Bellie Sivakumar

Chaos in Hydrology

Bridging Determinism and Stochasticity

Springer

Chaos in Hydrology

Bellie Sivakumar

Chaos in Hydrology

Bridging Determinism and Stochasticity

Springer

Bellie Sivakumar
School of Civil and Environmental Engineering
The University of New South Wales
Sydney, NSW
Australia

and

Department of Land, Air and Water Resources
University of California
Davis, CA
USA

ISBN 978-90-481-2551-7 ISBN 978-90-481-2552-4 (eBook)
DOI 10.1007/978-90-481-2552-4

Library of Congress Control Number: 2016946619

© Springer Science+Business Media Dordrecht 2017
This work is subject to copyright. All rights are reserved by the Publisher, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation, broadcasting, reproduction on microfilms or in any other physical way, and transmission or information storage and retrieval, electronic adaptation, computer software, or by similar or dissimilar methodology now known or hereafter developed.
The use of general descriptive names, registered names, trademarks, service marks, etc. in this publication does not imply, even in the absence of a specific statement, that such names are exempt from the relevant protective laws and regulations and therefore free for general use.
The publisher, the authors and the editors are safe to assume that the advice and information in this book are believed to be true and accurate at the date of publication. Neither the publisher nor the authors or the editors give a warranty, express or implied, with respect to the material contained herein or for any errors or omissions that may have been made.

Cover illustration: An aerial view of an Iceland river delta. © Justinreznick / Getty Images / iStock

Printed on acid-free paper

This Springer imprint is published by Springer Nature
The registered company is Springer Science+Business Media B.V. Dordrecht

To my parents, Sarojini and Bellie

Preface

It is possible that you have this book in your hands because of its intriguing name (Chaos) or simply by accident, but I hope that you will continue to read it for its contents and then also recommend it to others.

In common parlance, the word ‘chaos,’ derived from the Ancient Greek word Χάος, typically means a state lacking order or predictability; in other words, chaos is synonymous to ‘randomness.’ In modern dynamic systems science literature, however, the term ‘chaos’ is used to refer to situations where complex and ‘random-looking’ behaviors arise from simple deterministic systems with sensitive dependence on initial conditions; therefore, chaos and randomness are quite different. This latter definition has important implications for system modeling and prediction: randomness is irreproducible and unpredictable, while chaos is reproducible and predictable in the short term (due to determinism) but irreproducible and unpredictable only in the long term (due to sensitivity to initial conditions).

The three fundamental properties inherent in the above definition of chaos, namely (a) nonlinear interdependence; (b) hidden order and determinism; and (c) sensitivity to initial conditions, are highly relevant in almost all real systems. In hydrology, for instance: (a) nonlinear interactions are dominant among the components and mechanisms in the hydrologic cycle; (b) determinism and order are prevalent in daily temperature and annual river flow; and (c) contaminant transport in surface and sub-surface waters is highly sensitive to the time (e.g., rainy or dry season) at which the contaminants were released. The first property represents the ‘general’ nature of hydrologic phenomena, whereas the second and third represent their ‘deterministic’ and ‘stochastic’ natures, respectively. Further, despite their complexity and random-looking behavior, hydrologic phenomena may be governed only by a few degrees of freedom, another basic idea of chaos theory; for instance, runoff in a well-developed urban catchment depends essentially on rainfall.

This book is intended to address a fundamental question researchers in hydrology commonly grapple with: is the complex, irregular, and random-looking behavior of hydrologic phenomena simply the outcome of random (or stochastic) system dynamics, or is there some kind of order and determinism hidden behind? In other words, since simple deterministic systems can produce complex and random-looking outputs, as has been shown through numerous synthetic examples, is it reasonable then to ask if hydrologic systems can also belong to this category? A reliable answer to this question is important for proper identification of the type and complexity of hydrologic models to be developed, evaluation of data and computer requirements, determination of maximum predictability horizon for hydrologic processes, and assessment, planning, and management of water resources.

I approach the above question in a very systematic manner, by first discussing the general and specific characteristics of hydrologic systems, next reviewing the tools available at our disposal to study such systems, and then presenting the applications of such tools to various hydrologic systems, processes, and problems. In the end, I argue that chaos theory offers a balanced and middle-ground approach between the deterministic and stochastic extreme paradigms that are prevalent in hydrology (and in almost every other field) and, thus, serves as a bridge connecting the two paradigms.

The book is divided into four major parts, focusing on specific topics that I deem necessary to meet the intended goal. Part A (Hydrologic Systems and Modeling) covers the introduction to hydrology (Chap. 1), characteristics of hydrologic systems (Chap. 2), stochastic time series methods (Chap. 3), and modern nonlinear time series methods (Chap. 4). Part B (Nonlinear Dynamics and Chaos) details the fundamentals of chaos theory (Chap. 5), chaos identification and prediction (Chap. 6), and issues associated with chaos methods (Chap. 7), especially in their applications to real data. Part C (Applications of Chaos Theory in Hydrology) details the applications of chaos theory in hydrology, first with an overview of hydrologic applications (Chap. 8), followed by applications to rainfall (Chap. 9), river flow (Chap. 10), and other hydrologic data (Chap. 11), and then with studies on hydrologic data-related issues (Chap. 12). Part D (A Look Ahead) summarizes the current status (Chap. 13), offers future directions (Chap. 14), and includes a broader discussion of philosophical and pragmatic views of chaos theory in hydrology (Chap. 15).

