

Contents

Preface..... xix

Acknowledgements xxv

Part I Fundamentals for Modelling Spatial and Spatial-Temporal Data

1 Challenges and Opportunities Analysing Spatial and Spatial-Temporal Data..... 3

1.1 Introduction 3

1.2 Four Main Challenges When Analysing Spatial and Spatial-Temporal Data 4

1.2.1 Dependency 4

1.2.2 Heterogeneity 8

1.2.3 Data Sparsity..... 10

1.2.4 Uncertainty 12

1.2.4.1 Data Uncertainty 12

1.2.4.2 Model (or Process) Uncertainty 13

1.2.4.3 Parameter Uncertainty 13

1.3 Opportunities Arising from Modelling Spatial and Spatial-Temporal Data 14

1.3.1 Improving Statistical Precision 14

1.3.2 Explaining Variation in Space and Time 18

1.3.2.1 Example 1: Modelling Exposure-Outcome Relationships..... 18

1.3.2.2 Example 2: Testing a Conceptual Model at the Small Area Level 20

1.3.2.3 Example 3: Testing for Spatial Spillover (Local Competition) Effects 22

1.3.2.4 Example 4: Assessing the Effects of an Intervention 24

1.3.3 Investigating Space-Time Dynamics 27

1.4 Spatial and Spatial-Temporal Models: Bridging between Challenges and Opportunities 27

1.4.1 Statistical Thinking in Analysing Spatial and Spatial-Temporal Data: The Big Picture 27

1.4.2 Bayesian Thinking in a Statistical Analysis..... 30

1.4.3 Bayesian Hierarchical Models..... 33

1.4.3.1 Thinking Hierarchically..... 33

1.4.3.2 Incorporating Spatial and Spatial-Temporal Dependence Structures in a Bayesian Hierarchical Model Using Random Effects..... 36

1.4.3.3 Information Sharing in a Bayesian Hierarchical Model through Random Effects 37

1.4.4 Bayesian Spatial Econometrics..... 39

1.5 Concluding Remarks 40

1.6 The Datasets Used in the Book 41

1.7 Exercises 45

2 Concepts for Modelling Spatial and Spatial-Temporal Data: An Introduction to "Spatial Thinking"	47
2.1 Introduction	47
2.2 Mapping Data and Why It Matters	48
2.3 Thinking Spatially	52
2.3.1 Explaining Spatial Variation	52
2.3.2 Spatial Interpolation and Small Area Estimation	54
2.4 Thinking Spatially and Temporally	56
2.4.1 Explaining Space-Time Variation	56
2.4.2 Estimating Parameters for Spatial-Temporal Units	59
2.5 Concluding Remarks	59
2.6 Exercises	60
Appendix: Geographic Information Systems	61
3 The Nature of Spatial and Spatial-Temporal Attribute Data	63
3.1 Introduction	63
3.2 Data Collection Processes in the Social Sciences	63
3.2.1 Natural Experiments	64
3.2.2 Quasi-Experiments	67
3.2.3 Non-Experimental Observational Studies	68
3.3 Spatial and Spatial-Temporal Data: Properties	71
3.3.1 From Geographical Reality to the Spatial Database	71
3.3.2 Fundamental Properties of Spatial and Spatial-Temporal Data	74
3.3.2.1 Spatial and Temporal Dependence	74
3.3.2.2 Spatial and Temporal Heterogeneity	75
3.3.3 Properties Induced by Representational Choices	76
3.3.4 Properties Induced by Measurement Processes	83
3.4 Concluding Remarks	84
3.5 Exercises	84
4 Specifying Spatial Relationships on the Map: The Weights Matrix	87
4.1 Introduction	87
4.2 Specifying Weights Based on Contiguity	88
4.3 Specifying Weights Based on Geographical Distance	90
4.4 Specifying Weights Based on the Graph Structure Associated with a Set of Points	90
4.5 Specifying Weights Based on Attribute Values	92
4.6 Specifying Weights Based on Evidence about Interactions	92
4.7 Row Standardisation	93
4.8 Higher Order Weights Matrices	95
4.9 Choice of W and Statistical Implications	97
4.9.1 Implications for Small Area Estimation	97
4.9.2 Implications for Spatial Econometric Modelling	102
4.9.3 Implications for Estimating the Effects of Observable Covariates on the Outcome	104
4.10 Estimating the W Matrix	105
4.11 Concluding Remarks	106
4.12 Exercises	106
4.13 Appendices	107

