Title of Course: Bayesian Biostatistics II (Jan – Apr 2024)

A. Course Description

This will be an introductory course on Bayesian statistics and methods, with a particular focus on Bayesian hierarchical models for correlated health data in general and for small area spatiotemoral disease mapping data in particular. Examples of health science case studies will be illustrated using freeware R and WinBUGs. The Bayesian principles, theorem, and key ideas will be introduced with minimum use of mathematics.

B. Purpose and Objectives

- An introduction to the basic principles of Bayesian methods for data analysis
- An introduction to Bayesian hierarchical models for correlated spatial, temporal, and spatiotemporal health data
- An introduction to Bayesian disease mapping, its history, it relations with population and public health research and policy
- Learn, and gain working knowledge of, R and WinBUGs

C. Duration of course (specify dates)

Term 2 2023/2024 academic year, 13 weeks of 3-hour in-class lectures and/or discussions and/or presentations, one mid-term, and one final exam (see attached for details).

D. Class time and location

Thursdays 2-5pm, TBD

E. Criteria for evaluation of Student (Pass/Fail or percentage grades)

Pass/Fail

F. Instruction format and study plan per week (content and class schedule)

See attached.

G. Course Readings

1. Gelman A, and Hill J. Data Analysis Using Regression and Multilevel/Hierarchical Models. 2007. Cambridge
2. Carlin BP and Louis TA. Bayes and empirical Bayes methods for data analysis. Chapman & Hall, New York.
3. Gelman A, Carlin JB, Stern HS, and Rubin DB. Bayesian data analysis. Chapman & Hall, New York
4. Congdon P. Bayesian statistical modeling. Wiley, New York.

5. Miguel A. Martinez-Beneito and Paloma Botella-Rocamora. Disease MappingFrom Foundations toMultidimensional Modeling, CRC 2019

6. Andrew B Lawson. Bayesian disease mapping. CRC 2018

7. A selection of papers.

H. Credit value

3 credits

Weekly outline (tentative):

Week 1-6: Lectures (with in-class discussions) on Bayesian statistics and disease mapping

1. Introduction:

   Correlation health data (focusing on time series, spatial, and spatiotemporal data)
   Statistics and spatial statistics
   Binomial models for binary outcomes or disease proportions/rates
   Poisson models for count data,
   Disease mapping
   Useful probability distributions
   Frequentist and Bayesian statistics and inference (kinds of probability, assumption, hypothesis, information and data, evidence and data, opinion and data, likelihood, prior, and posterior, Bayes' theorem, etc)
   Bayesian hierarchical models, with examples (for longitudinal, multilevel, spatial and spatiotemporal data)

2. Bayesian hierarchical models for correlated health data, estimation and inference

   Data and related models will be presented. Empirical Bayes and fully Bayesian methods of estimation and inference will be presented. The concepts of hyper-parameter and hyper-prior will be discussed in greater depth.

   Introductions to WinBUGs and GeoBUGs, with examples

   MCMC implementation using WinBUGs will be illustrated (burn-in; thinning; assessing Markov chain convergence; trace plots; summarizing and presenting results)

   Case study: Repeated binary outcomes (Rat weight gain data)

3. **Bayesian hierarchical models for disease mapping, with estimation and inference:**

Key steps for Bayesian modeling revisited (model formulation, estimation, inference, sensitivity assessment, model fit and selection, etc)

Binomial models for disease mapping data will be discussed, with in depth discussions on frequentist's maximum likelihood (MLE) estimation and Bayesian posterior estimation. Notions of borrowing strength, spatial smoothing, non-spatial smoothing, latent effects, effects of omitted covariates will be introduced and discussed

Empirical Bayes model, Bayesian model, likelihood, prior, and posterior will be discussed. R and WinBUGs software will be used to present the classic and Bayesian approaches to point and interval estimation, and to quantify uncertainty.

Illustrative example: mapping NICU outcomes in Canada, part I

MCMC implementation using WBUGs will be introduced and illustrated (the WBUGs software, MCMC in general and implementation details such as burn-in, thinning, assessing Markov chain convergence, trace plots, summarizing and presenting results)

Case study: mapping road traffic injuries in BC, part I

4. Bayesian hierarchical Poisson models for mapping rare disease or health outcomes, with estimation and inference

Motivating and formulating Poisson models for rare disease or health outcomes

WinBUGs software will be used to present the Bayesian posterior estimation and inference, with point and interval risk estimation, and to quantify uncertainty. MCMC implementation using WinBUGs will be illustrated (burn-in; thinning; assessing Markov chain convergence; trace plots; summarizing and presenting results), with in-class practice for all students - using the WBUGs and for the case study: mapping road traffic injuries in BC, part II.

Notions of borrowing strength, spatial smoothing, non-spatial smoothing, latent effects, effects of omitted covariates will be revisited

5. Poisson regression models, estimation, and inference

Model formulation and Bayesian inference

MCMC implementation using WinBUGs will be illustrated (burn-in; thinning; assessing Markov chain convergence; trace plots; summarizing and presenting results), with in-class practice for all students - using the WBUGs and for the case study: mapping road traffic injuries in BC, part III.

Issues of co-linearity, confounding, ecological bias, error in covariates will be discussed

Illustrative example: mapping NICU outcomes in Canada, part II

6. Advanced topics on Bayesian disease mapping

   Empirical Bayes disease mapping
   Various CAR model formulations
   Univariate and multivariate disease mapping
   Spatiotemporal disease mapping
   New directions in Bayesian disease mapping

7. Mid-term exam/presentation

8. Spring reading break (no class)

Week 9-13 group projects (Put Canadian Health on Map)

This will be five weeks of 3-hour per week in-class lectures, discussions, web-search, data analysis, with weekly off-class group collaborations, for the following agenda (each represents one week's tasks/objectives)

9. Identify population and public health problems and challenges
10. Choose topics and identify and get data
11. Analyze the data
12. Interpret the results, write brief reports, prepare presentations
13. Group presentations

The final week of exam

14. Final exam/project: written report (in-depth, manuscript style)