I must emphasize that this book is about hydrology (and *not* about chaos theory), with focus on the applications of nonlinear dynamic and chaos concepts in hydrologic systems. Consequently, a significant portion of the presentation is devoted to hydrologic system characteristics, time series modeling in hydrology, relevance of nonlinear dynamic and chaos concepts in hydrology, and their applications and advances in hydrology, especially from an engineering perspective. The presentation about the fundamentals of chaos theory, methods for identification and prediction, and relevant issues in their applications is by no means exhaustive, and is deliberately kept to a minimum level that is needed to meet the above goal. However, the amount of literature cited on the theoretical aspects of chaos theory and methodological developments is extensive, which should guide the interested reader to further details. For the benefit of the reader, and especially for someone new to the field, I also attempt to be descriptive in reviewing the theoretical concepts, detailing the applications, and interpreting the outcomes. All this, I believe, makes this book suitable for both experienced researchers and new ones in hydrology and water resources engineering, and beyond.

Sydney, Australia and Davis, USA Bellie Sivakumar

Acknowledgments

This book is a result of my research in the area of chaos theory in hydrology over the last two decades, starting from my doctoral degree at the National University of Singapore. During this time, I have benefited from numerous colleagues and friends, funding agencies, research fellowships, and other invited research visits. The list is too long to mention here. Therefore, I will limit the list mostly to those that have directly contributed to the preparation of this book and to a few others that have been a great encouragement and support throughout.

The idea for writing a book on chaos theory in hydrology arose many years ago. However, the actual planning for this book occurred during one of my visits to Inha University, Korea, a few years ago. My sincere and special thanks to Hung Soo Kim (Inha University) and Ronny Berndtsson (Lund University, Sweden) for their support and contributions in planning for this book. They provided useful inputs in identifying the areas and topics to focus in this book and in outlining and organizing the contents. Apart from this book, both Ronny and Hung Soo have and continue to play important roles in advancing my research and career through our research collaborations.

Several colleagues and students provided help in the preparation of the book. Fitsum Woldemeskel offered significant help with the adoption and modification of a number of figures from existing publications, including my own. I am grateful to Fitsum for his time, effort, and generosity, at a critical time in the preparation of the book. Hong-Bo Xie provided Figs. 5.4, 5.6, and 5.7. Jun Niu provided Fig. 4.3. Carlos E. Puente provided Fig. 5.2. Seokhyeon Kim and R. Vignesh helped in the preparation of a few figures, especially in Chap. 12. Peter Young and Jun Niu offered useful inputs in the preparation of Sects. 4.3 and 4.6, respectively. Jun Niu and V. Jothiprakash also offered reviews for the manuscript. My sincere thanks to all of them for their time, effort, and generosity.

Many colleagues and friends have and continue to offer great encouragement and support to my academic, research, and professional activities. Their encouragement and support, especially during the earlier years, played an important role in writing this book. Among these are (in alphabetical order) Ronny Berndtsson,

Ji Chen, Eric Gaume, Thomas Harter, A.W. Jayawardena, Kenji Jinno, V. Jothiprakash, Akira Kawamura, Hung Soo Kim, Upmanu Lall, Chih-Young Liaw, Shie-Yui Liong, Rajeshwar Mehrotra, Jun Niu, Jonas Olsson, Kok-Kwang Phoon, Carlos E. Puente, Ashish Sharma, and Wesley W. Wallender. I am grateful to all of them, for their encouragement and support. Ji Chen and Carlos Puente deserve particular mention, especially for the regular contacts, interactions, and discussions, despite the geographic distances. Raj Mehrotra also deserves particular mention for his constant encouragement. My numerous conversations with Raj, especially over coffee(!) almost on a daily basis, have greatly helped me to keep my focus on the book.

Writing a book like this consumes an enormous amount of time. The material for this book has been gathered over many years and constantly updated over time. However, a significant part of the writing has been undertaken only during the past 2–3 years. I would like to thank the Australian Research Council (ARC) for the financial support through the Future Fellowship grant (FT110100328). This support has allowed me the time and flexibility to focus on the book more than it would have been otherwise possible.

My sincere thanks to the entire Springer team for their encouragement and support throughout the preparation of this book. Petra van Steenbergen and Hermine Vloemans deserve special mention, not only for their encouragement and support, but also for their patience and understanding.

Finally, I am grateful to my family, for their constant love, encouragement, and support, without which writing a book would have remained only a dream.

Sydney, Australia and Davis, USA Bellie Sivakumar

Contents

Part I Hydrologic Systems and Modeling

1 **Introduction** 3
   1.1 Definition of Hydrology 3
   1.2 Hydrologic Cycle 4
   1.3 Scientific Development of Hydrology 6
   1.4 Concept of Hydrologic System 9
   1.5 Hydrologic System Model 11
   1.6 Hydrologic Model Classification 13
      1.6.1 Physical Models 13
      1.6.2 Abstract Models 14
      1.6.3 Remarks 15
   1.7 Hydrologic Data and Time Series Modeling 15
   1.8 Physical Basis of Time Series Modeling 17
   1.9 Scope and Organization of the Book 19
   References 21

2 **Characteristics of Hydrologic Systems** 29
   2.1 Introduction 29
   2.2 Complexity 30
   2.3 Correlation and Connection 32
   2.4 Trend 34
   2.5 Periodicity, Cyclicity, and Seasonality 34
   2.6 Intermittency 36
   2.7 Stationarity and Nonstationarity 36
   2.8 Linearity and Nonlinearity 38
   2.9 Determinism and Randomness 39
   2.10 Scale, Scaling, and Scale-invariance 41
   2.11 Self-organization and Self-organized Criticality 43
   2.12 Threshold 44
   2.13 Emergence 46
   2.14 Feedback 47

2.15 Sensitivity to Initial Conditions. 48
2.16 The Class of Nonlinear Determinism and Chaos. 49
2.17 Summary 50
References. 50

