doherty, 2007). However,
(a) Q observed

95% confidence limits of whole data
95% confidence limits of individual event

Event 1

Discharge (mm/min)

Time (min)

(b) Event 2

Discharge (mm/min)

Time (min)

(c) Event 3

Discharge (mm/min)

Time (min)
Fig. 3.12. The simulation uncertainty of USF model for (a) Event 1; (b) Event 2; (c) Event 3; (d) Event 4; and (e) Event 5 using the whole data-based and individual event-based scenarios.

it is essential to estimate flood peaks with lesser uncertainty as compared to the low flows due to the high-risk factor associated with them. It is possible to do so by calibrating the model parameters using a specific objective function, which can initiate the type of simulation that the model is required to make.

In order to portray the differences in the model simulation uncertainty from both the scenarios, a detailed uncertainty analysis was further conducted using the P-factor and the two proposed model simulation uncertainty indices, $IQ_1$ and $IQ_2$. Fig. 3.13 shows the model simulation uncertainty for the whole data-based and the individual event-based scenarios using the P-factor, $IQ_1$, and $IQ_2$. The P-factor value, as defined by Eq. (3.4),
close to 100% represents the capability of the model to reasonably capture almost all the observed discharge values within the prediction range. Similarly, the values of $I_Q_1$ and $I_Q_2$ close to zero indicate low uncertainty of the model in simulating the discharge. It is clear from Fig. 3.13(a) that the obtained value of P-factor is higher for events 1, 2, and 5 in the individual event-based scenario and the whole data-based scenario showed higher values of P-factor during events 3 and 4. Even though the P-factor of individual event-based analysis is lower than the whole data-based analysis in events 3 and 4, the difference between the values is quite small. The individual event-based scenario
captured an almost equal number of observations with a very narrow prediction range, especially at the peak flows, in event 3 compared with the whole data-based scenario that resulted in an almost equal P-factor. The high uncertainty of parameter $z$ during event 4 in terms of parameter uncertainty indices, as shown in Fig. 3.10, could be a reason for the low P-factor exhibited by the individual event-based scenario in event 4. Subsequently, values of the proposed index $IQ_1$, derived from the individual event-based analysis were less than the values derived from whole data-based analysis in all the events except for event 1, as shown in Fig. 3.13(b). During event 1, the $IQ_1$ value of both the scenarios was similar and the whole data-based scenario received the least value. The results revealed that the width of the prediction range is narrow relative to the observed discharge values in the individual event-based analysis as compared to the whole data-based analysis. The individual event-based values of $IQ_2$ were also close to zero in all the events except for event 4, as illustrated in Fig. 3.13(c). The $IQ_2$ values were negative for events 4 and 5 in the whole data-based scenario, which indicates that the observed discharge values were lesser than the median values and lied in the lower confidence region. In the same way, values from the individual event-based analysis were mostly positive, except for events 1 and 3, and were found in the upper confidence region. Overall, considering all the indices, the simulation uncertainty was lower during the individual event-based analysis as compared to the whole data-based analysis.

3.3.4.2 Jackknife analysis

Further, the model simulation prediction range due to the parameter uncertainty estimated using the jackknife analysis under the whole data-based scenario was computed for each event by calculating the 95% CI of the simulated discharge series samples and is shown in Fig. 3.14. It is desirable to have a narrow range for the model and can be seen from Fig. 3.14(a) that the prediction range is wide at the peak flows compared to the range at the low flows of event 1 and it comprises most of the flows. However, the prediction range of event 2 was wide at the peak flows as well as at the low flows as demonstrated in Fig. 3.14(b). It can be envisaged from the figure that the 95% CI was able to capture the observed values during the flood peak, whereas the same was unable to bracket the recession flows. Likewise event 2, the prediction band illustrated in Fig. 3.14(c) was also not able to bracket the recession flows within it. However, the overall prediction band was narrow during event 3. During events 4 and 5, the flood peak values were falling inside the prediction band even though the low flows were not well captured as shown in
Fig. 3.14. The simulation uncertainty of USF model with block size 50 for the selected events.
The prediction range was wide during both the events. It is clear from the figure that the prediction range is narrow at the low flows similar to that observed in the bootstrap analysis and hence it can be envisaged that the model simulates peak discharge with high uncertainty compared with low flows. This can be attributed to the uncertainties involved in the rainfall during high flows.

Furthermore, a detailed uncertainty analysis was further conducted using the P-factor and the two proposed model simulation uncertainty indices, $IQ_1$ and $IQ_2$. Fig. 3.15 shows the model simulation uncertainty for the whole data-based scenario from the jackknife analysis using the P-factor, $IQ_1$, and $IQ_2$. It is clear from Fig. 3.15(a) that the highest P-factor value was obtained for event 1 which was around 53%. It was immediately followed by the event 4 with a value of approximately 51% and the remaining events exhibited P-factor values ranging between 30 and 40%. On average, the prediction range was able to bracket 43% of observed discharge values with block size 50. This result implicated that the model can capture around half of the observations within the prediction range with reasonable accuracy in the jackknife analysis. However, in comparison with the prediction range of the model from the bootstrap analysis under the whole data-based scenario, the performance was low in the jackknife analysis. A possible reason for the increased simulation uncertainty of the model in the jackknife analysis could be the use of a single block length of 50 in the parameter calibration. Subsequently, values of $IQ_1$, derived from the whole data-based analysis were ranging between 50 and 120 in which the highest values were depicted for events 4 and 5 by the model as shown.

![Fig. 3.15](image)

Fig. 3.15. The model simulation uncertainty from the jackknife analysis for the whole data-based scenario using the P-factor, and the two proposed model simulation uncertainty indices of $IQ_1$, and $IQ_2$. 
in Fig. 3.15(b). This pattern of high $IQ_1$ values for events 4 and 5 were also similar to that of observed in the bootstrap analysis although the bootstrap analysis showed slightly higher values for these events. The results revealed that the width of the prediction range is moderately narrow relative to the observed discharge values in the jackknife analysis. The values of $IQ_2$ were close to zero during event 4, whereas the remaining events showed deviations as illustrated in Fig. 3.15(c). The $IQ_2$ value was negative for event 5, which indicates that the observed discharge values were lesser than the median values and lied in the lower confidence region. The $IQ_2$ values of remaining events were positive and found in the upper confidence region. Overall, considering all the indices, the simulation uncertainty of the USF model was higher in the jackknife analysis as compared to the bootstrap analysis. Further research is required to determine whether the same or better results could be obtained when other block lengths are used.

3.3.5 Spatial variability of basin rainfall

The results revealed that the model simulation uncertainty varies from event to event, method to method that are used to analyze the uncertainty, and the considered data scenarios. This can be ascribed to the difference in parameter values in each event and in the whole data-based scenario. Usually, even for the same watershed, the characteristics of rainfall events are spatially distributed and different from others due to the effect of several meteorological factors, which will result in the different parameter values. Moreover, there will be an interaction between the spatial variability in rainfall and the spatial storage distribution, which controls the discharge, and finally, the discharge response at the outlet point to an averaged input will differ significantly from that to a distributed input (Shah et al., 1996). Therefore, further analysis was carried out in order to have a clear understanding about the extent of spatial variability of rainfall in the watershed. Fig. 3.16 shows percentage variation of total rainfall obtained from each rain gauge with respect to the mean rainfall from all the gauges. The percentage variation can be computed using the following formula.

$$\% \text{ variation}(i) = \frac{TR_i - TR}{TR}$$  \hspace{1cm} (3.7)

where $TR_i$ is the total rainfall from gauge $i$ (mm), and $\overline{TR}$ is the mean rainfall from all the gauges (mm). It is clear from Fig. 3.16 that during event 1, the variation of two gauges are around -30%, whereas the same in event 2 for one gauge is about -40%. These high percentage variation values of rainfall exhibited by several rain gauges indicate that there
is a relatively high spatial variability in rainfall during events 1 and 2. However, all the gauges showed relatively low variability except one gauge during event 3 which resulted in an overall low spatial variability in this event. Moving to events 4 and 5, almost all the gauges portrayed high percentage variation values ranging from -60% to 60% and exhibited the highest spatial variability. This high spatial variability exhibited by the rain gauges in each event can be attributed to their completely different rainfall pattern and this could be a cause of the high uncertainty in simulations.

Fig. 3.16. The percentage variation of total rainfall obtained from each rain gauge with respect to the mean rainfall from all the gauges.

During the whole data-based scenario, the model parameters were averaged spatially as well as temporally over the watershed without considering the spatial variability of rainfall as well as the meteorological factors that caused the rainfall events, and the estimated model parameters will be different from the true watershed parameters (Chaubey et al., 1999). This could be a possible reason for the high simulation uncertainty exhibited by the model in the whole data-based scenario under both the bootstrap and jackknife methods. However, during the individual event-based scenario, the catchment
properties are only spatially averaged, not temporally. This will lead to a reduced simulation uncertainty in the event-based scenario compared with the whole data-based scenario. At the same time, lumping up of the complex, spatially varying catchment properties such as rainfall, inflow, etc. in a model will induce considerable errors associated with the spatially averaged input data (Cooley, 2004) and further affect the model simulation uncertainty in both the data scenarios. Notwithstanding the problems associated with the spatial averaging of the watershed processes, the USF model was able to simulate the discharge with reasonable accuracy using the bootstrap approach associated with the SCE-UA method. Therefore, the bootstrap approach will contribute to the development of parsimonious hydrologic models (Selle and Hannah, 2010) with reliable estimates of parameter uncertainty even though it is computationally intensive compared to the jackknife analysis. In this study, we found that the range of simulation uncertainty due to the parameter uncertainty is relatively small. Apart from parameter uncertainty, input data measurement errors from all sources and model structure errors also cause model simulation uncertainty (Sivakumar and Berndtsson, 2010). However, it is not practicable to define the extent to which the other sources of uncertainties will affect the model simulation uncertainty based on our present study.

3.4 Conclusions

A residual-based bootstrap approach, under two different data scenarios of individual event-based and whole data-based scenarios, and a simplified jackknife approach, under the whole data-based scenario, associated with the SCE-UA global optimization algorithm were demonstrated for the analysis of calibrated parameter uncertainty and its subsequent effect on the model simulation of an urban-specific rainfall-runoff model, urban storage function (USF) model. The bootstrap approach was applied to the individual flood events for the first time due to the relevance of flood-runoff analysis in urban watersheds along with the available whole data in order to demonstrate the impact of different available data scenarios on the calibration uncertainty behavior of the parameters. Concurrently, the proposed simplified jackknife approach with a block length of 50 was also implemented to analyze the uncertainty behavior of the calibrated parameters of USF model under the whole data-based scenario. Both the approaches were applied to the residual time series that was computed as the difference between the observed and calibrated discharge time series. Both the approaches were utilized to analyze the calibration parameter uncertainty of the USF model in order to assess its
impact on the model simulation in the upper Kanda River basin, an urban watershed in Tokyo. The parameter uncertainty was expressed by estimating the confidence interval (CI) of the USF model parameters, and then the parameters from the highest to the lowest uncertainties were derived by utilizing two newly proposed parameter uncertainty indices that are based on the width of the confidence interval and the median value which will be useful in future studies in order to derive the parameters from the highest to the lowest uncertainty. The 95% CI of certain parameters converged to a very narrow range as compared to the search range while some parameters showed a wider confidence range from the lower to the upper limit of the search range in both the scenarios of bootstrap analysis. On the contrary, the 95% CI of all the parameters was relatively wide in the jackknife analysis. The highly uncertain parameters obtained were the same by the bootstrap and jackknife approaches even though the order of other model parameters was different.