Appendix 4.13.1 Building a Geodatabase in R 107

Appendix 4.13.2 Constructing the W Matrix and Accessing Data
Stored in a Shapefile 110

**5 Introduction to the Bayesian Approach to Regression Modelling with Spatial
and Spatial-Temporal Data 115**

5.1 Introduction 115

5.2 Introducing Bayesian Analysis 116

5.2.1 Prior, Likelihood and Posterior: What Do These Terms Refer To? 116

5.2.2 Example: Modelling High-Intensity Crime Areas 120

5.3 Bayesian Computation 121

5.3.1 Summarising the Posterior Distribution 121

5.3.2 Integration and Monte Carlo Integration 123

5.3.3 Markov Chain Monte Carlo with Gibbs Sampling 127

5.3.4 Introduction to WinBUGS 129

5.3.5 Practical Considerations when Fitting Models in WinBUGS 133

5.3.5.1 Setting the Initial Values 133

5.3.5.2 Checking Convergence 134

5.3.5.3 Checking Efficiency 136

5.4 Bayesian Regression Models 137

5.4.1 Example I: Modelling Household-Level Income 138

5.4.2 Example II: Modelling Annual Burglary Rates in Small Areas 143

5.5 Bayesian Model Comparison and Model Evaluation 147

5.6 Prior Specifications 148

5.6.1 When We Have Little Prior Information 148

5.6.2 Towards More Informative Priors for Modelling Spatial and
Spatial-Temporal Data 150

5.7 Concluding Remarks 151

5.8 Exercises 153

Part II Modelling Spatial Data

6 Exploratory Analysis of Spatial Data 159

6.1 Introduction 159

6.2 Techniques for the Exploratory Analysis of Univariate Spatial Data 160

6.2.1 Mapping 161

6.2.2 Checking for Spatial Trend 165

6.2.3 Checking for Spatial Heterogeneity in the Mean 168

6.2.3.1 Count Data 168

6.2.3.2 A Monte Carlo Test 169

6.2.3.3 Continuous-Valued Data 170

6.2.4 Checking for Global Spatial Dependence (Spatial Autocorrelation) 172

6.2.4.1 The Moran Scatterplot 173

6.2.4.2 The Global Moran's I Statistic 174

6.2.4.3 Other Tests for Assessing Global Spatial Autocorrelation 177

6.2.4.4 The Global Moran's I Applied to Regression Residuals 178

6.2.4.5 The Join-Count Test for Categorical Data 179

6.2.5	Checking for Spatial Heterogeneity in the Spatial Dependence Structure: Detecting Local Spatial Clusters	181
6.2.5.1	The Local Moran's I	182
6.2.5.2	The Multiple Testing Problem When Using Local Moran's I	185
6.2.5.3	Kulldorff's Spatial Scan Statistic	186
6.3	Exploring Relationships between Variables	191
6.3.1	Scatterplots and the Bivariate Moran Scatterplot.....	191
6.3.2	Quantifying Bivariate Association.....	193
6.3.2.1	The Clifford-Richardson Test of Bivariate Correlation in the Presence of Spatial Autocorrelation.....	193
6.3.2.2	Testing for Association "At a Distance" and the Global Bivariate Moran's I	195
6.3.3	Checking for Spatial Heterogeneity in the Outcome-Covariate Relationship: Geographically Weighted Regression (GWR)	195
6.4	Overdispersion and Zero-Inflation in Spatial Count Data	203
6.4.1	Testing for Overdispersion.....	204
6.4.2	Testing for Zero-Inflation	206
6.5	Concluding Remarks	207
6.6	Exercises	209
	Appendix. An R Function to Perform the Zero-Inflation Test by van Den Broek (1995).....	210
7	Bayesian Models for Spatial Data I: Non-Hierarchical and Exchangeable Hierarchical Models	213
7.1	Introduction	213