3 Stochastic Time Series Methods 63
3.1 Introduction 63
3.2 Brief History of Development of Stochastic Methods. 65
3.3 Hydrologic Time Series and Classification 66
3.4 Relevant Statistical Characteristics and Estimators 67
3.4.1 Mean 68
3.4.2 Variance 68
3.4.3 Coefficient of Variation 69
3.4.4 Skewness Coefficient. 69
3.4.5 Autocorrelation Function 69
3.4.6 Power Spectrum. 70
3.5 Parametric Methods 71
3.5.1 Autoregressive (AR) Models 71
3.5.2 Moving Average (MA) Models 73
3.5.3 Autoregressive Moving Average (ARMA) Models . . . 73
3.5.4 Gamma Autoregressive (GAR) Models 75
3.5.5 Periodic Models: PAR, PARMA, and PGAR Models. 76
3.5.6 Extension of AR, ARMA, PAR, and PARMA Models to Multiple Variables 79
3.5.7 Disaggregation Models 80
3.5.8 Markov Chain Models. 82
3.5.9 Point Process Models. 84
3.5.10 Other Models. 87
3.5.11 Remarks. 88
3.6 Nonparametric Methods 88
3.6.1 Bootstrap and Block Bootstrap 89
3.6.2 Kernel Density Estimate 90
3.6.3 *k*-Nearest Neighbor Resampling (KNNR) 92
3.6.4 *k*-Nearest Neighbors with Local Polynomial Regression 94
3.6.5 Others 95
3.7 Summary 96
References. 96

4 Modern Nonlinear Time Series Methods. 111
4.1 Introduction 111
4.2 Nonlinear Stochastic Methods. 112
4.3 Data-based Mechanistic Models 113
4.4 Artificial Neural Networks 115

4.5 Support Vector Machines 118
4.6 Wavelets 120
4.7 Evolutionary Computing 123
4.8 Fuzzy Logic 126
4.9 Entropy-based Models 128
4.10 Nonlinear Dynamics and Chaos 129
4.11 Summary 130
References 131

Part II Nonlinear Dynamics and Chaos

5 Fundamentals of Chaos Theory 149
5.1 Introduction 149
5.2 Definition of Chaos 150
5.3 Brief History of the Development of Chaos Theory 151
5.4 Dynamical Systems and Stability Analysis 153
5.5 Attractors 154
5.6 Bifurcations 156
5.7 Interaction and Interdependence 157
5.8 Sensitivity to Initial Conditions 158
5.9 State Space and Phase Space 159
5.10 Fractal and Fractal Dimension 161
5.11 Examples of Chaotic Dynamic Equations 161
  5.11.1 Logistic Map 162
  5.11.2 Henon Map 164
  5.11.3 Lorenz System 164
  5.11.4 Rössler System 167
5.12 Summary 168
References 169

6 Chaos Identification and Prediction Methods 173
6.1 Introduction 173
6.2 Linear Tools and Limitations 175
6.3 Phase Space Reconstruction 177
6.4 Correlation Dimension Method 179
  6.4.1 Basic Concept 179
  6.4.2 The Grassberger–Procaccia (G–P) Algorithm 180
  6.4.3 Identification of Number of System Variables 181
  6.4.4 An Example 181
  6.4.5 Improvements to the G–P Algorithm 182
6.5 False Nearest Neighbor (FNN) Algorithm 183
6.6 Lyapunov Exponent Method 184
6.7 Kolmogorov Entropy Method 186

6.8 Surrogate Data Method . . . 187
6.9 Poincaré Maps . . . 189
6.10 Close Returns Plot . . . 189
6.11 Nonlinear Prediction . . . 191
  6.11.1 Local Approximation Prediction . . . 191
  6.11.2 Inverse Approach to Chaos Identification . . . 192
6.12 Summary . . . 193
References . . . 194

7 Issues in Chaos Identification and Prediction . . . 199
7.1 Introduction . . . 199
7.2 Delay Time . . . 200
  7.2.1 Delay Time Selection . . . 201
  7.2.2 Delay Window Selection . . . 203
  7.2.3 Remarks . . . 204
7.3 Data Size . . . 205
  7.3.1 Effects of Data Size . . . 206
  7.3.2 Minimum Data Size . . . 207
7.4 Data Noise . . . 211
  7.4.1 Effects of Noise . . . 212
  7.4.2 Noise Level Determination . . . 214
  7.4.3 Noise Reduction . . . 216
  7.4.4 Coupled Noise Level Determination and Reduction: An Example . . . 219
7.5 Zeros in Data . . . 222
7.6 Other Issues . . . 223
7.7 Summary . . . 223
References . . . 224

Part III Applications of Chaos Theory in Hydrology

8 Overview . . . 231
8.1 Introduction . . . 231
8.2 Early Stage (1980s–1990s) . . . 232
8.3 Change of Course (2000–2006) . . . 236
8.4 Looking at Global-scale challenges (2007–) . . . 237
8.5 Summary . . . 239
References . . . 239

9 Applications to Rainfall Data . . . 245
9.1 Introduction . . . 245
9.2 Identification and Prediction . . . 246
  9.2.1 Chaos Analysis of Rainfall: An Example—Göta River Basin . . . 250

9.3 Scaling and Disaggregation/Downscaling 252
  9.3.1 Chaotic Scale-invariance: An Example—Leaf River Basin 252
  9.3.2 Chaotic Disaggregation: An Example—Leaf River Basin 255
  9.3.3 Others 260
9.4 Spatial Variability and Classification. 261
9.5 Others (Data Size, Noise Reduction, Zeros) 263
9.6 Summary 263
References. 264