Additionally, the effect of parameter uncertainty on the model simulation uncertainty was investigated by computing the 95% CI of the simulated discharge series generated from the both approaches, and by utilizing the P-factor and two other proposed indices for assessing the model simulation uncertainty. Investigations on the effect of parameter uncertainty on model simulations by the bootstrap analysis revealed that the model was able to bracket 71% and 58% of observed data, on average, within the prediction range of individual event-based and whole data-based scenarios respectively. This further indicates that the simulation uncertainty is low in the individual event-based analysis compared with the whole data-based analysis based on all the considered indices. In contrast, the USF model was able to bracket only 43% of the observations with block size 50 under the whole data-based scenario, on average, within the confidence band by the jackknife analysis. This further disclosed that the uncertainty analysis methods have a great impact on the simulation uncertainty of the USF model. Moreover, the prediction range was wider at the peak flows from the both methods and hence the USF model simulated peak discharge values had higher uncertainty than low flows.

Both the bootstrap and jackknife methods were able to quantify the parameter uncertainty of USF model in an urban watershed. As a conclusion, the parameter uncertainty and its effect on model simulation uncertainty were successfully evaluated and the characteristics of an urban specific rainfall-runoff model were explained (USF model) in detail using the bootstrap and jackknife approaches. This study primarily
focused on the residual-based bootstrap approach and the simplified jackknife approach for the calibration parameter uncertainty analysis and its subsequent effect on model simulation uncertainty. We applied only one block length in the jackknife approach, and further research is required to determine whether the same or better results could be obtained when other block lengths are used. It is also important to conduct similar studies, which analyze the effect of calibration parameter uncertainty on the model validation by utilizing more observations and different types of rainfall-runoff models in the urban watersheds, and the same will be carried out in our future studies.
CHAPTER 4

A GENERALIZED STORAGE FUNCTION MODEL

4.1 Introduction

Generally, in the conventional SF models, the rainfall is spatially averaged over the basin and assumed a spatially uniform rainfall across the basin. This spatially averaged rainfall was considered as the observed basin rainfall in the conventional models. However, in actual condition, the rainfall is spatially distributed over the watershed and this spatial variability will be quite high even in small urban watersheds (Yonese et al., 2017). The use of basin average rainfall will further result in the underestimation or overestimation of storm runoff based on the meteorological factors as well as the location of rainfall occurrence (Yonese et al., 2018). This effect will be profound in small urban watersheds due to the relatively short time of concentration and the high percent of impervious surfaces. The existing spatial variability in rainfall will contribute uncertainties to the basin average rainfall and finally to the model predictions, but to what extent is unknown.

The performance of different existing SF models have already been evaluated for an urban watershed and it was found that the USF model performs better as compared with conventional SF models (Padiyedath et al., 2018a; 2018b). The USF model well simulated the discharge in small to medium-sized urban watersheds for single and multi-peak flood events with different meteorological factor and peak discharge. The model also exhibited higher performance for different objective functions used during the model calibration (Takasaki et al., 2009). However, the USF model assumed a spatially uniform rainfall over the basin likewise the conventional SF models. So far, the rainfall spatial variability has not been considered in the SF models and thereby an attempt has been made for the first time to address this issue by introducing a new parameter called rainfall distribution factor, hereafter termed as $\gamma$, in the USF model. This parameter will either increase or reduce the basin average rainfall to adjust it with the true basin rainfall, which will further reduce the uncertainties involved to some extent. Further modifications are also possible using radar and dense rain gauge network data to gain a better understanding of the rainfall spatial variability. Based on the above discussions, this chapter aims to propose a generalized USF (GUSF) model with all possible loss components for the
storm-runoff analysis by considering the spatial rainfall distribution in the basin by the introduction of a new parameter, $\gamma$. The performance evaluation of the GUSF model along with the USF model was conducted to examine the effectiveness of parameter $\gamma$ in terms of hydrograph reproducibility and information criteria point of view.

4.2 Generalized USF (GUSF) model for discharge prediction

This section aims to slightly modify the existing USF model by the introduction of rainfall distribution factor, $\gamma$ in the model to consider the basin rainfall variability. This modified USF model is called as generalized USF (GUSF) model in this chapter hereinafter.

4.2.1 Methodology

4.2.1.1 Generalized USF (GUSF) model

The storage equation of GUSF model is the empirical representation of Hoshi’s SF model (Hoshi and Yamaoka, 1982) in which the observed river discharge $Q$ is replaced by $Q + q_R$, which is the discharge including the drainage from the sewer system for the urban area, where, $q_R$ is drainage from the basin through the combined sewer system (mm/min) and is given as:

$$s = k_1(Q + q_R)^{p_1} + k_2 \frac{d}{dt}(Q + q_R)^{p_2}$$  \hspace{1cm} (4.1)

where $s$: storage (mm), $Q$: observed river discharge (mm/min), $t$: time (min), $k_1, k_2, p_1, p_2$: model parameters. The GUSF model can also be applied in non-urban watersheds by omitting the $q_R$ component and the storage equation will be the same as that proposed by Hoshi. Combining the above expression of storage with the following continuity equation yields the nonlinear expression of GUSF model.

$$\frac{ds}{dt} = \gamma R + I - E - O - Q - q_R - q_l$$  \hspace{1cm} (4.2)

where $\gamma$: rainfall distribution factor, $R$: basin average rainfall (mm/min), $I$: inflow from other basins (mm/min), $E$: evapotranspiration (mm/min), $O$: water intake from the basin (mm/min), $q_l$: loss to the groundwater (mm/min). The basin average rainfall should consider as a fraction based on the spatial variability in rainfall and $\gamma$ will represent this fraction. Even though $\gamma$ looks similar to the runoff coefficient in its expression, the purpose of its incorporation is completely different from that of runoff coefficient. Substituting Eq. (4.1) into Eq. (4.2) will lead to a second-order Ordinary Differential
Equation (ODE). This second-order ODE is transformed into the first order ODE and can be numerically solved. The river discharge $Q$ will obtain from the solution. The GUSF is an eight parameter model with parameters $k_1, k_2, k_3, p_1, p_2, z, \alpha, \gamma$. Additionally, in order to analyze the effect of parameter $\gamma$ in the model, the USF model was considered without parameter $\gamma$ ($\gamma = 1$).

4.2.1.2 Parameter estimation and performance evaluation

The SCE-UA method proposed by Duan et al. (1992) was used to identify the optimal parameters of the two models with 100 generations and RMSE as the objective function to be minimized. The search range of parameters for SCE-UA is set as, $k_1$ (0-500), $k_2$ (0-5000), $k_3$ (0-1), $p_1$ (0-1), $p_2$ (0-1), $z$ (0-300), $\alpha$ (0-1), and $\gamma$ (0-10). Due to high spatial variability in rainfall, sometimes, the basin average rainfall will be very low even though high magnitude rainfall occurs near the basin outlet. Therefore, the basin average rainfall should consider as doubled, tripled, etc. in order to represent a high magnitude rainfall near the watershed outlet. Consequently, the maximum possible value of $\gamma$ was set as ten to incorporate the effect of a ten times higher magnitude rainfall resulting from the spatial distribution of rainfall in the basin. Moreover, the model calibration was conducted using two data scenarios: (i) individual event-based scenario where individual flood events were used and (ii) all event-based scenario where all the available events were used for the model calibration. Further, all event-based parameters were used to validate the model. The river discharge computed for each event by the two SF models was compared during calibration and validation in order to assess the reproducibility in terms of the additional parameter $\gamma$ using four error functions of RMSE, NSE, Percentage Error in Peak (PEP), and Percentage Error in Volume (PEV). Further, AIC was also used in order to identify the best model by comparing them for each event during calibration and validation.

4.2.2 Study area and data used

The target basin is the upper Kanda River basin at Koyo Bridge having an area of about 7.7 km$^2$ as shown in Fig. 4.1. The rainfall and water level data collected from the Bureau of Construction, Tokyo Metropolitan Government (TMG) at one-minute interval during 2003-2006 were used for the present study because the USF model was successfully established for the five selected flood events during this period compared with conventional SF models (Padiyedath et al., 2018a). Therefore, the same five flood events, whose 60-minute maximum rainfall ($R_{60}$) is greater than 30 mm, were used for
the calibration of the selected models. In the same manner, three events that are not included in the model calibration were selected for model validation as given in Table 4.1. The basin average rainfall (R) was determined using the Thiessen polygon method from the eight rain gauges scattered over the basin. The inflow component \( I \) was fixed at

![Index map of upper Kanda River basin.](image)

Table 4.1. Characteristics of target events in Kanda basin.

<table>
<thead>
<tr>
<th>Event No.</th>
<th>Event date</th>
<th>( R_{60} )  (mm/h)</th>
<th>Total R (mm)</th>
<th>Climatic factors</th>
<th>Number of peaks</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Calibration events (C)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C1</td>
<td>13-10-2003</td>
<td>53.9</td>
<td>57.5</td>
<td>Intensive localized storm</td>
<td>Single-peak</td>
</tr>
<tr>
<td>C2</td>
<td>25-06-2003</td>
<td>42.6</td>
<td>46.2</td>
<td>Frontal rainfall</td>
<td>Single-peak</td>
</tr>
<tr>
<td>C3</td>
<td>8~10/10/2004</td>
<td>42.0</td>
<td>261.1</td>
<td>Typhoon</td>
<td>Multi-peak</td>
</tr>
<tr>
<td>C4</td>
<td>11-09-2006</td>
<td>32.7</td>
<td>37.9</td>
<td>Frontal rainfall</td>
<td>Single-peak</td>
</tr>
<tr>
<td>C5</td>
<td>15-07-2006</td>
<td>31.5</td>
<td>31.5</td>
<td>Frontal rainfall</td>
<td>Single-peak</td>
</tr>
<tr>
<td><strong>Validation events (V)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>V1</td>
<td>25~26/8/2005</td>
<td>29.6</td>
<td>122.5</td>
<td>Typhoon</td>
<td>Multi-peak</td>
</tr>
<tr>
<td>V2</td>
<td>15~16/6/2006</td>
<td>29.1</td>
<td>94.5</td>
<td>Frontal rainfall</td>
<td>Multi-peak</td>
</tr>
<tr>
<td>V3</td>
<td>29~30/9/2004</td>
<td>27.9</td>
<td>68.5</td>
<td>Typhoon</td>
<td>Multi-peak</td>
</tr>
</tbody>
</table>
0.0012 mm/min based on the business annual report of the TMG. The outflow components $O$ and $E$ were set at zero. The maximum drainage, $q_{R\text{max}}$ was estimated at 0.033 mm/min using the Manning’s equation (Takasaki et al., 2009).

