
Contents

| | |
|--|-------------|
| Editors | xix |
| Contributors | xxi |
| Basic Symbols | xxvi |
| I Opening Remarks | 1 |
| 1 Handbook Outline | 3 |
| <i>Miguel de Carvalho, Raphaël Huser, Philippe Naveau & Brian J. Reich</i> | |
| 1.1 The Case for Statistics of Extremes | 3 |
| 1.2 A Back to the Future View on the Field | 4 |
| 1.3 Welcome to EVA: Further Resources | 6 |
| 1.4 Design and Structure | 7 |
| II Univariate Extremes | 9 |
| 2 Modeling Univariate Extremes—Why and How | 11 |
| <i>Anthony Davison & Ophélie Miralles</i> | |
| 2.1 Introduction | 11 |
| 2.2 Extremal Models | 12 |
| 2.2.1 Why Special Models? | 12 |
| 2.2.2 Maxima | 14 |
| 2.2.3 Threshold Exceedances | 15 |
| 2.2.4 Statistical Models | 17 |
| 2.2.5 Targets of Inference | 20 |
| 2.3 Illustrations | 22 |
| 2.3.1 Abisko Precipitation | 22 |
| 2.3.2 Venetian Tides | 24 |
| 2.3.3 Heat Waves | 27 |
| 2.3.4 Stock Markets | 30 |
| 2.3.5 Mortality from Disease Outbreaks | 32 |
| 2.4 Discussion | 34 |
| 2.5 Further Reading | 35 |
| 3 Learning About Extreme Value Distributions from Data | 37 |
| <i>Miguel de Carvalho & Viviana Carcaiso</i> | |
| 3.1 Introduction | 37 |
| 3.2 Further Background on GEV and GP Models | 39 |
| 3.2.1 The GEV Model—A Sample Maximum-Based Approach | 39 |
| 3.2.2 The GP Model—An Exceedance-Based Approach | 41 |
| 3.3 Likelihood-Based Inference for Extreme Value Distributions | 43 |
| 3.3.1 Maximum Likelihood Estimator | 43 |

| | | |
|----------|---|-----------|
| 3.3.2 | Interval Estimates | 45 |
| 3.3.3 | Block Maxima Data Examples | 48 |
| 3.3.4 | Peaks Over Threshold Data Examples | 49 |
| 3.4 | Learning About Transformations of Parameters | 51 |
| 3.5 | Diagnostics | 52 |
| 3.5.1 | PP-Plots and QQ-Plots | 53 |
| 3.5.2 | Quantile Residuals and QQ-Boxplots | 55 |
| 3.6 | Notes and Comments | 56 |
| 4 | Bayesian Methods for Extreme Value Analysis | 57 |
| | <i>Reetam Majumder, Benjamin A. Shaby & Brian J. Reich</i> | |
| 4.1 | The Bayesian Paradigm | 57 |
| 4.1.1 | Common Likelihood Functions for Extreme Value Analysis | 58 |
| 4.1.2 | Selecting the Prior Distribution | 59 |
| 4.2 | Bayesian Computation | 63 |
| 4.2.1 | Markov Chain Monte Carlo Sampling | 63 |
| 4.2.2 | Convergence Diagnostics | 64 |
| 4.2.3 | Software Review | 65 |
| 4.3 | Model Selection and Evaluation | 65 |
| 4.4 | Illustrations of Bayesian Methods | 67 |
| 4.4.1 | Simulation Study | 68 |
| 4.4.2 | Example: Precipitation at Fort Collins, Colorado | 69 |
| 4.5 | Hierarchical Models | 72 |
| 4.5.1 | Example: Streamflow in the Continental US | 74 |
| 5 | Jointly Modeling the Bulk and Tails | 79 |
| | <i>Philippe Naveau</i> | |
| 5.1 | Introduction | 79 |
| 5.2 | The Extended Generalized Pareto Distribution | 81 |
| 5.2.1 | Inference | 86 |
| 5.2.2 | Examples of Applications | 88 |
| 5.2.3 | Bayesian Approaches | 88 |
| 5.2.4 | Limitations and Extensions of EGP Class | 89 |
| 5.3 | Other Extended Distributions | 89 |
| 5.3.1 | Dynamic Weighted Models (Frigessi Type) | 90 |
| 5.3.2 | Treatment of Different Supports (Stein Type) | 91 |
| 5.3.3 | A GEV-Inspired Distribution | 92 |
| 5.3.4 | Gaussian-Seeded Models | 92 |
| 5.3.5 | Machine Learning-Based Approaches | 94 |
| 5.4 | Notes and Comments | 96 |
| 6 | Regression Models for Extreme Events | 99 |
| | <i>Miguel de Carvalho, Vianey Palacios, Lígia Henriques-Rodrigues & Myung Won Lee</i> | |
| 6.1 | Introduction | 99 |
| 6.2 | Regression for a Block Maximum Response | 101 |
| 6.2.1 | Modeling | 101 |
| 6.2.2 | Learning from Block Maxima Data | 103 |
| 6.2.3 | Regression Diagnostics | 104 |
| 6.3 | Regression for Pareto-Based Responses | 105 |
| 6.3.1 | Pareto-Type Response | 105 |
| 6.3.2 | Extended Generalized Pareto Response | 107 |