7.2	Estimating Small Area Income: A Motivating Example and Different Modelling Strategies.....	214
7.2.1	Modelling the 109 Parameters Non-Hierarchically	216
7.2.2	Modelling the 109 Parameters Hierarchically	217
7.3	Modelling the Newcastle Income Data Using Non-Hierarchical Models	218
7.3.1	An Identical Parameter Model Based on Strategy 1	218
7.3.2	An Independent Parameters Model Based on Strategy 2	220
7.4	An Exchangeable Hierarchical Model Based on Strategy 3.....	223
7.4.1	The Logic of Information Borrowing and Shrinkage.....	224
7.4.2	Explaining the Nature of Global Smoothing Due to Exchangeability.....	225
7.4.3	The Variance Partition Coefficient (VPC).....	226
7.4.4	Applying an Exchangeable Hierarchical Model to the Newcastle Income Data.....	228
7.5	Concluding Remarks	230
7.6	Exercises	230
7.7	Appendix: Obtaining the Simulated Household Income Data	231
8	Bayesian Models for Spatial Data II: Hierarchical Models with Spatial Dependence	233
8.1	Introduction	233
8.2	The Intrinsic Conditional Autoregressive (ICAR) Model	234
8.2.1	The ICAR Model Using a Spatial Weights Matrix with Binary Entries.....	234

8.2.1.1	The WinBUGS Implementation of the ICAR Model	236
8.2.1.2	Applying the ICAR Model Using Spatial Contiguity to the Newcastle Income Data	238
8.2.1.3	Results	240
8.2.1.4	A Summary of the Properties of the ICAR Model Using a Binary Spatial Weights Matrix	244
8.2.2	The ICAR Model with a General Weights Matrix	245
8.2.2.1	Expressing the ICAR Model as a Joint Distribution and the Implied Restriction on W	245
8.2.2.2	The Sum-to-Zero Constraint	246
8.2.2.3	Applying the ICAR Model Using General Weights to the Newcastle Income Data	247
8.2.2.4	Results	248
8.3	The Proper CAR (pCAR) Model	249
8.3.1	Prior Choice for ρ	251
8.3.2	ICAR or pCAR?	251
8.3.3	Applying the pCAR Model to the Newcastle Income Data	253
8.3.4	Results	253
8.4	Locally Adaptive Models	256
8.4.1	Choosing an Optimal W Matrix from All Possible Specifications	258
8.4.2	Modelling the Elements in the W Matrix	258
8.4.3	Applying Some of the Locally Adaptive Spatial Models to a Subset of the Newcastle Income Data	262
8.5	The Besag, York and Mollié (BYM) Model	266
8.5.1	Two Remarks on Applying the BYM Model in Practice	268
8.5.2	Applying the BYM Model to the Newcastle Income Data	269
8.6	Comparing the Fits of Different Bayesian Spatial Models	274
8.6.1	DIC Comparison	274
8.6.2	Model Comparison Based on the Quality of the MSOA-Level Average Income Estimates	276
8.7	Concluding Remarks	277
8.8	Exercises	279
9	Bayesian Hierarchical Models for Spatial Data: Applications	281
9.1	Introduction	281
9.2	Application 1: Modelling the Distribution of High Intensity Crime Areas in a City	282
9.2.1	Background	282
9.2.2	Data and Exploratory Analysis	283
9.2.3	Methods Discussed in Haining and Law (2007) to Combine the PHIA and EHIA Maps	285
9.2.4	A Joint Analysis of the PHIA and EHIA Data Using the MVCAR Model	286
9.2.5	Results	290
9.2.6	Another Specification of the MVCAR Model and a Limitation of the MVCAR Approach	293
9.2.7	Conclusion and Discussion	293
9.3	Application 2: Modelling the Association Between Air Pollution and Stroke Mortality	296