4.2.3 Results and discussion

4.2.3.1 Hydrograph reproducibility and performance evaluation

The SCE-UA method was applied for the parameter estimation of two models under the two selected data scenarios in the target basin. The individual event-based and the all event-based parameters of the models are shown in Table 4.2. It can be seen from the table that the parameter values are varying from event to event in both the models. The rainfall distribution factor, $\gamma$ in the GUSF model is showing values greater than one during events 1, 2, and 3, whereas the values are less than one in the remaining events. Further, to check the significance of the optimized value of $\gamma$, the spatial variability of total rainfall was plotted by interpolating the rainfall received at eight gauging stations as shown in Fig. 4.2 using the Kriging interpolation technique in the Surfer mapping software. Only two events were plotted out of five due to the page constraints. Fig. 4.2(a) shows that high rainfall is occurring near the watershed outlet during calibrated event 3.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Model</th>
<th>Event 1</th>
<th>Event 2</th>
<th>Event 3</th>
<th>Event 4</th>
<th>Event 5</th>
<th>All event</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k_1$</td>
<td>USF</td>
<td>94.89</td>
<td>279.1</td>
<td>46.31</td>
<td>305.06</td>
<td>307.81</td>
<td>58.5</td>
</tr>
<tr>
<td></td>
<td>GUSF</td>
<td>40.56</td>
<td>103.57</td>
<td>166.72</td>
<td>19.88</td>
<td>18.34</td>
<td>31.1</td>
</tr>
<tr>
<td>$k_2$</td>
<td>USF</td>
<td>241.52</td>
<td>464.29</td>
<td>539.73</td>
<td>2670.17</td>
<td>2954.01</td>
<td>973.0</td>
</tr>
<tr>
<td></td>
<td>GUSF</td>
<td>774.72</td>
<td>4992.86</td>
<td>4292.68</td>
<td>4986.99</td>
<td>4995.5</td>
<td>482.8</td>
</tr>
<tr>
<td>$k_3$</td>
<td>USF</td>
<td>0.91</td>
<td>0.67</td>
<td>0.01</td>
<td>0.1</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>GUSF</td>
<td>0.01</td>
<td>0.02</td>
<td>0.02</td>
<td>0.58</td>
<td>0</td>
<td>0.51</td>
</tr>
<tr>
<td>$p_1$</td>
<td>USF</td>
<td>0.12</td>
<td>0.03</td>
<td>0.39</td>
<td>0.02</td>
<td>0.02</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>GUSF</td>
<td>0.49</td>
<td>0.34</td>
<td>0.34</td>
<td>0.7</td>
<td>0.5</td>
<td>0.31</td>
</tr>
<tr>
<td>$p_2$</td>
<td>USF</td>
<td>0.97</td>
<td>0.32</td>
<td>0.45</td>
<td>0.03</td>
<td>0.02</td>
<td>0.71</td>
</tr>
<tr>
<td></td>
<td>GUSF</td>
<td>0.34</td>
<td>0.07</td>
<td>0.13</td>
<td>0.01</td>
<td>0.01</td>
<td>0.36</td>
</tr>
<tr>
<td>$z$</td>
<td>USF</td>
<td>202.52</td>
<td>275.55</td>
<td>4.42</td>
<td>299.34</td>
<td>299.76</td>
<td>28.3</td>
</tr>
<tr>
<td></td>
<td>GUSF</td>
<td>8.24</td>
<td>18.86</td>
<td>35.04</td>
<td>231.72</td>
<td>5.89</td>
<td>157.0</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>USF</td>
<td>0.87</td>
<td>0.88</td>
<td>0.43</td>
<td>0.93</td>
<td>0.9</td>
<td>0.57</td>
</tr>
<tr>
<td></td>
<td>GUSF</td>
<td>0.48</td>
<td>0.4</td>
<td>0.24</td>
<td>0.46</td>
<td>0.41</td>
<td>0.65</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>USF</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>GUSF</td>
<td>1.03</td>
<td>2.59</td>
<td>3.63</td>
<td>0.37</td>
<td>0.37</td>
<td>0.61</td>
</tr>
</tbody>
</table>
which will produce an immediate and intensive response at the outlet. At this point, the basin average rainfall should consider at a higher magnitude, which resulted in a $\gamma$ value of 3.63 as shown in Table 4.2. On the contrary, the spatial rainfall distribution of event 4 illustrated in Fig. 4.2(b) revealed that the high rainfall is occurring at a specific location farther from the outlet point which will generate a delayed and diminished response. This further reduced the value of $\gamma$ to 0.37 (Table 4.2). Therefore, it can be envisaged that the value of $\gamma$ can be either less or greater than one, unlike in the USF model which is always one.
(a) Event C1
(b) Event C2
(c) Event C3
Fig. 4.3. Reproduced hydrographs by the USF and GUSF models during calibration and validation.

Further, these optimally estimated parameters of both the models were used to reproduce the hydrographs during calibration and validation as shown in Fig. 4.3. Only three calibration and two validations events have been depicted in Fig. 4.3 out of the selected events. It can be envisaged from Fig. 4.3(a-c) that the 8-parameter GUSF model almost overlaps with the observed river discharge and accurately reproducing the peak in the calibration events except for event 3. On the contrary, the USF model shows a great deviation in the reproduced hydrograph at the recession limb and exhibits considerable deflection from the observed peak discharge. It is clear from Fig. 4.3(d-e) that the GUSF
model was able to reproduce the shape of the hydrograph, especially the rising and recession limbs during validation. However, the model slightly overestimated the highest peak discharge in all the events. In contrast, hydrograph reproduced by the USF model highly deviated from the observed hydrograph and lower predicted the highest peak although the remaining peaks were overestimated. The calibration and validation results exhibited that the GUSF model can more precisely reproduce the shape of the observed hydrograph as well as the peak discharge compared with the USF model. On the other hand, the USF model is not preserving the shape of the hydrograph as well as the peak discharge. The significant deviation demonstrated by the USF model at the recession limb can be attributed to the omission of spatial distribution factor $\gamma$. This indicates the necessity of parameter $\gamma$ in the USF model to describe the rainfall spatial variability in the basin.

Further, the hydrograph reproducibility by the two models during calibration and validation was analyzed using error functions of RMSE, NSE, PEP, and PEV as shown in Fig. 4.4. From Fig. 4.4(a) and (b), we can see that the GUSF model generates low RMSE close to zero and high NSE close to 100% during calibration as well as validation, except for calibration event 3. The RMSE and NSE values were close for both the models.
during event 3 even though the USF model exhibited slightly better performance. Calibration event 3 is a multi-peak event with the largest number of observations and the use of 100 generations may not be sufficient for its optimal parameter search using the SCE-UA method in the GUSF model. The PEP and PEV become positive for underestimation and Fig. 4.4(c) depicts that the PEP estimated by GUSF model is very low and not greater than 10% during both calibration and validation. Conversely, the USF model largely varies in its PEP values and lower predicted the peak flow in validation as well as in calibration events 4 and 5. Likewise the PEP, the GUSF model shows the best ranges of PEV values in Fig. 4.4(d) which is close to zero during calibration and reaches a maximum of 60% during validation. Simultaneously, the USF model generates higher values of PEV, especially during validation. The higher values of NSE coupled with the lower values of RMSE, PEP, and PEV for GUSF model in calibration and validation indicated that the hydrograph reproducibility by GUSF is the highest compared with the USF model.

4.2.3.2 AIC aspect

Further, the AIC aspect was also used to determine the best model for calibration and validation. Fig. 4.5 shows the $AIC_C$ values for the two models and it can be seen that the GUSF model received the lowest $AIC_C$ except for calibration event 3. This higher $AIC_C$ value of GUSF model for event 3 can be attributed to its higher RMSE during the event as shown in Fig. 4.5(a). The lower AIC values of GUSF model in most of the events can be explained as the effect of incorporated rainfall distribution factor, $\gamma$. Therefore, the GUSF is much more effective than the USF model with an additional optimized parameter.

![Fig. 4.5. The corrected AIC ($AIC_C$) values during calibration and validation.](image-url)
The inclusion of parameter $\gamma$ in the GUSF model aids to have a steep recession in the considered urban watershed and consequently found to be more suitable over the USF model for the use in urban watersheds. The rainfall distribution is temporally as well as spatially varying and the value of $\gamma$ will depend on meteorological factors, basin geology and geomorphology, etc. Not only parameter $\gamma$ is subject to change, but the remaining parameters of GUSF model will also vary in each event based on the meteorological factor and hence the real-time application of the model using the calibrated parameters is a challenging task. However, one solution to tackle this issue is the real-time prediction of the model parameters using data assimilation techniques which will improve the model effectiveness in an operational context even though the GUSF model performed well in validation.

4.3 Generalized SF (GSF) model for water level prediction

This chapter also aims to propose a generalized SF (GSF) model for the water level prediction from the rating curve relationship by considering the spatial distribution of rainfall over the basin and incorporating all the possible inflow and outflow components. Generally, the discharge estimated from the erroneous information of a rating curve will contribute to model prediction uncertainties (Bates and Townley, 1988). The direct use of observed water level for model development will reduce these uncertainties. There are studies, which utilized the rating curve relationship for water level and discharge prediction in basins using different models (Takasaki et al., 2005; Tamura et al., 2006; 2013); however, they do not utilize the SF models. Therefore, in the proposed GSF model, the discharge is replaced with the rating-curve relationship that includes the water level and rating curve constants. The rating curve constants are optimized for water level prediction along with other GSF model parameters. This avoids rating curve establishment of the target watersheds, particularly in partially gauged basins whose data availability is low. In addition, the concept of soil moisture parameter tank (SMPT) model (Ando et al., 1982) was incorporated to account for the groundwater-related loss from the basins (Takasaki et al., 2009). The proposed GSF model was applied to two watersheds in Japan to assess its applicability in both rural and urban watersheds: (i) the Iga watershed, a small to medium-sized semi-urban watershed, and (ii) the Oto watershed, a large rural watershed. Furthermore, to examine the effectiveness of the proposed GSF model with the spatial distribution factor and optimized rating curve constants, the model was compared to three other models in terms of hydrograph reproducibility and the Akaike
information criterion (AIC) aspect. Moreover, the sensitivity of the GSF model parameters was examined based on the Morris method (Morris, 1991), a global sensitivity analysis method.

4.3.1 Methodology

4.3.1.1 GSF model

SF models (Hoshi and Yamaoka, 1982; Kimura, 1961; Prasad, 1967) are flood-event-based lumped models used for simulating discharge hydrograph with hyetograph as input. They are characterized by the relationship between storage and discharge. They have different degrees of simplification that affect the input-output transformation (Takasao and Takara, 1988). In order to develop the GSF model for all the watersheds without the separation of effective rainfall and baseflow components from total rainfall and discharge respectively, it is essential to consider all inflow and outflow components of the watershed. Fig. 4.1 shows the schematic diagram of all the possible inflow and outflow components of a conceptual watershed. The inflow components in Fig. 4.6 are represented by rainfall $R$ (mm/min) and inflows from other basins $I$ (mm/min). The inflows from other basins can be mainly the groundwater inflows, irrigational flow, etc. The outflow components are constituted by the river discharge $Q$ (mm/min);

![Schematic diagram of all inflow and outflow components of a conceptual watershed.](image)

Fig. 4.6. Schematic diagram of all inflow and outflow components of a conceptual watershed.
evapotranspiration $E$ (mm/min); water intake from the basin $O$ (mm/min) for intended purposes such as water supply, agricultural needs, etc., and groundwater-related loss $q_l$ (mm/min).