| | | |
|----------------------------------|--|------------|
| 6.4 | Quantile Regression for Extremes | 109 |
| 6.4.1 | Induced Specifications | 109 |
| 6.4.2 | Direct Specification | 110 |
| 6.5 | Data Examples | 110 |
| 6.5.1 | California Wildfires | 110 |
| 6.5.2 | Hong Kong Temperature | 114 |
| 6.5.3 | Madeira Rainfall | 116 |
| 6.6 | Notes and Comments | 118 |
| III Multivariate Extremes | | 121 |
| 7 | Multivariate Extreme Value Theory | 123 |
| | <i>Philippe Naveau & Johan Segers</i> | |
| 7.1 | Introduction | 123 |
| 7.2 | Multivariate Generalized Pareto Distributions | 126 |
| 7.3 | Exponent Measures, Point Processes, and More | 134 |
| 7.4 | Multivariate Extreme Value Distributions | 144 |
| 7.5 | Examples of Parametric Models | 148 |
| 7.6 | Notes and Comments | 149 |
| 7.7 | Mathematical Complements | 150 |
| 8 | Measures of Extremal Dependence | 153 |
| | <i>David L. Carl, Simone A. Padoan & Stefano Rizzelli</i> | |
| 8.1 | Introduction | 153 |
| 8.2 | Modeling Extreme Value Dependence | 154 |
| 8.2.1 | Extremal Dependence | 156 |
| 8.2.2 | The Exponent and Angular Measures | 158 |
| 8.2.3 | The Extreme Quantile Regions $Q_n^{(1)}$ and $Q_n^{(2)}$ | 159 |
| 8.2.4 | The Extreme Quantile Region $Q_n^{(3)}$ | 160 |
| 8.3 | Learning from Data | 163 |
| 8.3.1 | Estimation Based on Empirical Measures | 163 |
| 8.3.2 | Estimation Based on the Likelihood | 165 |
| 8.3.2.1 | Frequentist Approach | 165 |
| 8.3.2.2 | Bayesian Approach | 166 |
| 8.4 | Simulation Study | 167 |
| 8.5 | Financial Data Example | 170 |
| 8.6 | Notes and Comments | 174 |
| 9 | Regression Models for Multivariate Extremes | 175 |
| | <i>Miguel de Carvalho & Daniela Castro-Camilo</i> | |
| 9.1 | Introduction | 175 |
| 9.2 | A Journey through Angular Surfaces | 177 |
| 9.2.1 | Angular Surface | 177 |
| 9.2.2 | Modeling and Inference | 181 |
| 9.2.3 | Regression Diagnostics | 182 |
| 9.3 | Smoothing for Angular Surfaces | 182 |
| 9.3.1 | A Bayesian P-Spline Approach | 182 |
| 9.3.2 | Model Assessment | 185 |
| 9.4 | An Introduction to Regression Manifolds | 185 |
| 9.4.1 | Framework | 185 |
| 9.4.2 | Learning from Data | 186 |