10 Applications to River Flow Data 267
10.1 Introduction 267
10.2 Identification and Prediction 268
  10.2.1 Chaos Analysis in River Flow: An Example—Coaracy Nunes/Araguari River Basin 272
10.3 Scaling and Disaggregation. 276
  10.3.1 Chaos and Scaling 276
  10.3.2 Chaotic Disaggregation of River Flow. 279
10.4 Spatial Variability and Classification. 285
10.5 Others 291
10.6 Summary 292
References. 292

11 Applications to Other Hydrologic Data 297
11.1 Introduction 297
11.2 Rainfall-runoff. 298
11.3 Lake Volume and Level 301
11.4 Sediment Transport. 302
11.5 Groundwater 310
  11.5.1 Solute Transport 311
  11.5.2 Arsenic Contamination 315
11.6 Others. 316
11.7 Summary 317
References. 318

12 Studies on Hydrologic Data Issues 321
12.1 Introduction 321
12.2 Delay Time. 322
12.3 Data Size 325
12.4 Data Noise 329
12.5 Zeros in Data 332
12.6 Others. 335
12.7 Summary 336
References. 336

Part IV A Look Ahead

13 Current Status 343
13.1 Introduction 343
13.2 Reliable Identification 344
13.3 Encouraging Predictions 346
13.4 Successful Extensions 347
13.5 Limitations and Concerns 349
13.6 Discussions and Debates 351
13.7 Summary 352
References 352

14 The Future 357
14.1 Introduction 357
14.2 Parameter Estimation 358
14.3 Model Simplification 359
14.4 Integration of Concepts 362
14.5 Catchment Classification Framework 363
14.6 Multi-variable Analysis 365
14.7 Reconstruction of System Equations 366
14.8 Downscaling of Global Climate Model Outputs 367
14.9 Linking Theory, Data, and Physics 368
14.10 Summary 369
References 370

15 Final Thoughts: Philosophy and Pragmatism 375
15.1 Introduction 375
15.2 Philosophy 376
15.3 Pragmatism 378
15.4 Closing Remarks 380
References 381

Index 383

About the Author

Bellie Sivakumar received his Bachelor degree in Civil Engineering from Bharathiar University (India) in 1992, Master degree in Hydrology and Water Resources Engineering from Anna University (India) in 1994, and Ph.D. degree in Civil Engineering from the National University of Singapore in 1999. After a one-year postdoctoral research at the University of Arizona, Tucson, USA, he joined University of California, Davis (UCDavis). At UCDavis, he held the positions of postgraduate researcher and Associate Project Scientist, and now holds an Associate position. He joined the University of New South Wales, Sydney, Australia in 2010, where he is currently an Associate Professor.

Bellie Sivakumar's research interests are in the field of hydrology and water resources, with particular emphasis on nonlinear dynamics, chaos, scaling, and complex networks. He has authored one book and more than 130 peer-reviewed journal papers. He has been an associate editor for several journals, including Hydrological Sciences Journal, Journal of Hydrology, Journal of Hydrologic Engineering, and Stochastic Environmental Research and Risk Assessment. He has received a number of fellowships throughout his career, including the ICSC World Laboratory Fellowship, Japan Society for the Promotion of Science Fellowship, Korea Science and Technology Societies' Brainpool Fellowship, and Australian Research Council Future Fellowship.

List of Figures

Figure 1.1 Schematic representation of hydrologic cycle (*source* US Geological Survey, http://water.usgs.gov/edu/watercycle.html; accessed May 5, 2015) 5
Figure 1.2 An example of a hydrologic time series: monthly rainfall data 16
Figure 4.1 Structure of a typical multi-layer perceptron with one hidden layer (*source* Sivakumar et al. (2002b)) 116
Figure 4.2 Structure of a typical node in the hidden layer or output layer (*source* Sivakumar et al. (2002b)) 116
Figure 4.3 Illustration of the wavelet transform process of **a** Mexican hat mother wavelet; and **b** its daughter wavelet for **c** annual precipitation of the whole Pearl River basin of South China, resulting in **d** wavelet coefficient map (*source* Jun Niu, personal communication) 122
Figure 4.4 Schematic representation of flow of information in a typical evolutionary computing algorithm 124
Figure 4.5 Components of a fuzzy rule system (*source* Hundecha et al. (2001)) 126
Figure 5.1 Attractors: **a** fixed point; **b** limit cycle; and **c** strange (*source* Kantz and Schreiber (2004)) 155
Figure 5.2 Bifurcation diagram (*source* Carlos E. Puente, personal communication) 157
Figure 5.3 Streamflow dynamics represented as: **a** state space (rainfall and temperature); and **b** phase space 160
Figure 5.4 Logistic map: **a** time series generated using $x_0 = 0.97$ and $k = 2.827$ (*top*), $x_0 = 0.97$ and $k = 3.50$ (*middle*), and $x_0 = 0.90$ and $k = 3.98$ (*bottom*); and **b** phase space diagram (*source* Hong-Bo Xie, personal communication) 163

Figure 5.5 Henon map: **a** time series; and **b** phase space diagram 165

Figure 5.6 Lorenz system: **a** time series (first component); and **b** phase space diagram (*source* Hong-Bo Xie, personal communication) 166

Figure 5.7 Rössler system: (*left*) time series; and (*right*) phase space diagram (*source* Hong-Bo Xie, personal communication). 168

Figure 6.1 Stochastic system (*left*) versus chaotic system (*right*): **a**, **b** time series; **c**, **d** autocorrelation function; and **e**, **f** power spectrum (*source* Sivakumar et al. (2007)) 176

Figure 6.2 Stochastic system (*left*) versus chaotic system (*right*): phase space diagram (*source* Sivakumar et al. (2007)) 178