The GSF model is an SF model considering the spatial distribution of rainfall over the basin for the prediction of water level at the outlet point. The relationship between storage and observed discharge in the GSF model for the prediction of water level is given by the following equation (Hoshi and Yamaoka, 1982; Padiyedath et al., 2018a):

$$s = k_1(Q)^{p_1} + k_2 \frac{d}{dt}(Q)^{p_2}$$  \hspace{1cm} (4.3)

where $s$: storage (mm), $Q$: river discharge computed from the established rating curve (mm/min), $t$: time (min), and $k_1, k_2, p_1, p_2$: model parameters. In the above storage equation, the discharge is replaced with the rating-curve relationship based on power-law,

$$Q = a(H - b)^\beta$$  \hspace{1cm} (4.4)

in which $a$ and $\beta$ are the rating curve constants, and $b$ is a constant which represents the gauge reading corresponding to zero discharge (Domeneghetti et al., 2012). Commonly, a quadratic rating curve relationship is assumed and the value of $\beta$ become two (Takasaki et al., 2005; Tamura et al., 2006). The resulting rating curve relationship is $Q = a(H - b)^2$. The constants $a$ and $b$ were also considered as the GSF model parameters which can be optimized during the model calibration. This will avoid the rating curve establishment of the target watersheds, especially in partially-gauged basins whose data availability is low. Therefore, the storage equation that represent the GSF model is,

$$s = k_1(a(H - b)^2)^{p_1} + k_2 \frac{d}{dt}(a(H - b)^2)^{p_2}$$  \hspace{1cm} (4.5)

where $H$: water level (m), $a, b$: rating curve constants. The associated continuity equation used in the GSF model, which include all the possible inflows and outflows as shown in Fig. 4.1, is given as,

$$\frac{ds}{dt} = \gamma R + I - E - O - Q - q_l$$  \hspace{1cm} (4.6)

where $\gamma$ is the rainfall distribution factor. The spatial rainfall distribution has been considered in the proposed GSF model by introducing a new parameter called rainfall distribution factor, $\gamma$, in the continuity equation. The basin average rainfall should consider as a fraction based on the spatial variability in rainfall and $\gamma$ will represent this fraction. Even though $\gamma$ looks similar to the runoff coefficient in its expression, the purpose of its incorporation is completely different from that of runoff coefficient because
all the possible loss components are already incorporated in the continuity Eq. (4.6) rather than considering the runoff coefficient. The main intention of inclusion of parameter $\gamma$ was to consider the spatial distribution of basin rainfall. Groundwater-related loss ($q_l$) in the GSF model was defined by considering the concept of SMPT model (Ando, et al., 1982) and is given by the following equation:

$$q_l = \begin{cases} k_3(s - z) & (s \geq z) \\ 0 & (s < z) \end{cases} \quad (4.7)$$

where $k_3$ and $z$ are the parameters. The water storage ($s$) in the watersheds should be greater than the infiltration hole height ($z$) to be contributed into the groundwater recharge as shown in Fig. 4.1. If the storage is higher than $z$, there will be a groundwater recharge which is obtained by multiplying the exceedance storage ($s - z$) by a proportional constant $k_3$ as explained by Ando, et al. (1982), otherwise there will be no groundwater contribution.

Substituting Eq. (4.5) into Eq. (4.6) will lead to a second-order ordinary differential equation (ODE) as follows:

$$k_2 \frac{d^2}{dt^2}(a(H - b)^2)^{p_2} = -k_1 \frac{d}{dt}(a(H - b)^2)^{p_1} + \gamma R + I - E - O - a(H - b)^2 - q_l \quad (4.8)$$

In order to solve the second-order ODE, the change of variables is performed as follows:

$$x_1 = (a(H - b)^2)^{p_2} \quad (4.9)$$

$$x_2 = \frac{dx_1}{dt} = \frac{d}{dt}\{(a(H - b)^2)^{p_2}\} \quad (4.10)$$

Substituting Eq. (4.7) into Eq. (4.8) and performing the change of variables will lead to the emergence of two first-order ODEs concerning two conditions shown in Eq. (4.7).

When $s \geq z$, the first-order ODE is as follows:

$$\frac{dx_2}{dt} = -\left(\frac{k_1}{k_2}\right)\left(\frac{p_1}{p_2}\right)x_1^{(p_1/p_2 - 1)}x_2 - \left(\frac{1}{k_2}\right)x_1^{(1/p_2)} - \left(\frac{k_1k_3}{k_2}\right)x_1^{(p_1/p_2)} - k_3x_2 + \left(\frac{1}{k_2}\right)(\gamma R + I - E - O + k_3z) \quad (4.11a)$$

In the case of $s < z$, the first-order ODE concerning the same processes are given by the following:

$$\frac{dx_2}{dt} = -\left(\frac{k_1}{k_2}\right)\left(\frac{p_1}{p_2}\right)x_1^{(p_1/p_2 - 1)}x_2 - \left(\frac{1}{k_2}\right)x_1^{(1/p_2)} + \left(\frac{1}{k_2}\right)(\gamma R + I - E - O) \quad (4.11b)$$
The water level, \( H \) can be estimated by solving the two, simultaneous, non-linear ODEs of \( \frac{dx_1}{dt} \) (Eq. 4.10) and \( \frac{dx_2}{dt} \) (Eq. 4.11) numerically. In order to solve the two first-order simultaneous ODEs, we used the Runge-Kutta-Gill method.

The proposed GSF model is a nine-parameter model with optimized parameters \( k_1, k_2, k_3, p_1, p_2, z, \gamma, a, b \) used for the water level prediction. The other models considered in this study are, (i) 8 parameter model – the GSF model without parameter \( \gamma \), (ii) 7 parameter model – the GSF model with fixed values of parameters \( a \) and \( b \) obtained from the established rating curve by the authorities, and (iii) 6 parameter model – the GSF model without parameter \( \gamma \) and with fixed values of parameters \( a \) and \( b \). These three SF models were compared with the GSF model in order to analyze its effectiveness with optimized parameters of \( \gamma, a, \) and \( b \).

4.3.1.2 Model calibration and validation

The SCE-UA method proposed by Duan et al. (1992) was used to estimate the optimum parameter values of GSF model. It is a well-known, global optimization strategy developed for effective and efficient optimization for calibrating the watershed models. The SCE-UA method has been found to be a useful technique for complex parameter identification problems in hydrologic modeling (Canfield and Lopes, 2004; Canfield et al., 2002; Eckhardt and Arnold, 2001; Kawamura et al., 2004). This method is based on the synthesis of four concepts: competitive evolution, controlled random search, simplex method, and complex shuffling. The algorithmic parameters of SCE-UA were selected as

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
<th>Search range</th>
</tr>
</thead>
<tbody>
<tr>
<td>( k_1 )</td>
<td>Physical watershed characteristics (Sugiyama et al., 1997)</td>
<td>[0, 500]</td>
</tr>
<tr>
<td>( k_2 )</td>
<td>Loop relationship between the storage and discharge (Prasad, 1967)</td>
<td>[0, 5000]</td>
</tr>
<tr>
<td>( k_3 )</td>
<td>Groundwater related loss</td>
<td>[0, 1]</td>
</tr>
<tr>
<td>( p_1 )</td>
<td>Index of flow regime (Sugiyama et al., 1997)</td>
<td>[0, 1]</td>
</tr>
<tr>
<td>( p_2 )</td>
<td>Non-linear unsteady flow effects (Hoshi and Yamaoka, 1982)</td>
<td>[0, 1]</td>
</tr>
<tr>
<td>( z )</td>
<td>Infiltration hole height</td>
<td>[0, 500]</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>Rainfall distribution factor</td>
<td>[0, 10]</td>
</tr>
<tr>
<td>( a )</td>
<td>Rating curve constant</td>
<td>[0, 100]</td>
</tr>
<tr>
<td>( b )</td>
<td>Rating curve constant</td>
<td>[-100, 100]</td>
</tr>
</tbody>
</table>
per the recommendations of Duan et al. (1993). The population is partitioned into several complexes, each of which is permitted to evolve independently. The number of complexes, \( C \), was set equal to 20 and the number of populations in each complex, \( m = 2k + 1 \), where \( k \) is the number of parameters to be estimated. The objective function to be minimized using the SCE-UA method was selected as the root mean square error (RMSE) between the observed and computed water levels using the estimated parameters. A wide range of possible minimum and maximum were used as the search range for optimal parameters using SCE-UA and is shown in Table 4.3 (Padiyedath et al., 2018a; Takasaki et al., 2009). The maximum possible value of \( \gamma \) was set as 10 in order to incorporate the effect of a ten times higher magnitude rainfall resulting from the spatial distribution of rainfall in the basin because sometimes, the basin average rainfall will be very low even though high magnitude rainfall occurs near the basin outlet.

The data set for calibration and validation should be selected in such a way that the calibration segment is long enough for a meaningful calibration, the remainder serving for validation. A simple split-sample test (Klemes, 1986) was carried out in which the first 70% of the data from 2013-2015 was used for calibration and the last 30% in 2016 for validation. The model calibration was carried out using two data scenarios: (i) individual event-based scenario where individual flood events were used, and (ii) all event-based scenario where all the available events were used for the model calibration. Further, all event-based parameters were used to validate the model.

4.3.1.3 Performance evaluation

The calibration and validation performance of the GSF model along with the 8, 7, and 6 parameter models in reproducing the observed water level hydrograph were assessed using four performance evaluation criteria.

1. RMSE
3. Percentage error in peak water level (PEP):
   
   \[
   
   \text{PEP} = [1 - (\text{computed peak water level} / \text{observed peak water level})] \times 100; \text{ and}
   \]

4. Percentage error in area under the water level hydrograph (PEA):

   \[
   
   \text{PEA} = [1 - (\text{computed area under water level hydrograph} / \text{observed area under water level hydrograph})] \times 100
   \]
Further, AIC was also used in order to identify the most effective model by comparing the different models for each event.

4.3.1.4 Sensitivity analysis

Sensitivity analysis (SA) is used to examine how a model output is influenced by the uncertainty in the model factors such as model parameters and model inputs (Neumann, 2012). It has become an essential criterion in the development and evaluation of environmental models (Saltelli et al., 2000; Jakeman et al., 2006), providing a powerful framework for use in the development, operation, calibration, optimization and application of computational models (King and Perera, 2013). SA methods can be classified as either local or global. In local SA, each factor is perturbed in turn while keeping all the others fixed at their nominal value (Baroni and Tarantola, 2014). On the other hand, global SA estimates the effects of factor variations on outputs within the entire allowable ranges of input space (Jiang et al., 2015). Global SA methods range from qualitative screening (Campolongo et al., 2011; Morris, 1991; Saltelli et al., 2010) to quantitative techniques based on variance decomposition (Baroni and Tarantola, 2014). In this study, we are utilizing the Morris global sensitivity analysis (Morris, 1991) which is a screening method based on elementary effects to identify a subset of parameters that have the greatest influence on outputs.