| | | |
|-----------|--|------------|
| 9.4.3 | Regression Diagnostics | 187 |
| 9.5 | Data Examples | 188 |
| 9.5.1 | Hurricane Data | 188 |
| 9.5.2 | NASDAQ–NYSE Data, I | 191 |
| 9.5.3 | NASDAQ–NYSE Data, II | 193 |
| 9.6 | Notes and Comments | 194 |
| 10 | Conditional Extremes Modeling | 199 |
| | <i>Emma S. Simpson & Jennifer L. Wadsworth</i> | |
| 10.1 | Introduction | 199 |
| 10.2 | Multivariate Conditional Extremes Modeling | 200 |
| 10.2.1 | Main Modeling Assumption | 201 |
| 10.2.2 | Model Fitting | 202 |
| 10.2.3 | Model Fitting Diagnostics | 205 |
| 10.2.4 | Estimation of Joint Probabilities | 206 |
| 10.2.5 | Assessing Uncertainty | 208 |
| 10.2.6 | Threshold Selection | 210 |
| 10.3 | Spatial Conditional Extremes Modeling | 212 |
| 10.3.1 | Motivation: Netherlands Temperature Data | 212 |
| 10.3.2 | Model and Assumptions | 214 |
| 10.3.3 | Estimation of Extreme Events | 216 |
| 10.3.4 | Model Diagnostics | 217 |
| 10.4 | Summary of Further Extensions | 218 |
| 11 | Principal Component Analysis for Multivariate Extremes | 221 |
| | <i>Daniel Cooley, Anne Sabourin & Troy Wixson</i> | |
| 11.1 | Introduction | 221 |
| 11.2 | PCA for Extremes | 224 |
| 11.2.1 | Classical PCA as Optimal Orthogonal Projection | 224 |
| 11.2.2 | Regular Variation | 226 |
| 11.2.3 | PCA for Regular Variation | 227 |
| 11.3 | Extremal PCA: Setup and Estimation | 228 |
| 11.3.1 | Probabilistic Setup | 228 |
| 11.3.2 | Estimation | 230 |
| 11.4 | Principal Components and Interpretation | 231 |
| 11.4.1 | Extremal Principal Components | 231 |
| 11.4.2 | The τ -Mapping for Modeling on the Positive Orthant | 233 |
| 11.5 | Applications | 234 |
| 11.5.1 | Financial Data | 234 |
| 11.5.2 | Precipitation Data | 236 |
| 11.6 | Perspectives | 240 |
| 12 | Clustering Methods for Multivariate Extremes | 243 |
| | <i>Phyllis Wan & Anja Janßen</i> | |
| 12.1 | Background and Motivation | 243 |
| 12.1.1 | Framework and a First Example | 244 |
| 12.1.2 | Estimation of the Angular Measure | 246 |
| 12.1.3 | Concomitant Extremes | 248 |
| 12.1.4 | K -means Clustering | 248 |
| 12.2 | Spherical K -means Clustering for Extremes | 250 |
| 12.2.1 | Algorithm | 250 |

| | | |
|--------|---|-----|
| 12.2.2 | Implementation | 251 |
| 12.2.3 | Consistency | 252 |
| 12.3 | Spherical K -principal Components Clustering for Extremes | 252 |
| 12.3.1 | Algorithm | 252 |
| 12.3.2 | In the Context of Concomitant Extremes | 254 |
| 12.3.3 | Implementation | 255 |
| 12.3.4 | Consistency | 255 |
| 12.4 | Spectral Clustering for Extremes | 256 |
| 12.4.1 | Algorithm | 256 |
| 12.4.2 | Implementation | 258 |
| 12.4.3 | Consistency | 258 |
| 12.5 | Choice of K | 258 |
| 12.6 | Example: Clusters in Extreme River Flow | 259 |