9.3.1	Background and Data	296
9.3.2	Modelling.....	300
9.3.3	Interpreting the Statistical Results	302
9.3.4	Conclusion and Discussion	305
9.4	Application 3: Modelling the Village-Level Incidence of Malaria in a Small Region of India	308
9.4.1	Background.....	308
9.4.2	Data and Exploratory Analysis.....	308
9.4.3	Model I: A Poisson Regression Model with Random Effects.....	310
9.4.4	Model II: A Two-Component Poisson Mixture Model.....	311
9.4.5	Model III: A Two-Component Poisson Mixture Model with Zero-Inflation	313
9.4.6	Results	314
9.4.7	Conclusion and Model Extensions	318
9.5	Application 4: Modelling the Small Area Count of Cases of Rape in Stockholm, Sweden.....	321
9.5.1	Background and Data	321
9.5.2	Modelling.....	322
9.5.2.1	A "Whole-Map" Analysis Using Poisson Regression.....	322
9.5.2.2	A "Localised" Analysis Using Bayesian Profile Regression.....	323
9.5.3	Results	326
9.5.3.1	"Whole Map" Associations for the Risk Factors.....	326
9.5.3.2	"Local" Associations for the Risk Factors	326
9.5.4	Conclusions	329
9.6	Exercises	330
10	Spatial Econometric Models.....	333
10.1	Introduction	333
10.2	Spatial Econometric Models	334
10.2.1	Three Forms of Spatial Spillover	334
10.2.2	The Spatial Lag Model (SLM).....	335
10.2.2.1	Formulating the Model.....	335
10.2.2.2	An Example of the SLM	336
10.2.2.3	The Reduced Form of the SLM and the Constraint on δ	337
10.2.2.4	Specification of the Spatial Weights Matrix.....	338
10.2.2.5	Issues with Model Fitting and Interpreting Coefficients	339
10.2.3	The Spatially-Lagged Covariates Model (SLX).....	339
10.2.3.1	Formulating the Model.....	339
10.2.3.2	An Example of the SLX Model	340
10.2.4	The Spatial Error Model (SEM)	340
10.2.5	The Spatial Durbin Model (SDM).....	341
10.2.5.1	Formulating the Model.....	341
10.2.5.2	Relating the SDM Model to the Other Three Spatial Econometric Models	342
10.2.6	Prior Specifications	342
10.2.7	An Example: Modelling Cigarette Sales in 46 US States.....	343
10.2.7.1	Data Description, Exploratory Analysis and Model Specifications	343
10.2.7.2	Results.....	345