Consider a model for which an output $y$ is a function of $k$ parameters $\theta_i, i = 1, 2, ..., k$. For a given value of $\theta$, the elementary effect of the $i^{th}$ parameter is given by the following equation,

$$d_i(\theta) = \frac{f(\theta, \theta_2, ..., \theta_{i-1}, \theta_{i+1}, ..., \theta_k) - f(\theta)}{\Delta}$$

(4.12)

where $\Delta$ is the magnitude of step, which is a multiple of $1/(p-1)$; $p$ is the number of levels over which the variables can be sampled and $f(\theta)$ is the target function value for the parameter vector $\theta$ (Shin et al., 2013). Each $\theta_i$ will be assumed to be scaled to take on values in the interval $[0, 1]$, and scaled to appropriate ranges of the input variables after performing the analysis to compute the elementary effect (Morris, 1991; King and Perera, 2013). Campolongo et al. (2007) suggested a convenient choice for the Morris parameters that the $p$ is preferentially even and $\Delta$ equal to $p/2(p-1)$. Therefore, in this study, the setting was $p=10$ and $\Delta=p/2(p-1)$. The $d_i$ calculation process is repeated a number of times ($r$), and the mean ($\mu$) and standard deviation ($\sigma$) values of the $r$ samples of $d_i$ are used as Morris sensitivity indices. Instead of using $\mu$, Campolongo et al. (2007) used an
improved measure $\mu_i = \frac{1}{r} \sum_{j=1}^{r} |d_j(\theta_i)|$, which is the mean of the absolute values of $r$ samples of the elementary effect of the $i$th parameter. Therefore, this study uses $\mu^*$ with $r=20$ since the $r$ value is typically between 10 and 50 as explained by Campolongo et al. (2007). The $\mu^*$ and $\sigma$ indicate the influence of each parameter on the target function. A high $\mu^*$ value implies that a parameter has an important overall influence on the target function, and a high value of $\sigma$ implies that a parameter has strong interactions with other parameters (i.e. one parameter interacts with other parameters) or the effect of the parameter is nonlinear (Morris, 1991; Shin et al., 2013; van Griensven et al., 2006).

4.3.2 Study area and data used

4.3.2.1 Study area

The proposed GSF model was applied in two watersheds of Iga and Oto within the Okazaki city, the middle part of Aichi Prefecture, Japan as shown in Fig. 4.7. Okazaki City is the third biggest city in Aichi Prefecture with a population of around 400,000 people. It has a humid subtropical climate and an elevation ranging from 0 m to 789 m above sea level (Rimba et al., 2017). The central city consists of alluvial plains whereas the eastern part of the city is a mountainous area which has an altitude of 789 m and the rest is lowland area which has an altitude ranging between 0 and 300 m (Okazakishi, 2019). The major land use within this area is agriculture including paddy fields. Precipitation occurs throughout the year with an annual rainfall of about 1200 mm where the maximum is received in the summer season (i.e., June to September) and during typhoon phenomena. The temperature range is from $-1^\circ$C to $36^\circ$C with an average annual temperature of $17^\circ$C (Rimba et al., 2017).

The Iga River (Fig. 4.7(c)) is a tributary of the Yahagi River, which is a typical small to medium sized semi-urban watershed with an area of about 9.6 km$^2$ at Iga Bridge. It lies between latitudes 34.98° N and 34.95° N and longitudes 137.17° E and 137.23° E. The Oto River (Fig. 4.7(d)) is another tributary of Yahagi River which is a relatively large rural watershed with an area of about 216.46 km$^2$ at Chiharazawa. It lies between latitudes 34.88° N and 35.02° N and longitudes 137.23° E and 137.42° E. In the past decades, heavy rains and flooding occurred in the basins due to typhoons and intensive localized rainfall in which the flood in 2008 was the most severe with a rainfall intensity of about 146.5 mm/h (Okazakishi, 2015). Around 1110 and 2255 houses were flooded above and below floor levels respectively (Adachi, 2009; Rimba et al., 2017) and two people died.
Fig. 4.7. Index map of (a) Japan, (b) Iga and Oto basins within the Okazaki city of Aichi prefecture, (c) Iga basin at Iga Bridge, and (d) Oto basin at Chiharazawa.
Recently, typhoon Malakas caused torrential rainfall in 2016 with an intensity of more than 100 mm/h. The flood survey was conducted during the flood by the local government of Okazaki City and Ministry of Land, Infrastructure, Transportation, and Tourism (MLIT) and are undertaking countermeasures on the watershed and river improvement.

### Table 4.4. Characteristics of the selected events for Iga and Oto basins.


<table>
<thead>
<tr>
<th>Event No.</th>
<th>Event date</th>
<th>Peak H (m)</th>
<th>R₆₀ (mm)</th>
<th>Average R (mm)</th>
<th>Meteorological factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10/9/2015</td>
<td>24.1</td>
<td>32.9</td>
<td>40.3</td>
<td>Typhoon</td>
</tr>
<tr>
<td>2</td>
<td>7–8/9/2013</td>
<td>23.9</td>
<td>42.9</td>
<td>44.8</td>
<td>Frontal event</td>
</tr>
<tr>
<td>3</td>
<td>8–9/9/2015</td>
<td>23.9</td>
<td>18.6</td>
<td>134.2</td>
<td>Typhoon</td>
</tr>
<tr>
<td>4</td>
<td>15–16/10/2013</td>
<td>23.7</td>
<td>14.3</td>
<td>138.7</td>
<td>Typhoon</td>
</tr>
<tr>
<td>5</td>
<td>26–27/5/2014</td>
<td>23.7</td>
<td>14.2</td>
<td>68.9</td>
<td>Frontal event</td>
</tr>
</tbody>
</table>

#### Validation events – Iga basin (2016)

<table>
<thead>
<tr>
<th>Event No.</th>
<th>Event date</th>
<th>Peak H (m)</th>
<th>R₆₀ (mm)</th>
<th>Average R (mm)</th>
<th>Meteorological factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>19–21/9/2016</td>
<td>24.5</td>
<td>47.9</td>
<td>161.5</td>
<td>Typhoon</td>
</tr>
<tr>
<td>2</td>
<td>18–19/3/2016</td>
<td>23.6</td>
<td>17.7</td>
<td>51.0</td>
<td>Frontal event</td>
</tr>
</tbody>
</table>

#### Calibration events – Oto basin (2013-2015)

<table>
<thead>
<tr>
<th>Event No.</th>
<th>Event date</th>
<th>Peak H (m)</th>
<th>R₆₀ (mm)</th>
<th>Average R (mm)</th>
<th>Meteorological factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15–16/9/2013</td>
<td>5.7</td>
<td>56.1</td>
<td>229.1</td>
<td>Typhoon</td>
</tr>
<tr>
<td>2</td>
<td>8–9/9/2015</td>
<td>2.6</td>
<td>14.3</td>
<td>119.5</td>
<td>Typhoon</td>
</tr>
<tr>
<td>3</td>
<td>24–25/9/2014</td>
<td>2.5</td>
<td>22.1</td>
<td>106.3</td>
<td>Typhoon</td>
</tr>
<tr>
<td>4</td>
<td>29–30/3/2014</td>
<td>2.5</td>
<td>20.3</td>
<td>108.5</td>
<td>Frontal event</td>
</tr>
<tr>
<td>5</td>
<td>16–18/8/2015</td>
<td>2.4</td>
<td>29.8</td>
<td>77.1</td>
<td>Frontal event</td>
</tr>
</tbody>
</table>

#### Validation events – Oto basin (2016)

<table>
<thead>
<tr>
<th>Event No.</th>
<th>Event date</th>
<th>Peak H (m)</th>
<th>R₆₀ (mm)</th>
<th>Average R (mm)</th>
<th>Meteorological factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3–4/5/2016</td>
<td>2.0</td>
<td>24.8</td>
<td>81.4</td>
<td>Frontal event</td>
</tr>
<tr>
<td>2</td>
<td>22–23/12/2016</td>
<td>1.8</td>
<td>20.9</td>
<td>69</td>
<td>Frontal event</td>
</tr>
</tbody>
</table>
4.3.2.2 Data used

The rainfall and water level data at ten-minute intervals were collected from the Okazaki City Government during 2013-2016 for the study. The water level data at the Iga Bridge as well as the Chiharazawa stations (Fig. 4.7) were collected which constitute the observed water level values for the model calibration and performance evaluation. The average rainfall of each basin was determined using the Thiessen polygon method from the rain gauges scattered over the basin as shown in Fig. 4.7 (c) and (d). Five target events were selected from the data for the calibration in each basin, whose 60-minute maximum rainfall ($R_{60}$) is greater than 10 mm and is capable of producing flash floods. In the same manner, two events, which are not included in the model calibration were selected for the validation purpose of the model. Table 4.4 shows the characteristics of the selected rainfall events for calibration and validation. The inflow component, $I$ in the continuity equation was zero since there is no inflow to the basin. The water intake $O$ from the basin and evapotranspiration $E$ were set at zero.

4.3.3 Results and discussion

4.3.3.1 Model calibration

The proposed GSF model along with three other models was implemented to the two selected watersheds of Iga and Oto. The SCE-UA method was applied for parameter estimation of the models with RMSE as the objective function. The convergence of parameters was checked and it was found that the parameters converged before the 100th generation in each SCE-UA application run for all the models as shown in Fig. 4.8. Therefore, the best parameter set among the total population at the 100th generation with the minimum RMSE was used for further hydrograph reproduction. The total population generated in each generation was based on the number of parameters in the models as explained in section 4.3.1.2.

Fig. 4.9 shows the calibrated parameters of the models for the selected five events from both individual event-based and all event-based scenarios for both the basins. Fig. 4.9(a)–(f) shows the parameters $k_1, k_2, k_3, p_1, p_2, z$ respectively, and these are associated with all the four considered models. It is clear from Fig. 4.9(a) that the parameter $k_1$ varies between models as well as among events for both the watersheds. The variation was low in the Iga basin whereas the Oto basin exhibited high variability. The $k_1$ value of Oto basin is higher than 100 in most of the events whereas the Iga basin often exhibited
values less than 100. The parameter $k_1$ represents the physical watershed characteristics like watershed area, stream length, slope, etc. (Sugiyama et al., 1997). Park et al. (2012) reported that the parameter $k_1$ has high relevance with the basin characteristics in such a way that any increase in the basin area, as well as the stream length, will lead to the increase in parameter $k_1$. Oto basin is a large basin compared with the Iga, which further resulted in relatively higher $k_1$ values for the Oto basin. The $k_2$ values were almost similar for the models among the events except for some as shown in Fig. 4.9(b). Likewise parameter $k_1$, $k_2$ values of the Oto basin is quite high for all the models compared with the values of Iga basin in all the considered events. The parameter $k_2$ was found to depend on the main channel characteristics, the shape of the basin, amount and duration of rainfall, etc. (Prasad, 1967) which further derived higher $k_2$ values for Oto basin. The GSF model exhibited high variability in parameter $k_3$ only for the Oto basin whereas the 8 parameter

![Parameter convergence pattern](image-url)
model, which is not considering the effect of $\gamma$, values were quite different among events for both the basins as illustrated in Fig. 4.9(c). The $p_1$ values in Fig. 4.9(d) were almost close for all the models in both the basins even though they vary among the events. In addition, parameter $p_1$ demonstrated an opposite trend of parameter $k_2$ where the $p_1$ values of Oto basin were low compared to that of Iga basin for all considered models.

Fig. 4.9. The calibrated parameters of GSF, 8, 7, and 6 parameter models for the Oto and Iga basins. ‘C’ indicates calibrated parameters from individual events and ‘V’ indicates the calibrated parameters from all the events.
Parameter $p_2$ exhibited variation in values for the models among the events in the Iga basin whereas the values were identical in the Oto basin as shown in Fig. 4.9(e). The $p_2$ values of Iga basin were higher compared with the Oto basin values, which further indicates a relatively higher unsteady flow in the semi-urban Iga basin (Hoshi and Yamaoka, 1982).