13 Graphical Models for Multivariate Extremes 263

Sebastian Engelke, Manuel Hentschel, Michaël Lalancette & Frank Röttger

| | | |
|--------|---|-----|
| 13.1 | Introduction | 263 |
| 13.2 | Background | 266 |
| 13.2.1 | Multivariate Extreme Value Theory | 266 |
| 13.2.2 | Conditional Independence and Graphical Models | 269 |
| 13.3 | Graphical Modeling in Extremes | 270 |
| 13.3.1 | Extremal Graphical Models | 270 |
| 13.3.2 | Multivariate Pareto Distributions | 273 |
| 13.3.3 | Max-Stable Distributions | 274 |
| 13.4 | Extremal Tree and Block Graph Models | 275 |
| 13.4.1 | Trees and Block Graphs | 276 |
| 13.4.2 | Parameter Estimation | 277 |
| 13.4.3 | Structure Learning | 278 |
| 13.5 | Hüsler–Reiss Graphical Models | 279 |
| 13.5.1 | Properties | 279 |
| 13.5.2 | Parameter Estimation | 280 |
| 13.5.3 | Structure Learning | 282 |
| 13.6 | Application | 284 |
| 13.7 | Notes and Comments | 286 |
| A.1 | Appendix: Separation in DAGs | 288 |
| A.2 | Appendix: Additional Figures | 289 |

IV Spatial and Temporal Extremes 291

14 Time Series in Extremes 293

Graeme Auld, Lambert De Monte & Ioannis Papastathopoulos

| | | |
|--------|---|-----|
| 14.1 | Introduction | 293 |
| 14.2 | Background on Extremes of Stationary Time Series | 296 |
| 14.2.1 | How Does Serial Dependence Influence Extremes? | 296 |
| 14.2.2 | Extremal Types Theorem for Stationary Time Series | 298 |
| 14.2.3 | Extremal Index and Cluster Size Distribution | 300 |
| 14.2.4 | Declustering and Estimation of the Extremal Index | 302 |
| 14.3 | Case Study | 304 |
| 14.3.1 | Pre-Processing the Data | 304 |
| 14.3.2 | A Block Maxima Approach | 305 |
| 14.3.3 | A Threshold Exceedance Approach | 306 |

| | | |
|-----------|---|------------|
| 14.4 | Conditional Extremes of Time Series | 308 |
| 14.4.1 | Standardization | 309 |
| 14.4.2 | Conditional Extremes | 309 |
| 14.4.3 | Inference for Functionals of the Time Series Given an Exceedance | 314 |
| 14.4.4 | Model Checking | 315 |
| 14.5 | Case Study Revisited | 316 |
| 14.5.1 | Pre-Processing the Data | 316 |
| 14.5.2 | A Conditional Extremes Approach | 316 |
| 14.6 | Concluding Remarks | 319 |
| 15 | Max-Stable Processes for Spatial Extremes | 321 |
| | <i>Kirstin Strokorb & Marco Oesting</i> | |
| 15.1 | Introduction | 321 |
| 15.2 | Theory | 323 |
| 15.2.1 | Marginal Standardization | 324 |
| 15.2.2 | Spectral Representation | 325 |
| 15.2.3 | Max-Domain of Attraction | 327 |
| 15.2.4 | Dependence Measures and Mixing Properties | 327 |
| 15.3 | Models | 329 |
| 15.3.1 | Mixed Moving Maxima | 330 |
| 15.3.2 | Brown–Resnick Processes | 330 |
| 15.3.3 | Extremal- t Processes | 333 |
| 15.3.4 | Reich–Shaby Model and Generalizations | 334 |
| 15.3.5 | Further Remarks on Model Building | 335 |
| 15.4 | Statistical Inference | 336 |
| 15.4.1 | The Block Maxima Paradigm | 336 |
| 15.4.2 | Likelihood-Based Inference | 338 |
| 15.4.3 | Other Approaches | 339 |
| 15.5 | Simulation | 340 |
| 15.5.1 | Unconditional Simulation | 340 |
| 15.5.2 | Conditional Simulation | 342 |
| 15.6 | Application | 343 |
| 15.7 | Concluding Remarks | 347 |
| 16 | Pareto Processes for Threshold Exceedances in Spatial Extremes | 349 |
| | <i>Clément Dombry, Juliette Legrand & Thomas Opitz</i> | |
| 16.1 | Introduction | 349 |
| 16.2 | Theory of Pareto Processes | 352 |
| 16.2.1 | The Simple Pareto Process | 352 |
| 16.2.2 | The Generalized Pareto Process | 355 |
| 16.2.3 | Risk Functionals and r -Pareto Processes | 356 |
| 16.2.4 | Generalized r -Pareto Processes | 358 |
| 16.3 | Models, Simulation, and Statistical Inference | 360 |
| 16.3.1 | Pareto Process Models | 360 |
| 16.3.2 | Simulation of Pareto Processes | 361 |
| 16.3.3 | Statistical Inference for Pareto Processes | 365 |
| 16.4 | Application Example | 369 |
| 16.5 | Conclusion | 374 |