Figure 6.3 Stochastic system (*left*) versus chaotic system (*right*): correlation dimension (*source* Sivakumar et al. (2007)). . . . 182

Figure 6.4 Lyapunov exponent computation: Wolf et al. (1985) algorithm (*source* Vastano and Kostelich (1986)). 185

Figure 7.1 Time series plot of **a** stochastic series (artificial random series); and **b** chaotic series (artificial Henon map) (*source* Sivakumar (2005a)) 208

Figure 7.2 Correlation dimension results for stochastic series with **a** 100 points; **b** 200 points; **c** 300 points; **d** 500 points; **e** 1000 points; and **f** 5000 points. Embedding dimension m = 1–10 (from *left* to *right*) (*source* Sivakumar (2005a)) 209

Figure 7.3 Correlation dimension results for chaotic series with **a** 100 points; **b** 200 points; **c** 300 points; **d** 500 points; **e** 1000 points; and **f** 5000 points. Embedding dimension m = 1–10 (from *left* to *right*) (*source* Sivakumar (2005a)) 210

Figure 7.4 Phase space plots for Henon data: **a** noise-free; **b** 8 % noisy; **c** 4.1 % noise-reduced; **d** 8.2 % noise-reduced; and **e** 12.3 % noise-reduced (*source* Sivakumar et al. (1999b)) 220

Figure 7.5 Local slopes versus Log r for Henon data: **a** noise-free; **b** 8 % noisy; **c** 4.1 % noise-reduced; **d** 8.2 % noise-reduced; and **e** 12.3 % noise-reduced (*source* Sivakumar et al. (1999b)) 221

Figure 7.6 Relationship between correlation exponent and embedding dimension for noise-free, 8 % noisy, and noise-reduced Henon data (*source* Sivakumar et al. (1999b)) 222

Figure 9.1 Chaos analysis of monthly rainfall from Göta River basin: **a** time series; **b** phase space; **c** Log C(r) versus Log r; **d** relationship between correlation exponent and embedding dimension; **e** relationship between correlation coefficient and embedding dimension; and **f** comparison between time series plot of predicted and observed values (*source* Sivakumar et al. (2000, 2001a)) 251
Figure 9.2 Correlation dimension analysis of rainfall data at different temporal scales from the Leaf River basin: **a** time series of daily data; **b** Log C(r) versus Log r plot for daily data; **c** correlation exponent versus embedding dimension for daily data; and **d** correlation dimension versus embedding dimension for daily, 2-, 4-, and 8-day data (*source* Sivakumar (2001a)). 254
Figure 9.3 Schematic representation of distributions of weights of rainfall transformation between two different temporal scales (*source* Sivakumar et al. (2001b)). 255
Figure 9.4 Correlation dimension analysis of distributions of weights of rainfall data in the Leaf River basin: **a** time series of weights between 12- and 6-h resolutions; **b** Log C(r) versus Log r for **a**; **c** correlation exponent versus embedding dimension for **a**; and **d** correlation exponent versus embedding dimension for distributions of weights of rainfall data between different successively doubled resolutions (*source* Sivakumar et al. (2001b)) 257
Figure 9.5 Chaotic disaggregation of rainfall data from 12-h resolution to 6-h resolution in the Leaf River basin: **a** relationship between correlation coefficient and number of neighbors (m_{opt} = 4); **b** relationship between correlation coefficient and embedding dimension ($k'_{opt} = 10$); **c** comparison between time series of modeled and observed rainfall values (m_{opt} = 4; $k'_{opt} = 10$); and **d** scatterplot of modeled and observed rainfall values (m_{opt} = 4; $k'_{opt} = 10$) (*source* Sivakumar et al. (2001b)) 259
Figure 9.6 Analysis of variability of monthly rainfall in Western Australia: **a** mean; **b** standard deviation; **c** maximum; **d** percentage number of zeros; and **e** correlation dimension (*source* Sivakumar et al. (2014)). 262

Figure 10.1 Correlation dimension analysis of monthly runoff from Coaracy Nunes/Araguari River basin in Brazil: **a** time series; **b** phase space; **c** Log C(r) versus Log r; and **d** relationship between correlation exponent and embedding dimension (*source* Sivakumar et al. (2001b, 2005)) 272
Figure 10.2 Nonlinear local approximation prediction analysis of monthly runoff from Coaracy Nunes/Araguari River basin in Brazil: **a** correlation coefficient; **b** RMSE; and **c** coefficient of efficiency (*source* Sivakumar et al. (2001b)) 274
Figure 10.3 Nonlinear local approximation prediction analysis of monthly runoff from Coaracy Nunes/Araguari River basin in Brazil: **a** time series comparison (*source* Sivakumar et al. (2002c)); and **b** scatter plot (*source* Sivakumar et al. (2001b)) 275
Figure 10.4 Nonlinear local approximation prediction analysis of monthly runoff from Coaracy Nunes/Araguari River basin in Brazil for different lead times: **a** correlation coefficient; **b** RMSE; and **c** coefficient of efficiency (*source* Sivakumar et al. (2001b)) 277
Figure 10.5 Correlation dimension of streamflow at different temporal scales: **a** Kentucky River, Kentucky, USA; **b** Merced River, California, USA; and **c** Stillaguamish River, Washington State, USA (*source* Regonda et al. (2004)) 278
Figure 10.6 Chaotic disaggregation of streamflow from 2-day to daily scale in the Mississippi River basin at St. Louis, Missouri, USA—effect of number of neighbors: **a** relationship between correlation coefficient and number of neighbors; and **b** relationship between root mean square error and number of neighbors (*source* Sivakumar et al. (2004)) 282
Figure 10.7 Chaotic disaggregation of streamflow between successively doubled resolutions in the Mississippi River basin at St. Louis, Missouri, USA: **a** 2-day to daily ($m = 3$, $k' = 3$); **b** 4-day to 2-day ($m = 3$; $k' = 5$); **c** 8-day to 4-day ($m = 2$, $k' = 50$); and **d** 16-day to 8-day ($m = 3$; $k' = 20$) (*source* Sivakumar et al. (2004)) 283
Figure 10.8 Western United States and locations of 117 streamflow stations (*source* Sivakumar and Singh (2012)) 286