It can be envisaged from Fig. 4.9(f) that there is high variability in the $z$ values of all the models among the events for both the basins. Fig. 4.9(g) exhibits the spatial distribution factor $\gamma$, which is present only in the 9-parameter GSF and 7 parameter models, whereas the 8 and 6 parameter models are not considering the effect of $\gamma$. The GSF and 7 parameter models revealed either $\gamma$ values greater than one or equal to one for the Iga basin as shown in Fig. 4.9(g). This represents a higher magnitude of rainfall near the outlet compared with the basin average rainfall. On the other hand, the Oto basin showed very low values in comparison with the Iga basin and none of the values was higher than one for the models, which indicate a higher basin average rainfall compared with the rainfall near the basin outlet. Fig. 4.9(h) and (i) demonstrate the rating curve constants $a$ and $b$ respectively which are present in the GSF and 8 parameter models, while the 7 and 6 parameter models included fixed values of $a$ and $b$ from the established rating curve rather than optimizing for comparison with the GSF and 8 parameter models. The parameter $a$ is varying from event to event in both the basins for the GSF and 8 parameter models as shown in Fig. 4.9(h) and the calibrated values are far compared with the fixed value represented by the red line in Fig. 4.9(h). The parameter $b$, which represents the water level corresponding to zero discharge, exhibited a high level of agreement with the fixed value in both the basins as depicted in Fig. 4.9(i).

Further, to check the significance of the optimized value of $\gamma$ in the GSF model, the spatial variability of total rainfall was plotted as shown in Fig. 4.10. Spatial variability of two calibration events and one validation event from each basin was plotted. It can be seen from Fig. 4.10(a1-a3) that heavy rainfall is occurring near the watershed outlet of Iga basin compared with the upstream regions. This will produce an immediate and intensive response at the outlet since the Iga basin is a semi-urban watershed. However, the basin average rainfall of these events (Table 4.4) is quite low compared with the high rainfall at the outlet. At this point, the basin average rainfall should be increased to incorporate this actual rainfall effect near the outlet, which further resulted in a $\gamma$ value of greater than one for the GSF model as shown in Fig. 4.9(g). On the contrary, Oto basin
demonstrated high variability in basin rainfall as shown in Fig. 4.10(b1-b3). The gauges near the outlet are receiving a very small amount of rainfall compared with the basin average rainfall and the high rainfall is occurring at a specific location farther from the outlet point, which will generate a delayed and diminished response. The use of basin average rainfall may lead to the overestimation of water level and a reduced $\gamma$ value is needed to compensate this effect, which further resulted in a $\gamma$ value of less than one as shown in Fig. 4.9(g). The results revealed that the parameter $\gamma$ have physical significance in relation to the spatial rainfall distribution in the basin. The GSF model with parameter
\( \gamma \) can adjust the basin average rainfall in order to cope with the spatial variation of rainfall in the basin. Therefore, it can be envisaged that the value of \( \gamma \) can be either less or greater than one based on rainfall spatial variability and is not always one.

It is evident from the above results that the Iga and Oto basin parameter values are not identical in all the events for different models and shows high variation in most of the events. This indicates that the same set of model parameters cannot be used for basins with dissimilar physical characteristics (Pickup, 1977). Generally, during the parameter estimation, the model attempts to either reduce or increase each parameter in association with the other parameters based on its model structure in order to get the best combination, which will lead to the better performance. However, it is worth mentioning that no calibration can guarantee the uniqueness of the obtained parameter sets due to a concept called equifinality (Beven and Freer, 2001).

4.3.3.2 Hydrograph reproducibility

First and foremost, the calibration performance of GSF model along with other models was analyzed by estimating the water level reproducibility with optimized parameters for both the watersheds. Fig. 4.11 and 4.12 show the reproduced water level for the calibration events using the models with the parameters shown in Fig. 4.9 in the Iga basin and Oto basin respectively. It is clear from Fig. 4.11(a1-a5) of the Iga basin that the 9 parameter GSF model nearly overlaps with the observed water level hydrograph and reproduces the shape slightly better than other models. All the models were capable of accurate reproduction of the peak water level during all the events, except in event 1. During event 1, the peak predicted by the GSF model was most close to the observed peak compared with the peaks estimated by other models even though the model was unable to reproduce the peak water level accurately. The low hydrograph reproducibility by the 8 and 6 parameter models, especially in event 1, indicates that the incorporation of rainfall distribution factor is indispensable in order to achieve better performance by the models. All the models demonstrated a relatively low performance during event 1, which can be attributed to the shortest number of observations available in the event for calibration with the highest peak compared with other events. It can be seen from Fig. 4.12(b1-b5) of Oto basin that the GSF model along with other models reproduced the shape of the observed hydrograph with small discrepancies at the rising and recession limbs and consistently underestimated the peak water level slightly. This similar hydrograph reproducibility revealed by the models in the Oto basin can be attributed to
their almost near values of rainfall distribution factor, γ as shown in Fig. 4.9(g). However, likewise in the Iga basin, the GSF model was the one that simulated the hydrograph as well as peak water level most close to the observed hydrograph compared with other models.

The 7 and 6 parameter models are expected to reproduce the water level hydrograph more accurately compared with the GSF and 8 parameter models respectively since the parameters a and b are derived from the established rating curve for the 7 and 6 parameter models. However, the 7 and 6 parameter models have reproduced the water level with minor variations likewise the GSF and 8 parameter models respectively. The hydrograph reproducibility results revealed that the GSF model could more accurately reproduce the shape of the observed water level hydrograph as well as the peak water level compared to that reproduced using the other models during calibration.
Fig. 4.11. The reproduced hydrographs by models for Iga basin (a1-a5) during calibration.
Oto basin

Event 1

Event 2

Event 3

Event 4

Event 5

Rainfall (mm/10 min)

H (m)

Time (10 min)
Further, the models were validated by estimating the hydrograph reproducibility for the two selected events of Iga and Oto watersheds as shown in Fig. 4.13 and 4.14 respectively. The validation of the model for Iga basin illustrated in Fig. 4.13(a1-a2) shows that all the models demonstrated a notable deviation in the shape of the reproduced hydrograph and considerably underestimated the peak water level in both the validation events. The peak water level of validation event 1 is the highest compared with the peak

Fig. 4.12. The reproduced hydrographs by models for Oto basin (b1-b5) during calibration.
Fig. 4.13. The reproduced hydrographs by models for Iga basin (a1-a2) during validation. of calibration events and the models were unable to accurately predict the peaks of event 1. This further shows that the models have low extrapolation potential outside the range of the calibration data set even though the 7 and 6 parameter models managed to estimate the peak water level accurately to some extent during event 1. The model validated in the Oto basin as shown in Fig. 4.14(b1-b2) portrayed that the GSF model along with other models significantly deviated from the observed hydrograph at the recession limb with an overestimated late prediction of peak water level. However, the GSF model accurately reproduced the rising limb compared with other models. Therefore, it can be envisaged that the models exhibited relatively similar reproducibility during validation, which was low compared with the reproducibility during calibration. The results further revealed that none of the models showed consistent performance during validation in both the basins.
Fig. 4.14. The reproduced hydrographs by models for Oto basin (b1-b2) during validation.

4.3.3.3 Performance evaluation

From Figs. 4.11, 4.12, 4.13, and 4.14, it is not easy to readily discern the difference between the simulated water level hydrographs of the different models. Hence, we evaluated the performance of these models during calibration and validation using RMSE, NSE, and other error functions of PEP, and PEA as shown in Fig. 4.15. From Fig. 4.15(a1) and (a2), we can see that the GSF model generates the least RMSE values close to zero and highest NSE values close to 100% in all the calibration events for the Iga basin. This low RMSE and high NSE of GSF model can be interpreted as to its high hydrograph reproducibility during calibration, which further reveals that the SCE-UA method has successfully identified the optimal parameters for the model during each event. The GSF
model was followed by the 7 parameter model which also considers the effect parameter $\gamma$. The GSF and 8 parameter models exhibited low performance in validation event 1, the multi-peak event with the highest peak, irrespective of their large number of parameters compared with other models even though all the models portrayed a comparable performance in validation event 2. Fig. 4.15(a3) and (a4) depict that the PEP and PEA values estimated by the models are close to zero and not greater than 1% and 10% respectively during calibration. On the other hand, during validation, the 7 and 6 parameter models with a fixed $a$ and $b$ parameter values from the established rating curve

Fig. 4.15. The performance evaluation of different models during calibration and validation for Iga basin (a1-a4) and Oto basin (b1-b4). ‘C’ and ‘V’ indicate the calibration and validation respectively.
based on the actual basin observations demonstrated a low PEP and PEA values. During calibration in the Oto basin, all the models exhibited similar RMSE and NSE values in which the GSF model giving slightly lower RMSE and higher NSE values compared with other models as shown in Fig. 4.15(b1) and (b2). The RMSE and NSE values were quite close during validation also even though the models showed lower performance compared with that during calibration. Fig. 4.15(b3) reveals that the PEP values estimated by the models were relatively similar and not greater than 20% during both calibration and validation. Fig. 4.15(b4) shows that the PEA values of the models are almost identical and are within 25% during calibration, whereas the models showed a high variation in the PEA values during validation with values reaching a maximum of 50%. This further reveals that the models have a consistent performance during calibration whereas the performance highly varies in validation.

Further, to compare the capabilities of different models for simulating the water level, the simulated water level was analyzed and correlated with observed values using the linear regression equation. The scatter plots and the associated coefficient of determination values (R²) are shown in Fig. 4.16. All the events in calibration and validation were considered for the regression analysis in both the basins. It is clear from Fig. 4.16(a1-a4) and (c1-c4) that the GSF model giving the highest correlation with an R² value of 0.99 for both the basins during calibration compared with other models. During validation in the Iga basin, all the models exhibited comparable R² values as shown in Fig. 4.16(b1-b4). On the contrary, the GSF model demonstrated a significantly high R² value of 0.96 compared with other models in the validation of Oto basin as illustrated in Fig. 4.16(d1-d4). It can be envisaged from the Fig. 4.16 that there is always an overall lower prediction in the simulated water level by all the models except during the validation in Oto basin in which the water level is overestimated. Overall, the water level simulated by the 9 parameter GSF model demonstrated high agreement with the observed water level during both calibration and validation even though there was an underestimation or overestimation in the predictions.
Iga basin

Simulated H (m)

(a1) GSF

R^2 = 0.99

(b1) Calibration

Observed H (m)

GSF

(a2) 8 Parameter

R^2 = 0.97

(b2) Validation

Observed H (m)

Iga basin

(a3) 7 Parameter

R^2 = 0.98

(b3)

Observed H (m)

(a4) 6 Parameter

R^2 = 0.98

(b4)

Observed H (m)
Fig. 4.16. Scatter plot of observed water level versus simulated by the models in the (i) Iga basin calibration (a1-a4) and validation (b1-b4), and (ii) Oto basin calibration (c1-c4) and validation (d1-d4).
In an operational context, there was high variability in the different model performance and the GSF model could not outperform the other models unlike in the calibration for the small semi-urban Iga basin as well as for the relatively large Oto basin. A model calibrated with data from a given time period could perform well or poorly when evaluated over the validation period, depending on the information content and variability of the calibration data (Singh et al., 2013). This happens because the model can provide a modest level of credibility limited to interpolation within the range of the database used during calibration and have limited extrapolation potential as explained by Klemes (1986). Increasing the length of the calibration data set can make the calibration more reliable and improve the extrapolation potential of the model. In addition, there will be a change in the calibrated parameters with respect to the changes in calibration data, errors in input data, change in model structure, etc. (Beven and Freer, 2001). This means that several combinations of parameter values can allow the model to provide outputs close to observations. As a result, taking into account of additional observations in calibration could help for a better representation of the model parameters by reducing the number of acceptable parameter values (Horritt, 2000; Bates, 2004).