| | |
|---|------------|
| 17 Subasymptotic Models for Spatial Extremes | 377 |
| <i>Likun Zhang, Christian Rohrbeck & Thomas Opitz</i> | |
| 17.1 Introduction | 377 |
| 17.1.1 Asymptotic Frameworks | 378 |
| 17.1.2 Subasymptotic Extensions | 379 |
| 17.1.3 Statistical Methodology | 380 |
| 17.1.4 Structure of this Chapter and Supplemental Material | 380 |
| 17.2 Diagnostic Tools | 381 |
| 17.2.1 The χ and $\bar{\chi}$ Diagnostics | 381 |
| 17.2.2 Level-Dependent Extremal Coefficients for Maxima | 384 |
| 17.3 Models for Threshold Exceedances in Original Events | 385 |
| 17.3.1 General Construction of Scale- and Location-Mixtures | 385 |
| 17.3.2 Models Based on Gaussian Processes | 386 |
| 17.3.3 Inverted Max-Stable Processes | 387 |
| 17.3.4 Statistical Inference | 389 |
| 17.4 Max-Infinitely Divisible Models for Blockwise Maxima | 391 |
| 17.4.1 General Construction Principle | 392 |
| 17.4.2 Spatial max-id Models Based on Gaussian Processes | 392 |
| 17.4.3 Statistical Inference | 393 |
| 17.5 Case Study | 393 |
| 17.5.1 Blockwise Maxima Framework | 394 |
| 17.5.2 Peaks-Over-Threshold Framework | 396 |
| 17.6 Conclusion and Outlook | 399 |
| | |
| 18 Space-Time Modeling of Extremes | 401 |
| <i>Marco Oesting & Kirstin Strokorb</i> | |
| 18.1 Introduction | 401 |
| 18.2 Modeling of Spatio-Temporal Dependence | 403 |
| 18.2.1 General Strategies | 403 |
| 18.2.2 Separable Space-Time Covariance Models | 408 |
| 18.2.3 Nonseparable Space-Time Covariance Models | 408 |
| 18.3 Space-Time Max-Stable Processes | 411 |
| 18.3.1 Models | 412 |
| 18.3.2 Inference | 414 |
| 18.4 Space-Time Pareto Processes | 416 |
| 18.5 Subasymptotic Models for Space-Time Extremes | 417 |
| 18.5.1 Conditional Extremes Approach in Space and Time | 417 |
| 18.5.2 Other Subasymptotic Approaches | 419 |
| 18.6 Conclusion | 420 |
| | |
| V Emerging Topics | 423 |
| | |
| 19 Causality and Extremes | 425 |
| <i>Valérie Chavez-Demoulin & Linda Mhalla</i> | |
| 19.1 Introduction | 425 |
| 19.2 Quantile Treatment Effect: An Extremal Approach | 427 |
| 19.3 Causal Structural Models for Extremes | 429 |
| 19.3.1 Definitions and Representations | 429 |
| 19.3.2 Identifiability of the Models | 433 |
| 19.4 Causal Structure Learning for Extremes | 435 |
| 19.4.1 Score-Based Causal Discovery | 436 |