- 10.3 Interpreting Covariate Effects..... 346
 - 10.3.1 Definitions of the Direct, Indirect and Total Effects of a Covariate..... 346
 - 10.3.2 Measuring Direct and Indirect Effects without the SAR Structure on the Outcome Variables..... 347
 - 10.3.2.1 For the LM and SEM Models..... 347
 - 10.3.2.2 For the SLX Model..... 347
 - 10.3.3 Measuring Direct and Indirect Effects When the Outcome Variables are Modelled by the SAR Structure 350
 - 10.3.3.1 Understanding Direct and Indirect Effects in the Presence of Spatial Feedback..... 350
 - 10.3.3.2 Calculating the Direct and Indirect Effects in the Presence of Spatial Feedback..... 351
 - 10.3.3.3 Some Properties of Direct and Indirect Effects 351
 - 10.3.3.4 A Property (Limitation) of the Average Direct and Average Indirect Effects Under the SLM Model..... 354
 - 10.3.3.5 Summary 354
 - 10.3.4 The Estimated Effects from the Cigarette Sales Data..... 355
- 10.4 Model Fitting in WinBUGS..... 356
 - 10.4.1 Derivation of the Likelihood Function 357
 - 10.4.2 Simplifications to the Likelihood Computation..... 361
 - 10.4.3 The Zeros-Trick in WinBUGS..... 361
 - 10.4.4 Calculating the Covariate Effects in WinBUGS 362
- 10.5 Concluding Remarks 365
 - 10.5.1 Other Spatial Econometric Models and the Two Problems of Identifiability 365
 - 10.5.2 Comparing the Hierarchical Modelling Approach and the Spatial Econometric Approach: A Summary..... 367
- 10.6 Exercises 370
- 11 Spatial Econometric Modelling: Applications 373**
 - 11.1 Application 1: Modelling the Voting Outcomes at the Local Authority District Level in England from the 2016 EU Referendum..... 373
 - 11.1.1 Introduction..... 373
 - 11.1.2 Data 374
 - 11.1.3 Exploratory Data Analysis..... 375
 - 11.1.4 Modelling Using Spatial Econometric Models..... 375
 - 11.1.5 Results 378
 - 11.1.6 Conclusion and Discussion 381
 - 11.2 Application 2: Modelling Price Competition Between Petrol Retail Outlets in a Large City 382
 - 11.2.1 Introduction..... 382
 - 11.2.2 Data 383
 - 11.2.3 Exploratory Data Analysis..... 383
 - 11.2.4 Spatial Econometric Modelling and Results..... 384
 - 11.2.5 A Spatial Hierarchical Model with t_4 Likelihood 385
 - 11.2.6 Conclusion and Discussion 388
 - 11.3 Final Remarks on Spatial Econometric Modelling of Spatial Data..... 388
 - 11.4 Exercises 389
 - Appendix: Petrol Retail Price Data..... 390

Part III Modelling Spatial-Temporal Data

12 Modelling Spatial-Temporal Data: An Introduction	395
12.1 Introduction	395
12.2 Modelling Annual Counts of Burglary Cases at the Small Area Level: A Motivating Example and Frameworks for Modelling Spatial-Temporal Data	398
12.3 Modelling Small Area Temporal Data	401
12.3.1 Issues to Consider When Modelling Temporal Patterns in the Small Area Setting	403
12.3.1.1 Issues Relating to Temporal Dependence	403
12.3.1.2 Issues Relating to Temporal Heterogeneity and Spatial Heterogeneity in Modelling Small Area Temporal Patterns	404
12.3.1.3 Issues Relating to Flexibility of a Temporal Model	404
12.3.2 Modelling Small Area Temporal Patterns: Setting the Scene	406
12.3.3 A Linear Time Trend Model	407
12.3.3.1 Model Formulations	407
12.3.3.2 Modelling Trends in the Peterborough Burglary Data	411
12.3.4 Random Walk Models	416
12.3.4.1 Model Formulations	417
12.3.4.2 The RW1 Model: Its Formulation Via the Full Conditionals and Its Properties	418
12.3.4.3 WinBUGS Implementation of the RW1 Model	421
12.3.4.4 Example: Modelling Burglary Trends Using the Peterborough Data	421
12.3.4.5 The Random Walk Model of Order 2	424
12.3.5 Interrupted Time Series (ITS) Models	426
12.3.5.1 Quasi-Experimental Designs and the Purpose of ITS Modelling	426
12.3.5.2 Model Formulations	428
12.3.5.3 WinBUGS Implementation	429
12.3.5.4 Results	432
12.4 Concluding Remarks	434
12.5 Exercises	435
Appendix: Three Different Forms for Specifying the Impact Function f	436
13 Exploratory Analysis of Spatial-Temporal Data	439
13.1 Introduction	439
13.2 Patterns of Spatial-Temporal Data	440
13.3 Visualising Spatial-Temporal Data	443
13.4 Tests of Space-Time Interaction	448
13.4.1 The Knox Test	449
13.4.1.1 An Instructive Example of the Knox Test and Different Methods to Derive a p-Value	451
13.4.1.2 Applying the Knox Test to the Malaria Data	453
13.4.2 Kulldorff's Space-Time Scan Statistic	454
13.4.2.1 Application: The Simulated Small Area COPD Mortality Data	456
13.4.3 Assessing Space-Time Interaction in the Form of Varying Local Time Trend Patterns	459