4.3.3.4 AIC aspect

In addition to hydrograph reproducibility and performance evaluation, AIC aspect was also used in order to identify the effective model based on the number of model parameters for calibration and validation. Fig. 4.17(a1) and (b1) show the AICc values of different models for both the basins during calibration and validation. It can be seen from Fig. 4.17(a1) that the GSF model has the lowest AICc during events 1 and 3. The 8 parameter model received the lowest AICc value for event 2 whereas the 7 parameter model had the least value in events 4 and 5. The effective model for the Iga basin was changing from event to event during calibration based on AICc values. However, in the validation, the 6 parameter model with the least number of parameters exhibited the least AICc values. During calibration in the Oto basin, the GSF model showed the least AICc values in two events (events 3 and 5) and the 7 parameter model has also got the lowest values in two events (events 1 and 4) while the 8 parameter model received the least AICc value only in event 2 as shown in Fig. 4.17(b1). All the models showed identical AICc values in validation event 1 although the 7 parameter model received the least AICc value in validation event 2. From Fig. 4.17(a1) and (b1), it is not easy to clearly distinguish the difference between the AICc values of the models. Therefore, we analyzed the AICc
values using an associated statistic known as Akaike weight (AW) to depict the differences distinctly and to quantify the plausibility of the models as being the best approximating.

Fig. 4.17(a2) and (b2) show the AW for both the basins during calibration and validation. The weight exhibits an opposite trend to that of the AIC$_C$ values and the model with the highest weight is the best (Hurvich and Tsai, 1989). Like the AIC$_C$ score, the GSF model received the highest weights during events 1 and 3 during calibration in the Iga basin as shown in Fig. 4.17(a2). The 7 parameter model has got the highest weight during events 4 and 5 whereas the 8 parameter model received the highest AW value in event 2, which was followed by the GSF model. The AW values in the Oto basin revealed the same trend that was observed in the Iga basin in which the highest weight was received by the 7 parameter model in events 1 and 4 as shown in Fig. 4.17(b2). In the same manner, the GSF model portrayed the highest values in events 3 and 5, whereas the 8 parameter model got better AW in event 2. The AW value of calibration event 2 was higher for the
8 parameter model in both the basins even though the lowest RMSE in event 2 was obtained for 9 parameter GSF model. This can be attributed to the small difference in RMSE values between the GSF model and one parameter less 8 parameter model. The high AW values of GSF and 7 parameter models in most of the calibration events of both the basins can be ascribed to the effect of incorporated parameter $\gamma$. This further indicates that the rainfall distribution factor has a high influence on the overall performance of the model. During validation, none of the models exhibited a consistent performance based on the AW values in both the basins.

The effectiveness of the models based on AIC aspect revealed that both the GSF and 7 parameter models exhibited comparable performance during calibration. In comparison with the GSF model with optimized parameters $a$ and $b$, the 7 parameter model is expected to give good results with fixed values of rating curve parameters $a$ and $b$, which are obtained from the actual basin observations. However, the GSF model outperformed the 7 parameter model in most of the events. Therefore, we can conclude that the GSF model is much more effective with optimized values of $a$ and $b$ for the use in ungauged and partially gauged watersheds compared with the 7 parameter model. The 8 and 6 parameter models without the rainfall distribution factor ($\gamma$) showed relatively less support based on AIC aspect which further confirms the need for this parameter in the GSF model. It is clear from the validation results that none of the considered model is reliable in an operational context based on AIC aspect and further research after including more calibration events is needed to improve their operational adequacy.

4.3.3.5 Sensitivity analysis of GSF model

Further, to analyze the effect of different parameters in the GSF model, Morris sensitivity analysis was performed. Table 4.5 shows the $\mu^*$ values obtained from sensitivity analysis and associated ranking of parameters in the Iga and Oto basins for the objective function of RMSE. It is clear from the table that the parameter $b$ has the highest $\mu^*$ value that further indicates that it is the most sensitive parameter of GSF model predictions in both the basins since it represents the gauge reading corresponding to zero discharge (Domeneghetti et al., 2012). Parameter $b$ was followed by the parameter $p_2$ in the Iga and Oto basins because it constitutes the non-linear unsteady flow effects (Hoshi and Yamaoka, 1982). Apart from $b$ and $p_2$, the ranking order of sensitive parameters was different in both the basins. In the Iga basin, the parameters $a$, $p_1$, and $k_2$ showed $\mu^*$ values close to parameter $p_2$, while the remaining parameters received small $\mu^*$ values
and the associated sensitivity ranking was low. In the Oto basin, all the remaining parameters exhibited relatively low $\mu^*$ values. Further, Fig. 4.18 shows the screening plot from the sensitivity analysis with $\mu^*$ values on the x-axis and $\sigma$ values on the y-axis (Zhan et al., 2013). It is clear from Fig. 4.18(a) that the parameters $p_2$, $p_1$, $b$, $k_2$ and $a$ have strong interactions with other parameters in Iga basin since they got high values of $\sigma$ and the other parameters showed relatively low interactions. The parameter $b$ showed the highest $\mu^*$ value which further revealed that it has a strong influence of the model performance while the parameters $k_2$, $a$, $p_1$, and $k_2$ demonstrated a moderate influence. The effect of other parameters on the model performance was negligible. In the Oto basin, parameter $b$ exhibited the highest $\mu^*$ and $\sigma$ values, which indicate that it is the parameter with a strong influence on model performance as well as strong interaction with other parameters as shown in Fig. 4.18(b). The parameter $p_2$ portrayed high interactions with other parameters after parameter $b$ and the remaining parameters demonstrated relatively low interactions and negligible influence on model performance. The sensitivity analysis revealed that the order of sensitive parameters is changing from basin to basin. van Griensven et al. (2006) examined the sensitivity of SWAT model parameters and found that the sensitive parameters will vary between catchments. Shin et al. (2013) strengthened the results of van Griensven et al. (2006) that sensitivities of parameters in a rainfall-runoff model are site-specific, and cannot be assumed from previous work in other catchments.

Table 4.5. Morris sensitivity index ($\mu^*$) and associated ranking of GSF model for RMSE in the Iga and Oto basins.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Iga basin</th>
<th>Oto basin</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\mu^*$</td>
<td>Rank</td>
</tr>
<tr>
<td>$k_1$</td>
<td>80.86</td>
<td>6</td>
</tr>
<tr>
<td>$k_2$</td>
<td>130.85</td>
<td>5</td>
</tr>
<tr>
<td>$k_3$</td>
<td>63.26</td>
<td>8</td>
</tr>
<tr>
<td>$p_1$</td>
<td>162.58</td>
<td>4</td>
</tr>
<tr>
<td>$p_2$</td>
<td>208.65</td>
<td>2</td>
</tr>
<tr>
<td>$z$</td>
<td>38.98</td>
<td>9</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>70.90</td>
<td>7</td>
</tr>
<tr>
<td>$a$</td>
<td>190.33</td>
<td>3</td>
</tr>
<tr>
<td>$b$</td>
<td>332.55</td>
<td>1</td>
</tr>
</tbody>
</table>
Overall, the results revealed that the reliability of a model could only be assessed on large test samples with varied catchments. It is also worth noting that, in calibration and validation, models with a different number of parameters produced quite different results. The models with a large number of parameters did not provide the best predictions in several events that further reveals that the complexity alone cannot guarantee good and reliable performances (Perrin et al., 2001). The structure of the model (i.e. the parameterization for rainfall spatial variability) is of critical importance for the model performance rather than the number of optimized parameters (Gan et al., 1997). The proposed GSF model was able to take care of the spatial variability in rainfall over the basin during calibration. However, the rainfall distribution is temporally as well as spatially variable and the value of $\gamma$ will depend on meteorological factors, basin geology and geomorphology, etc. Not only parameter $\gamma$ is subject to change, but the remaining parameters of GSF model will also vary in each event based on the meteorological factor and hence the real-time application of the model using the calibrated parameters is a challenging task. However, one solution to tackle this issue is the real-time prediction of the model parameters using data assimilation techniques, which will improve the model effectiveness in an operational context. Further modifications are also possible by the use of radar and dense network of rain gauge data to gain a better understanding of the rainfall spatial variability.

Fig. 4.18. Morris sensitivity indices for the objective function RMSE in (a) Iga basin and (b) Oto basin.
4.4 Conclusions

First and foremost, a generalized storage function (GSF) model was proposed for the prediction of water level from the rating curve relationship by considering the spatial distribution of rainfall over the basin and incorporating all the possible inflow and outflow components. The proposed GSF model along with three other models were then applied in two watersheds of (i) Iga watershed, a semi-urban watershed, and (ii) Oto watershed, a rural watershed in Japan to check its applicability in different types of watersheds with optimized parameters. The model calibration revealed that the Iga and Oto basin parameter values are not identical in all the events and shows high variation in most of the events, which further indicates that the same set of model parameters cannot be used for basins with dissimilar physical characteristics. The different model performances during calibration and validation were analyzed and the GSF model exhibited higher performance during calibration whereas none of the models showed consistent performance during validation in both the basins. Further, the AIC aspect was also used in order to determine the effective model for calibration and validation. In comparison with the GSF model with optimized parameters $a$ and $b$, the 7 parameter model is expected to give good results with fixed values of rating curve parameters $a$ and $b$, which are obtained from the actual basin observations. However, the GSF model outperformed the 7 parameter model in most of the events. Therefore, we can conclude that the GSF model is much more effective with optimized values of $a$ and $b$ for the use in ungauged and partially gauged watersheds compared with the 7 parameter model based on AIC aspect. Any of the considered models were not reliable in an operational context based on AIC aspect and further research after including more calibration events is needed to improve their operational adequacy. Lastly, Morris sensitivity analysis was carried out to identify the sensitive parameters of the proposed GSF model. Overall, it can be concluded that the GSF model performed well in both the watersheds irrespective of nature and well as the size of the basin. However, there is a need for the improvement of the model for the application in an operational context using data assimilation approaches. The future research will focus on these points and will carry out an effort for the real-time prediction of water level using the proposed GSF model.

The results from GSF model simulations revealed that the incorporation of rainfall distribution factor ($\gamma$) could improve the performance of the model significantly. Therefore, an attempt has been made to slightly modify the existing USF model by the
introduction of rainfall distribution factor, $\gamma$ in the model to consider the basin rainfall variability and this modified USF model is called as generalized USF (GUSF) model. The GUSF model was applied to five selected flood events of the upper Kanda basin, Tokyo along with USF model in order to evaluate the effectiveness of $\gamma$ in the GUSF model. The results revealed that GUSF model has the least RMSE (high NSE) compared with the USF model for most of the events which further shows that the SCE-UA method has successfully identified the optimal parameters. The lower values of PEP and PEV received by GUSF model further indicate that the incorporation of rainfall distribution factor, $\gamma$ can drastically improve the performance of the model. In addition, the summary of AIC results shows that the GUSF received the highest AW in most of the events compared with the USF model, which make it the parsimonious model. As a conclusion, the GUSF model can be considered as the best for not only the hydrograph reproducibility but also the most parsimonious based on the AIC perspective in most of the flood events in an urban watershed when compared with the USF model, if the optimal parameters are successfully identified for the events.
Chapter 5
CHAPTER 5

GENERAL CONCLUSIONS AND RECOMMENDATIONS

Flood is considered as one of the severe natural disasters due to the associated flood risk and costs in both rural and urban areas. The extreme events of the high flood will always affect the nearby population and indirectly causes an enormous threat to human life, properties, etc. Therefore, the accurate prediction of the hydrograph in advance, which includes the estimation of flood peak, time to peak, volume, lag time, etc., is important for the flood mitigation in order to avoid losses. For this purpose, the rainfall-runoff models are important tools and they play a central role in flood management. Among the different conceptual lumped rainfall-runoff models, storage function (SF) models have been widely used in many parts of the world, especially in Japan, not only because of their ease of use in computation and handling but also because of the ease by which they express the nonlinear relationship of the rainfall-runoff process using simple equations.