| | | |
|-----------|---|------------|
| 19.4.2 | Causal Discovery for Recursive Max-Linear Models | 438 |
| 19.5 | Data Application | 439 |
| 19.5.1 | Motivation and Data Description | 439 |
| 19.5.2 | Methods | 440 |
| 19.5.3 | Results | 441 |
| 19.6 | Notes and Comments | 444 |
| 20 | On the Simulation of Extreme Events with Neural Networks | 447 |
| | <i>Michaël Allouche, Stéphane Girard & Emmanuel Gobet</i> | |
| 20.1 | Introduction | 447 |
| 20.2 | Generative Modeling | 448 |
| 20.2.1 | Theoretical Framework | 449 |
| 20.2.2 | Neural Networks | 449 |
| 20.2.3 | Generative Adversarial Network | 452 |
| 20.2.4 | Variational Auto-Encoders | 453 |
| 20.2.5 | Diffusion Models | 454 |
| 20.3 | Simulating Extremes with Generative Adversarial Networks (GANs) | 455 |
| 20.3.1 | Performance Assessment | 455 |
| 20.3.2 | Computational Aspects | 456 |
| 20.3.3 | Financial Data Illustration | 456 |
| 20.3.4 | Simulated Bivariate Data | 458 |
| 20.4 | Extreme Value Framework | 459 |
| 20.4.1 | Heavy-Tailed Distributions | 459 |
| 20.4.2 | Examples of Heavy-Tailed Distributions | 460 |
| 20.5 | Adapting Generative Methods to Extremes | 460 |
| 20.5.1 | Improvements of GANs | 461 |
| 20.5.2 | Other Architectures | 463 |
| 20.5.3 | Simulating Extremes with GANs | 464 |
| 20.6 | Notes and Comments | 464 |
| A1 | Appendix: Copulas | 467 |
| A1.1 | Archimedean Copulas | 467 |
| A1.2 | Quantifying Dependence | 467 |
| A1.3 | Inference for Kendall's Dependence Metrics | 468 |
| 21 | Extreme Quantile Regression with Deep Learning | 469 |
| | <i>Jordan Richards & Raphaël Huser</i> | |
| 21.1 | Motivation | 469 |
| 21.2 | An Introduction to Extreme Quantile Regression | 470 |
| 21.2.1 | General Setting | 471 |
| 21.2.2 | Why Not Use Classical Nonparametric Methods? | 471 |
| 21.2.3 | Parametric Extreme Quantile Regression—Why and How | 474 |
| 21.2.4 | Why do Deep Regression? | 475 |
| 21.3 | Deep Extreme Quantile Regression | 476 |
| 21.3.1 | Neural Network Architectures | 477 |
| 21.3.2 | Training Neural Networks | 479 |
| 21.3.3 | Practical Considerations | 480 |
| 21.3.4 | Computational Software and Implementation | 484 |
| 21.3.5 | A Note on Computational Expense | 484 |
| 21.4 | Simulation Study | 485 |
| 21.5 | Example: European Precipitation Data | 488 |
| 21.6 | Further Topics and Concluding Remarks | 491 |