- 13.4.3.1 Exploratory Analysis of the Local Trends in the Peterborough Burglary Data.....460
 - 13.4.3.2 Exploratory Analysis of the Local Time Trends in the England COPD Mortality Data460
 - 13.5 Concluding Remarks463
 - 13.6 Exercises464
- 14 Bayesian Hierarchical Models for Spatial-Temporal Data I: Space-Time Separable Models.....465
 - 14.1 Introduction465
 - 14.2 Estimating Small Area Burglary Rates Over Time: Setting the Scene.....465
 - 14.3 The Space-Time Separable Modelling Framework.....467
 - 14.3.1 Model Formulations467
 - 14.3.2 Do We Combine the Space and Time Components Additively or Multiplicatively?.....469
 - 14.3.3 Analysing the Peterborough Burglary Data Using a Space-Time Separable Model.....470
 - 14.3.4 Results474
 - 14.4 Concluding Remarks478
 - 14.5 Exercises479
- 15 Bayesian Hierarchical Models for Spatial-Temporal Data II: Space-Time Inseparable Models.....481
 - 15.1 Introduction481
 - 15.2 From Space-Time Separability to Space-Time Inseparability: The Big Picture481
 - 15.3 Type I Space-Time Interaction484
 - 15.3.1 Example: A Space-Time Model with Type I Space-Time Interaction484
 - 15.3.2 WinBUGS Implementation486
 - 15.4 Type II Space-Time Interaction.....486
 - 15.4.1 Example: Two Space-Time Models with Type II Space-Time Interaction489
 - 15.4.2 WinBUGS Implementation490
 - 15.5 Type III Space-Time Interaction490
 - 15.5.1 Example: A Space-Time Model with Type III Space-Time Interaction.....491
 - 15.5.2 WinBUGS Implementation492
 - 15.6 Results from Analysing the Peterborough Burglary Data.....493
 - 15.7 Type IV Space-Time Interaction498
 - 15.7.1 Strategy 1: Extending Type II to Type IV.....499
 - 15.7.2 Strategy 2: Extending Type III to Type IV501
 - 15.7.2.1 Examples of Strategy 2502
 - 15.7.3 Strategy 3: Clayton’s Rule504
 - 15.7.3.1 Structure Matrices and Gaussian Markov Random Fields505
 - 15.7.3.2 Taking the Kronecker Product506
 - 15.7.3.3 Exploring the Induced Space-Time Dependence Structure via the Full Conditionals.....508
 - 15.7.4 Summary on Type IV Space-Time Interaction.....512
 - 15.8 Concluding Remarks513
 - 15.9 Exercises515