Figure 10.9 Phase space diagram: **a** Station #10032000; **b** Station #13317000; **c** Station 11315000; **d** Station #11381500; **e** Station #12093500; **f** Station #14185000; **g** Station #8408500; and **h** Station #11124500 (*source* Sivakumar and Singh (2012)) 288

Figure 10.10 Correlation dimension: **a** Station #10032000; **b** Station #13317000; **c** Station 11315000; **d** Station #11381500; **e** Station #12093500; **f** Station #14185000; **g** Station #8408500; and **h** Station #11124500 (*source* Sivakumar and Singh (2012)) 290

Figure 10.11 Grouping of streamflow stations according to correlation dimension (d) estimates: low dimensional (d ≤ 3); medium dimensional (3 < d ≤ 6); high dimensional (d > 6.0); and unidentifiable (d not identifiable) (*source* Sivakumar and Singh (2012)). 291

Figure 11.1 Correlation dimension analysis of monthly runoff coefficient from Göta River basin: **a** time series; **b** phase space; **c** log C(r) versus Log r; and **d** relationship between correlation exponent and embedding dimension (*source* Sivakumar et al. (2000, 2001a)) 299

Figure 11.2 Nonlinear local approximation prediction analysis of monthly runoff coefficient from Göta River basin: **a** relationship between correlation coefficient and embedding dimension; and **b** comparison between time series plots of predicted and observed values (*source* Sivakumar et al. (2000)) 300

Figure 11.3 Time series plots for sediment data from the Mississippi River basin at St. Louis, Missouri, USA: **a** discharge; **b** suspended sediment concentration; and **c** suspended sediment load (*source* Sivakumar and Wallender (2005)). 303

Figure 11.4 Phase space plots for sediment data from the Mississippi River basin at St. Louis, Missouri, USA: **a** discharge; **b** suspended sediment concentration; and **c** suspended sediment load (*source* Sivakumar and Wallender (2005)). 304

Figure 11.5 Correlation dimension results for sediment data from the Mississippi River basin at St. Louis, Missouri, USA: **a**, **b** discharge; **c**, **d** suspended sediment concentration and **e**, **f** suspended sediment load (*source* Sivakumar and Jayawardena (2002)) 305

Figure 11.6 One-day ahead prediction accuracy versus embedding dimension for daily discharge, suspended sediment concentration, and suspended sediment load in the Mississippi River basin at St. Louis, Missouri, USA: **a** correlation coefficient; and **b** coefficient of efficiency (*source* Sivakumar and Wallender (2005)). 306
Figure 11.7 Time series and scatter plot comparisons of one-day ahead predictions for daily sediment data in the Mississippi River basin at St. Louis, Missouri, USA: **a**, **b** discharge; **c**, **d** suspended sediment concentration; and **e**, **f** suspended sediment load (*source* Sivakumar and Wallender (2005)) 308
Figure 11.8 Prediction accuracy versus lead time for daily discharge, suspended sediment concentration, and suspended sediment load in the Mississippi River basin at St. Louis, Missouri, USA: **a** correlation coefficient; and **b** coefficient of efficiency. Embedding dimension (m) = 3 (*source* Sivakumar and Wallender (2005)). 309
Figure 11.9 Correlation dimension analysis of solute transport process in two facies medium (sand 20 %, clay 80 %) with anisotropy condition 2:1 and 50:1: **a** time series plot; **b** phase space diagram; **c** Log C(r) versus Log r plot; and **d** correlation exponent versus embedding dimension (*source* Sivakumar et al. (2005)). 311
Figure 11.10 Correlation dimension analysis of solute transport process in three facies medium (sand 21.26 %, clay 53.28 %, loam 25.46 %) with anisotropy condition 2:1 and 50:1 and field entropy: **a** time series plot; **b** phase space diagram; **c** Log C(r) versus Log r plot; and **d** correlation exponent versus embedding dimension (*source* Sivakumar et al. (2005)) 312
Figure 11.11 Effect of volume proportions on solute transport behavior in two facies medium (with anisotropy condition 2:1 and 300:1): sand 15 %, clay 85 %; sand 25 %, clay 75 %; sand 35 %, clay 65 %; and sand 60 %, clay 40 % (*source* Sivakumar et al. (2005)) 313
Figure 11.12 Sensitivity of dynamic behavior of solute transport process to anisotropy conditions in two facies medium: sand 20 %, clay 80 % (*source* Sivakumar et al. (2005)) . . . 313
Figure 11.13 Effect of entropy on solute transport behavior in three facies medium (sand 21.26 %, clay 53.28 %, loam 25.46 %) with anisotropy condition 5:1 and 300:1 (*source* Sivakumar et al. (2005)) 314