The selection of appropriate models for the intended purpose is very important. Hence, there is a need for the comparative studies of rainfall-runoff models due to the existence of a variety of models to evaluate their ability to predict discharge and to provide guidelines for end-users. In addition, the predictions made using rainfall-runoff models are inherently uncertain and it is necessary to carry out parameter uncertainty analysis of a calibrated model because it is one of the major sources of uncertainty. Hence, an appropriate uncertainty consideration of the model parameters is necessary although it has been often ignored until recently. Further, there is a need for a generalized SF (GSF) model that can be applied in all the watersheds without requiring the effective rainfall as their input by incorporating all the possible inflow and outflow components and the rainfall spatial variability since it has not been considered in the SF models so far. Based on the aforementioned discussions, this thesis had three main objectives and the significant conclusions based on these objectives are briefly outlined as follows.

5.1 An effective SF model for urban watersheds and associated uncertainty analysis

Rapid urbanization is considered to be an important factor that contributes to flood risk. Therefore, flood prediction in urban watersheds using appropriate runoff models is essential to avoid the harmful effects of floods. There are various storage function (SF)
models such as Kimura, Prasad, Hoshi, and urban storage function (USF) models that have been widely used in different parts of the world as rainfall-runoff models in which the USF model was recently developed in Japan for the specific application in urban watersheds. However, the identification of an appropriate model remains challenging in the field of hydrology. Therefore, an effective SF model was identified from the existing conventional ones for an urban watershed in terms of hydrograph reproducibility and from an Akaike information criterion (AIC) perspective. For this purpose, the relatively new USF model and four conventional SF models of Hoshi, Prasad, Kimura, and the linear model were selected. The SCE-UA global optimization method was used for the parameter optimization of each model with root mean square error (RMSE) as the objective function. The reproducibility of the hydrograph was evaluated using the performance evaluation criteria of RMSE, Nash-Sutcliffe efficiency (NSE), and other error functions of peak, volume, time to peak, lag time, and runoff coefficient. The results revealed that the higher values of NSE coupled with the lower values of RMSE and other error functions indicated that the hydrograph reproducibility of USF had been the highest among the SF models. Furthermore, AIC and Akaike weight (AW) were used to identify the most effective model among all those based on the information criteria perspective. The USF model received the lowest AIC score and the highest AW during most of the events, which indicates that it is the most parsimonious model compared to the other SF models. Moreover, uncertainty characterization of the SF model parameters was also conducted to analyze the effect of each parameter on model performance. The results also exhibited that the Kimura’s model without lag time failed to outperform in the flood prediction in comparison with the other SF models. Therefore, to know about the effect of lag time in Kimura’s model, the Kimura’s model with lag time was analyzed for its ability to reproduce the shape of the hydrograph as well as the hysteresis loop. The model was also compared with the Prasad’s model since both the models have same number of optimized parameters. The results portrayed that the inclusion of optimized lag time can considerably enhance the performance of Kimura’s model and its incorporation is inevitable. It was also noted that the models with the same number of optimized parameters produced quite different results, which can be attributed to the difference in model structure.

However, the predictions made using rainfall-runoff models are inherently uncertain and it is important to recognize and account for this uncertainty, especially in urban
watersheds due to the high flood risk in these areas. Recent studies on hydrological model uncertainty mostly refer to the identification of model parameter uncertainty. However, such studies are somewhat limited using the bootstrap and jackknife approaches, nonparametric methods, which makes no prior assumptions on the model structure and thus are more flexible. Hence, the calibrated parameter uncertainty analysis and its effect on the model simulation uncertainty of the identified effective 7-parameter USF model were carried out using the bootstrap and jackknife resampling approaches. Both the approaches were applied to the residual time series that was computed as the difference between the observed and calibrated discharge time series. The parameter uncertainty was expressed by estimating the confidence interval (CI) of the USF model parameters, and then the parameters from the highest to the lowest uncertainties were derived by utilizing two newly proposed parameter uncertainty indices. Initially, a residual-based bootstrap approach associated with the SCE-UA global optimization algorithm was demonstrated for the analysis of calibrated parameter uncertainty and its subsequent effect on the model simulation of an urban-specific rainfall-runoff model, urban storage function (USF) model, under two different data scenarios of individual event-based and whole data-based scenarios. On the other hand, the jackknife method was applied only to the whole data-based scenario to analyse the calibrated parameter uncertainty. The USF model parameters from the highest to the lowest uncertainties were derived in both the bootstrap and jackknife approaches by utilizing two newly proposed parameter uncertainty indices, which can make the best use of CI. The highly uncertain parameters obtained were the same by both the approaches even though the order of other model parameters was different.

Moreover, investigations were carried out to examine the effect of calibrated model parameter uncertainty on model prediction. The USF model bracketed a large number of observations within the prediction range under the individual event-based scenario compared with the whole data-based scenario by the bootstrap approach. This further indicates that the residual-based bootstrap approach along with the SCE-UA method reasonably well predicted the prediction range of USF model, specifically in the individual event-based scenario. In comparison with the bootstrap approach, the USF model bracketed a reduced number of observations within the 95% CI prediction range by the jackknife method. Further, for a better understanding of simulation uncertainty, we defined and demonstrated two model simulation uncertainty indices and implemented in
both approaches. The values of simulation uncertainty indices were comparable by both
the approaches. The results also exhibited that the simulation uncertainty is low in the
individual event-based analysis and hence the proposed indices could be useful in future
studies in order to derive parameters from the highest to the lowest uncertainty of different
rainfall-runoff models in the watersheds worldwide.

5.2 A GSF model for the water level prediction

The prediction of water level information is very important from a disaster point of
view to make an early warning about the flooding and to carry out control and evacuation
activities compared with the uncertain discharge predictions obtained from the
established rating curve. However, an efficient and effective water level prediction
system is still lacking. Therefore, we have to develop a precise technique for flood water
level prediction and monitoring as an alarming system to prevent future disasters. A 9-
parameter generalized storage function (GSF) model was proposed for the prediction of
water level from the rating curve relationship by considering the spatial distribution of
rainfall over the basin by introducing a parameter named as rainfall distribution factor (γ)
and incorporating all the possible inflow and outflow components. The GSF model
optimizes not only parameter γ but also the rating curve constants a and b along with
other model parameters which will reduce the efforts taken for the rating curve
establishment of the target watersheds. The proposed GSF model was then applied in two
watersheds of (i) Iga watershed, a semi-urban watershed, and (ii) Oto watershed, a rural
watershed in Japan to examine its applicability in different types of watersheds with
optimized parameters. Three other models were also applied in the watersheds for
comparison with the GSF model and are (i) 8 parameter model - the GSF model without
parameter γ, (ii) 7 parameter model - the GSF model with fixed values of parameters a
and b obtained from the established rating curve by the authorities, and (iii) 6 parameter
model - the GSF model without parameter γ and with fixed values of parameters a and b.

The model calibration revealed that the Iga and Oto basin parameter values are not
identical in all the events and shows high variation in most of the events, which further
indicates that the same set of model parameters cannot be used for basins with dissimilar
physical characteristics. The different model performances during calibration and
validation were analyzed and the GSF model exhibited higher performance during
calibration whereas none of the models showed consistent performance during validation
in both the basins. Further, the AIC aspect was also used in order to determine the
effective model for calibration and validation. In comparison with the GSF model with optimized parameters $a$ and $b$, the 7 parameter model is expected to give good results with fixed values of rating curve parameters $a$ and $b$, which are obtained from the actual basin observations. However, the GSF model outperformed the 7 parameter model in most of the events. Therefore, we can conclude that the GSF model is much more effective with optimized values of $a$ and $b$ for the use in ungauged and partially gauged watersheds compared with the 7 parameter model based on AIC aspect. Any of the considered models were not reliable in an operational context based on AIC aspect and further research after including more calibration events is needed to improve their operational adequacy. Lastly, global sensitivity analysis (Morris method) was carried out to identify the sensitive parameters of the proposed GSF model with RMSE as the objective function.

Furthermore, the effect of spatial rainfall variability was investigated in the USF model by incorporating the parameter $\gamma$, which is named as the GUSF model. The GUSF model was then applied to five selected flood events of the Kanda basin, Tokyo along with USF model in order to evaluate the effectiveness of $\gamma$ in the GUSF model. Both the models were examined in terms of the error evaluation criteria's of RMSE, NSE, and other error functions of peak and volume. The results revealed that GUSF model has the least RMSE (high NSE) compared with the USF model for most of the events which further shows that the SCE-UA method has successfully identified the optimal parameters. The lower values of PEP and PEV received by GUSF model further indicate that the incorporation of spatial distribution factor can drastically improve the performance of the model. Further, the Akaike information criterion (AIC) and Akaike weight (AW) were used to establish the best model among two based on the information criteria perspective. The summary of AIC results shows that the GUSF received the highest AW in most of the events compared with the USF model which make it the parsimonious model which indicate that the introduction of parameter $\gamma$ can greatly improve the performance of USF model.

5.3 Recommendations for future research

The results of this study suggest six broad avenues for future work:

1) Comparison of different SF models with a fully dynamical model in terms of the discharge simulation will be challenging. It is necessary to carry out such comparative
studies to provide guidelines for a large group of research community based on the intended purposes.

2) Apart from the calibrated parameter uncertainty, it is necessary to analyze the other sources of uncertainties that affect the USF model predictions. It is also important to conduct studies, which analyze the effect of calibration parameter uncertainty on the USF model validation by utilizing more observations and applying in different urban watersheds.

3) It is not always clear how uncertainty analysis will contribute to improving decision making even though the concept of model uncertainty is well recognized in the research community. Therefore, further research should be carried out by incorporating the uncertainty analysis results in risk-based decision-making.

4) Application of GSF model for the water level prediction in different types of catchments with different physical characteristics is a requisite to evaluate their applicability and further associated structural modifications.

5) Research on flood water level prediction has long been a subject of interest. Researcher regularly generate statistical model based on past data in conventional way to predict flood water level. The proposed GSF model performed well in the calibration whereas exhibited limited performance during validation. Therefore, it is necessary to predict river water levels in real time utilizing the GSF model. Several studies showed that the particle filter algorithm is a very efficient method to solve problems of nonlinear systems such as flood routing systems although it is still rarely applied to real-time water level forecasting. Therefore, there is a need for the improvement of the GSF model for the application in an operational context using the particle filter approach.

6) The rainfall-runoff modelling was carried out in a lumped manner using different SF models. A spatially-lumped catchment modelling is recommended by modifying the existing model structure and dividing the catchment into smaller sub-catchments.

The expected findings from the above future research endeavors will be vital for the decision-making and associated flood risk reduction by the development of improved and enhanced rainfall-runoff models.
REFERENCES