| | |
|---|------------|
| 22 Risk Measures Beyond Quantiles | 493 |
| <i>Abdelaati Daouia & Gilles Stupfler</i> | |
| 22.1 Introduction | 493 |
| 22.2 Empirical Motivation | 497 |
| 22.3 Spectral Risk Measures | 498 |
| 22.4 M-Quantile Risk Measures: From L^1 to Convex Optimization | 506 |
| 22.5 Towards Multivariate Risk Assessment | 510 |
| 22.6 Notes and Comments | 515 |
| | |
| VI Applications and Case Studies | 521 |
| | |
| 23 Detection and Attribution of Extreme Weather Events: A Statistical Review | 523 |
| <i>Richard L. Smith</i> | |
| 23.1 Introduction | 523 |
| 23.2 Overview of GEV/GPD Analyses | 525 |
| 23.3 Methods for Extreme Event Attribution | 526 |
| 23.4 World Weather Attribution | 528 |
| 23.4.1 Philip et al. (2020) | 529 |
| 23.4.2 van Oldenbourgh et al. (2021) | 530 |
| 23.4.3 Analysis of the 2021 Pacific Northwest Heatwave | 532 |
| 23.4.4 Analysis of the January 2025 Los Angeles Wildfires | 533 |
| 23.5 Alternative Statistical Approaches | 535 |
| 23.6 Examples | 538 |
| 23.6.1 GEV Analysis | 538 |
| 23.6.2 Threshold Exceedance Approach | 541 |
| 23.7 Conclusions | 543 |
| | |
| 24 Evaluation of Extreme Forecasts and Projections | 545 |
| <i>Thordis L. Thorarinsdottir</i> | |
| 24.1 Introduction | 545 |
| 24.2 Notation and Benchmark Example | 547 |
| 24.3 Comparing Predictive Accuracy | 548 |
| 24.3.1 Scoring Functions and Scoring Rules | 549 |
| 24.3.2 Evaluating Functionals | 550 |
| 24.3.3 Selecting the Appropriate Quantile | 551 |
| 24.3.4 Predictions of Risk and Categorical Events | 552 |
| 24.3.5 Distributional Forecasts | 553 |
| 24.3.6 Scoring Rules with a Focus on the Tail | 555 |
| 24.3.7 Comparing two Distributions | 557 |
| 24.3.8 Uncertainty and Significance of Accuracy Assessments | 558 |
| 24.3.9 Accuracy of Benchmark Forecasts | 559 |
| 24.4 Analyzing Predictive Performance | 561 |
| 24.4.1 Calibration | 562 |
| 24.4.2 Calibration of Benchmark Forecasts | 563 |
| 24.4.3 Score Decomposition | 564 |
| 24.5 Relevant R Software | 565 |
| 24.6 Summary and Discussion | 565 |

| | |
|---|------------|
| 25 Statistical Modeling of Extreme Precipitation | 567 |
| <i>Carlo Gaetan, Thomas Opitz & Gwladys Toulemonde</i> | |
| 25.1 Introduction | 567 |
| 25.2 Data Characteristics | 569 |
| 25.3 Univariate Modeling of Extreme Precipitation | 570 |
| 25.3.1 Selected Comments on Block Maxima Approach | 570 |
| 25.3.2 Selected Comments on Peaks Over Threshold Approach | 570 |
| 25.3.3 Nonasymptotic Approach | 571 |
| 25.3.4 Estimation Methods | 573 |
| 25.4 Intensity-Duration-Frequency Curves | 574 |
| 25.5 Regional Frequency Analysis | 577 |
| 25.6 Nonstationarity and Covariate Modeling | 578 |
| 25.6.1 Regression Approach | 578 |
| 25.6.2 Random Effects and Bayesian Regression | 579 |
| 25.6.3 Detecting Temporal Nonstationarity | 579 |
| 25.6.4 Statistical Downscaling of Extreme Precipitation | 580 |
| 25.6.5 Analysis of German Heavy Rainfall | 581 |
| 25.7 Towards Stochastic Weather Generator Models | 582 |
| 25.8 Conclusions and Perspectives | 586 |
| 26 Statistics of Extremes for Wildfires | 589 |
| <i>Jonathan Koh</i> | |
| 26.1 Introduction | 589 |
| 26.1.1 Wildfire Drivers, Models, and Extremes | 590 |
| 26.1.2 Data Sources and Covariates | 592 |
| 26.2 Extreme Value Models for Wildfires | 595 |
| 26.2.1 Fire Occurrence, Incidence, and Frequency | 595 |
| 26.2.2 Fire Size | 598 |
| 26.3 Case Studies for the Analysis of Wildfire Size | 600 |
| 26.3.1 A Step-by-Step Guide with <i>EVTxgboost</i> | 600 |
| 26.3.2 A Step-by-Step Guide with <i>INLA</i> | 604 |
| 26.4 Future Perspectives using EVT | 609 |
| 27 Statistics of Extremes for Landslides and Earthquakes | 611 |
| <i>Rishikesh Yadav, Luigi Lombardo & Raphaël Huser</i> | |
| 27.1 Introduction | 611 |
| 27.2 Hazard Definition | 613 |
| 27.3 Wenchuan Earthquake-Induced Landslide Dataset | 614 |
| 27.4 Joint Areal Model and Bayesian Inference Framework | 617 |
| 27.4.1 Bayesian Hierarchical Modeling Framework for Counts and Sizes | 617 |
| 27.4.2 Unified EVT-Motivated Models for Moderate and Extreme Landslide Sizes | 618 |
| 27.4.3 Bayesian Inference | 621 |
| 27.5 Results on Wenchuan Landslide Dataset | 622 |
| 27.6 Discussion | 631 |
| 27.7 Data and Code Availability | 632 |