Figure 11.14 Relationship between correlation exponent and embedding dimension for three different regions: **a** region A (whole of Bangladesh) focal well A-1; **b** region B (Holocene) focal well B-1; and **c** region C (Pleistocene) focal well C-1 (*source* Hossain and Sivakumar (2006)) 316
Figure 12.1 Relationship between percentage of false nearest neighbors and embedding dimension for monthly streamflow time series from the Quinebaug River at Jewett City (USGS Station #1127000) in Connecticut, USA: effect of delay time 324
Figure 12.2 False nearest neighbor dimensions for monthly streamflow time series from 639 stations in the United States: **a** delay time $\tau = 1$; **b** delay time $\tau = 3$; **c** delay time $\tau = 12$; **d** delay time τ = ACF value; and **e** delay time τ = AMI value (*source* Vignesh et al. (2015)) 325
Figure 12.3 Monthly runoff time series from Göta River basin, Sweden (*source* Sivakumar (2005a)) 327
Figure 12.4 Correlation dimension results for runoff time series from Göta River basin, Sweden: **a** 120 points; **b** 240 points; **c** 360 points; **d** 600 points; **e** 1080 points; and **f** 1560 points. Embedding dimension $m = 1$ to 10 (from *left* to *right*) (*source* Sivakumar (2005a)) 328
Figure 12.5 Noise reduction results for daily rainfall data from Station 05: **a** relationship between noise level removed and number of iterations for different neighborhood sizes (r) with 4.6 % noise level (estimated) to be removed; and **b** relationship between correlation coefficient and embedding dimension for original and 4.6 % noise-reduced rainfall data with different neighborhood sizes; and **c** relationship between correlation coefficient and embedding dimension for original and different levels of noise-reduced rainfall data (*source* Sivakumar et al. (1999c)) 330
Figure 12.6 Correlation dimension results for rainfall data of different resolutions in the Leaf River basin, Mississippi, USA: **a** data with zeros; and **b** data without zeros (*source* Sivakumar (2005b)) 334

List of Tables

Table 8.1 A short list of chaos studies in hydrology 233

Table 9.1 Statistics and correlation dimension results for rainfall data at different temporal scales in the Leaf River basin, Mississippi, USA (*source* Sivakumar (2001a)) 253

Table 9.2 Characteristics and correlation dimension results for rainfall weights between different resolutions in the Leaf River basin, Mississippi, USA (*source* Sivakumar et al. (2001b)) 256

Table 9.3 Results of rainfall disaggregation in the Leaf River basin, Mississippi, USA (*source* Sivakumar et al. (2001b)) 260

Table 10.1 Nonlinear local approximation prediction results for monthly runoff data from the Coaracy Nunes/Araguari River in Brazil (*source* Sivakumar et al. (2001b)) 277

Table 10.2 Statistics of streamflow data at different temporal resolutions in the Mississippi River basin at St. Louis, Missouri, USA (unit = $m^3\ s^{-1}\ d_s$, where d_s is the scale of observations in days) (*source* Sivakumar et al. (2004)) . . . 281

Table 10.3a 2-day to daily streamflow disaggregation results in the Mississippi River basin at St. Louis, Missouri, USA (*source* Sivakumar et al. (2004)). 283

Table 10.3b 4-day to 2-day streamflow disaggregation results in the Mississippi River basin at St. Louis, Missouri, USA (*source* Sivakumar et al. (2004)). 284

Table 10.3c 8-day to 4-day streamflow disaggregation results in the Mississippi River basin at St. Louis, Missouri, USA (*source* Sivakumar et al. (2004)). 284

Table 10.3d 16-day to 8-day streamflow disaggregation results in the Mississippi River basin at St. Louis, Missouri, USA (*source* Sivakumar et al. (2004)). 284

Table 10.4 Overall statistics of streamflow data at 117 stations in the western United States. 287

Table 11.1 Statistics of daily discharge, suspended sediment concentration, and suspended sediment load data in the Mississippi River basin at St. Louis, Missouri, USA (*source* Sivakumar and Wallender (2005)) 304
Table 11.2 One-day ahead (T = 1) predictions for discharge, suspended sediment concentration, and suspended sediment load from the Mississippi River basin at St. Louis, Missouri, USA (*source* Sivakumar and Wallender (2005)) 307
Table 11.3 Predictions for different lead times for discharge, suspended sediment concentration, and suspended sediment load from the Mississippi River at St. Louis, Missouri, USA (*m* = 3 in all cases) (*source* Sivakumar and Wallender (2005)). 309

Part I

Hydrologic Systems and Modeling

Chapter 1
Introduction

Abstract In simple terms, hydrology is the study of the waters of the Earth, including their occurrence, distribution, and movement. The constant circulation of water and its change in physical state is called the *hydrologic cycle*. The study of water started at least a few thousands years ago, but the modern scientific approach to the hydrologic cycle started in the seventeenth century. Since then, hydrology has witnessed a tremendous growth, especially over the last century, with significant advances in computational power and hydrologic data measurements. This chapter presents a general and introductory account of hydrology. First, the concept of the hydrologic cycle is described. Next, a brief history of the scientific development of hydrology is presented. Then, the concept of hydrologic system is explained, followed by a description of the hydrologic system model and model classification. Finally, the role of hydrologic data and time series modeling as well as the physical basis of time series modeling are highlighted.

1.1 Definition of Hydrology

The name 'hydrology' was derived from the Greek words 'hydro' (water) and 'logos' (study), and roughly translates into 'study of water.' Different textbooks may offer different definitions, but all of them generally reflect the following working definition:

> Hydrology is the science that treats the waters of the Earth, their occurrence, circulation and distribution, their chemical and physical properties, and their interactions with their environments, including their relations to living things.