16 Applications in Modelling Spatial-Temporal Data	517
16.1 Introduction	517
16.2 Application 1: Evaluating a Targeted Crime Reduction Intervention	518
16.2.1 Background and Data	518
16.2.2 Constructing Different Control Groups	520
16.2.3 Evaluation Using ITS	521
16.2.4 WinBUGS Implementation	523
16.2.5 Results	523
16.2.6 Some Remarks	526
16.3 Application 2: Assessing the Stability of Risk in Space and Time	527
16.3.1 Studying the Temporal Dynamics of Crime Hotspots and Coldspots: Background, Data and the Modelling Idea	527
16.3.2 Model Formulations	530
16.3.3 Classification of Areas	531
16.3.4 Model Implementation and Area Classification	532
16.3.5 Interpreting the Statistical Results	535
16.4 Application 3: Detecting Unusual Local Time Patterns in Small Area Data	539
16.4.1 Small Area Disease Surveillance: Background and Modelling Idea	539
16.4.2 Model Formulation	540
16.4.3 Detecting Unusual Areas with a Control of the False Discovery Rate	543
16.4.4 Fitting BaySTDetect in WinBUGS	543
16.4.5 A Simulated Dataset to Illustrate the Use of BaySTDetect	546
16.4.6 Results from the Simulated Dataset	546
16.4.7 General Results from Li et al. (2012) and an Extension of BaySTDetect	548
16.5 Application 4: Investigating the Presence of Spatial-Temporal Spillover Effects on Village-Level Malaria Risk in Kalaburagi, Karnataka, India	550
16.5.1 Background and Study Objective	550
16.5.2 Data	551
16.5.3 Modelling	552
16.5.4 Results	553
16.5.5 Concluding Remarks	556
16.6 Conclusions	558
16.7 Exercises	560

Part IV Addendum

17 Modelling Spatial and Spatial-Temporal Data: Future Agendas?	565
17.1 Topic 1: Modelling Multiple Related Outcomes Over Space and Time	565
17.2 Topic 2: Joint Modelling of Georeferenced Longitudinal and Time-to-Event Data	567
17.3 Topic 3: Multiscale Modelling	567
17.4 Topic 4: Using Survey Data for Small Area Estimation	568
17.5 Topic 5: Combining Data at Both Aggregate and Individual Levels to Improve Ecological Inference	571

17.6 Topic 6: Geostatistical Modelling.....572

17.6.1 Spatial Dependence573

17.6.2 Mapping to Reduce Visual Bias574

17.6.3 Modelling Scale Effects.....574

17.7 Topic 7: Modelling Count Data in Spatial Econometrics.....575

17.8 Topic 8: Computation.....575

References577

Index.....597

study our world in ever finer geographical detail. With the increasing temporal frequency with which such data are collected, we are also in a better position to observe, measure and evaluate changes taking place over sometimes short time spans. Such spatial and spatial-temporal precision in the data we have access to should help us to better understand our changing world and provide us with information that can be used to inform policy-making and to evaluate the effectiveness of any intervention.

But to reap the full benefits of such precision in our data we need to be able to obtain reliable estimates of attribute properties for these small spatial and spatial-temporal units. Estimators for small geographical areas suffer from many problems, including data sparsity and data uncertainty that undermine *statistical precision*. Unreliable estimation of variability associated with small area estimates undermines the benefits that can be derived from such data. The big question that lies behind this book is: can we have the best of both worlds – spatial and spatial-temporal precision *and* statistical precision? Here, the answer to that question follows a path that leads through data modelling.

What Are the Aims of the Book?

- To provide students and researchers whose interests lie in the analysis of social, economic, political and public health data with an introduction to modelling fine-grained spatial and spatial-temporal data. This includes data collected for small areas such as census tracts, where populations may be numbered in the low hundreds, and data collected at point sites. Throughout the book, we consider situations where the small areas partitioning the study region are fixed in their locations, sizes and shapes, or, when point sites are of interest, they are fixed in their location. Random variation is associated with the attributes (i.e. the data we observe), *not* the spatial objects to which the attribute values are attached.
- To present spatial and spatial-temporal modelling at a level that is accessible to students and researchers from all areas of the social, political, economic and public health sciences who have a grounding in statistical theory up to and including the simple linear regression model and who have a basic understanding of matrices and matrix manipulation. This means that we believe parts of the book should be accessible to social science students who are following a quantitative path through their undergraduate degree, and fully accessible to postgraduate students and those researchers further along in their careers whose work involves analysing quantitative data. For students of statistics whose interests have been aroused by the sorts of questions social scientists habitually wrestle with, we hope