| | |
|---|------------|
| 28 Tail Risk Analysis for Financial Time Series | 633 |
| <i>Anna Kiriliouk & Chen Zhou</i> | |
| 28.1 Introduction | 633 |
| 28.2 Exploratory Analysis | 635 |
| 28.2.1 Heavy-Tailedness | 636 |
| 28.2.2 Serial Dependence | 637 |
| 28.2.3 Serial Dependence in Extremes | 639 |
| 28.3 Unconditional Risk Analysis | 641 |
| 28.4 Conditional Risk Analysis | 645 |
| 28.5 Backtesting | 648 |
| 28.6 The Tail Dependence Coefficient | 650 |
| 28.7 Key Takeaways | 652 |
| 28.8 Notes and Comments | 653 |
| | |
| 29 Statistics of Extremes for the Insurance Industry | 655 |
| <i>Hansjörg Albrecher & Jan Beirlant</i> | |
| 29.1 Introduction | 655 |
| 29.2 Reinsurance and Data | 657 |
| 29.3 Adaptations of the Classical Tail Analysis | 659 |
| 29.3.1 Truncation | 660 |
| 29.3.2 Tempering | 662 |
| 29.4 Censoring | 664 |
| 29.5 Full Models for Claims | 667 |
| 29.6 Regression Modeling | 671 |
| 29.7 Multivariate Modeling | 672 |
| 29.8 Natural Catastrophe Insurance and Climate Change | 673 |
| | |
| 30 Statistics of Extremes for Neuroscience | 675 |
| <i>Paolo V. Redondo, Matheus B. Guerrero, Raphaël Huser & Hernando Ombao</i> | |
| 30.1 Introduction | 675 |
| 30.1.1 Background | 676 |
| 30.1.2 Motivating Dataset | 677 |
| 30.1.3 Chapter Organization | 677 |
| 30.2 Common Methodologies for Analyzing EEG Data | 678 |
| 30.2.1 Limitations of Other Time Series Methods | 680 |
| 30.3 EEG Analysis through the Lens of EVT | 680 |
| 30.3.1 Univariate Extremes Modeling of EEG Channels | 681 |
| 30.3.2 Extremal Dependence Between EEG Channels | 684 |
| 30.3.3 Conditional Extremal Modeling of EEG Channels | 685 |
| 30.3.4 Uncertainty Quantification via Bootstrapping | 689 |
| 30.4 Discussion and Further Extensions | 690 |
| | |
| 31 Statistics of Extremes for Incomplete Data, with Application to Lifetime and Liability Claim Modeling | 691 |
| <i>Léo R. Belzile & Johanna G. Nešlehová</i> | |
| 31.1 Introduction | 691 |
| 31.2 England and Wales Semisupercentenarians | 693 |
| 31.2.1 Sampling Frame of Excess Lifetimes | 693 |
| 31.2.2 Semiparametric Models | 694 |
| 31.2.3 Goodness-of-Fit | 696 |
| 31.2.4 Mortality Patterns | 697 |

| | |
|---|------------|
| 31.3 Liability Claims | 698 |
| 31.3.1 Copula Models Under Censoring | 699 |
| 31.3.2 Assessing and Estimating Extremal Dependence | 700 |
| 31.3.3 Censored Likelihood for Bivariate Data | 705 |
| 31.3.4 Inference for Reinsurance Total Payments | 708 |
| 31.4 Outlook | 708 |
| Sources | 711 |
| Index | 769 |