Within hydrology, various sub-fields exist. In keeping with the essential ingredients of the above definition, these sub-fields may depend on the region (e.g. over the land surface, below the land surface, mountains, urban areas) or property (e.g. physical, chemical, isotope) or interactions (e.g. atmosphere, environment, ecosystem) or other aspects (e.g. tools used for studies) of water. There may also be significant overlaps between two or more sub-fields, and even inter-change of terminologies depending on the emphasis for water in studies of the

© Springer Science+Business Media Dordrecht 2017

B. Sivakumar, *Chaos in Hydrology*, DOI 10.1007/978-90-481-2552-4_1

Earth-ocean-atmospheric system. Some of the popular sub-fields within hydrology are:

- Surface hydrology—study of hydrologic processes that operate at or near the Earth’s surface
- Sub-surface hydrology (or Groundwater hydrology or Hydrogeology)—study of the presence and movement of water below the Earth’s surface
- Vadose zone hydrology—study of the movement of water between the top of the Earth’s surface and the groundwater table
- Hydrometeorology—study of the transfer of water and energy between land and water body surfaces and the lower atmosphere
- Hydroclimatology—study of the interactions between climate processes and hydrologic processes
- Paleohydrology—study of the movement of water and sediment as they existed during previous periods of the Earth’s history
- Snow hydrology—study of the formation, movement, and effects of snow
- Urban hydrology—study of the hydrologic processes in urban areas
- Physical hydrology—study of the physical mechanisms of hydrologic processes
- Chemical hydrology—study of the chemical characteristics of water
- Isotope hydrology—study of the isotopic signatures of water
- Ecohydrology (or Hydroecology)—study of the interactions between hydrologic processes and organisms
- Hydroinformatics—the adaptation of information technology to hydrology and water resources applications.

1.2 Hydrologic Cycle

The constant movement of water and its change in physical state on the Earth (in ocean, land, and atmosphere) is called the *hydrologic cycle* or, quite simply, *water cycle*. The hydrologic cycle is the central focus of hydrology. A schematic representation of the hydrologic cycle is shown in Fig. 1.1. A description of the hydrologic cycle can begin at any point and return to that same point, with a number of processes continuously occurring during the cycle; however, oceans are usually considered as the origin. In addition, depending upon the scope or focus of the study, certain processes (or components) of the hydrologic cycle may assume far more importance over the others and, hence, such may be described in far more detail. In what follows, the hydrologic cycle is described with oceans as the origin and processes on and above/below the land surface assuming more importance. For further details, including other descriptions of the hydrologic cycle, the reader is referred to Freeze and Cherry (1979), Driscoll (1986), Chahine (1992), Maidment (1993), and Horden (1998), among others.

Water in the ocean evaporates and becomes atmospheric water vapor (i.e. moisture). Some of this water vapor is transported and lifted in the atmosphere until

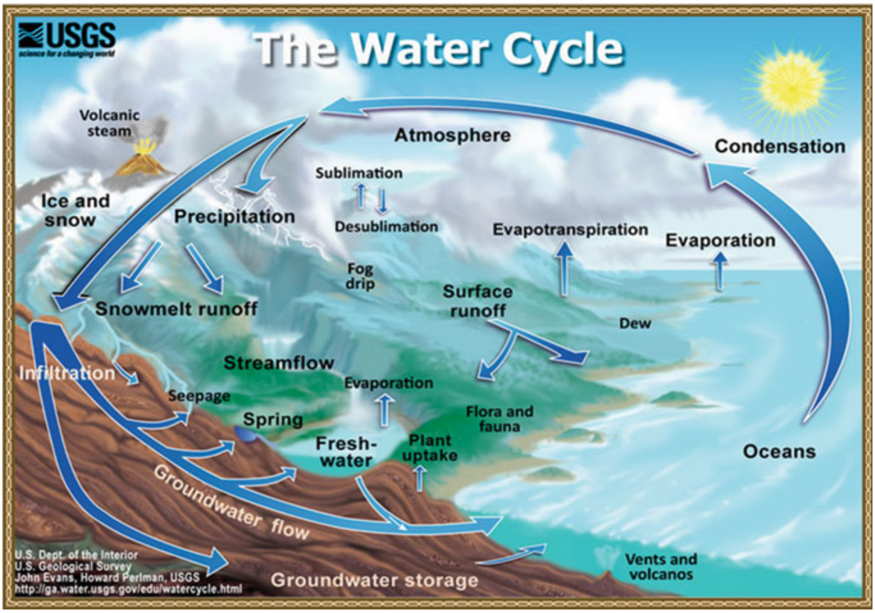

Fig. 1.1 Schematic representation of hydrologic cycle (*source* US Geological Survey, http://water.usgs.gov/edu/watercycle.html; accessed May 5, 2015)

it condenses and falls as precipitation, which sometimes evaporates or gets intercepted by vegetation before it can reach the land surface. Of the water that reaches the land surface by precipitation, some may evaporate where it falls, some may infiltrate the soil, and some may run off overland to evaporate or infiltrate elsewhere or to enter streams. The water that infiltrates the ground may evaporate, be absorbed by plant roots, and then transpired by the plants, or percolate downward to groundwater reservoirs (also called *aquifers*). Water that enters groundwater reservoirs may either move laterally until it is close enough to the surface to be subject to evaporation or transpiration, reach the land surface and form springs, seeps or lakes, or flow directly into streams or into the ocean. Stream water can accumulate in lakes and surface reservoirs, evaporate or be transpired by riparian vegetation, seep downward into groundwater reservoirs or flow back into the ocean, where the cycle begins again.

Although the concept of the hydrologic cycle is simple, the phenomenon is enormously complex and intricate. It is not just one large cycle but rather composed of many inter-related cycles of continental, regional, and local extent. Each phase of the hydrologic cycle also provides opportunities for temporary accumulation and storage of water, such as snow and ice on the land surface, moisture in the soil and groundwater reservoirs, water in ponds, lakes, and surface reservoirs, and vapor in the atmosphere. Although the total volume of water in the global hydrologic cycle