Bayesian Spatiotemporal Analysis of Socio-Ecologic Drivers of Ross River Virus Transmission in Queensland, Australia

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Abstract. This study aims to examine the impact of socio-ecologic factors on the transmission of Ross River virus (RRV) infection and to identify areas prone to social and ecologic-driven epidemics in Queensland, Australia. We used a Bayesian spatiotemporal conditional autoregressive model to quantify the relationship between monthly variation of RRV incidence and socio-ecologic factors and to determine spatiotemporal patterns. Our results show that the average increase in monthly RRV incidence was 2.4% (95% credible interval (CrI): 0.1–4.5%) and 2.0% (95% CrI: 1.6–2.3%) for a 1°C increase in monthly average maximum temperature and a 10 mm increase in monthly average rainfall, respectively. A significant spatiotemporal variation and interactive effect between temperature and rainfall on RRV incidence were found. No association between Socio-economic Index for Areas (SEIFA) and RRV was observed. The transmission of RRV in Queensland, Australia appeared to be primarily driven by ecologic variables rather than social factors.

INTRODUCTION

Ross River virus (RRV) infection is the most common and widespread mosquito-borne disease in Australia and some Pacific island nations.^{1,2} Nearly 40 species of mosquitoes belonging to six genera have been confirmed as vectors of RRV in Australia.² *Ochlerotatus vigilax* and *Culex annulirostris* are probably the major vectors of RRV in Queensland.³ Over the last 16 years (1993–2008), 68,538 laboratory-confirmed RRV cases have been reported to the Australian Department of Health and Ageing.⁴ Ross River virus causes a nonfatal but debilitating disease characterized by arthritis, rash, fever, fatigue, and myalgia.^{2,5} Geographically scattered RRV cases are usually recorded throughout the year, with the majority of cases in the period from January to May. As the distribution of RRV varies with time and place, it is important to examine the impact of socio-ecologic factors on the transmission of RRV infection for the purposes of targeted surveillance and risk management.

Methods for displaying, analyzing, and predicting spatial and temporal distributions of diseases have been considerably advanced over the last two decades. Bayesian spatiotemporal models provide a flexible and robust approach for spatiotemporal analysis and disease mapping.⁶ Bayesian conditional autoregressive (CAR) models are increasingly being used to estimate spatial variation in disease risk between spatially aggregated units, such as the administrative divisions of a country.^{7,8} These models offer convenient platforms for incorporating and estimating spatial correlation while simultaneously estimating covariate effects. Recently, Bayesian spatiotemporal models have been used to study the geographical distribution of tropical diseases including malaria, schistosomiasis, and filariasis.^{7,9,10}

A number of studies showed the relationship between the incidence of RRV disease and weather variables (temperature, rainfall, humidity, southern oscillation index, and sea level) but not in an explicitly spatiotemporal context.^{11–17} In this study,

we used Bayesian spatiotemporal analysis to describe associations between monthly RRV incidence and socio-ecologic factors and to examine their potential impact on the transmission of RRV in Queensland, Australia.

MATERIALS AND METHODS

Study area. Queensland, located in the northeast of Australia, covers ~1,727,000 km², with 7,400 km of mainland coastline (9,800 km including islands). It has a typically subtropical climate with average temperatures of 25°C in summer and 15°C in winter. Rainfall varies regionally and seasonally, ranging from < 150 mm per annum in the southwest region to > 4,000 mm per annum on the far northern coast. Queensland consists of 125 statistical local government areas (LGA), with populations ranging from 312 to 888,449 people.

Data collection. We obtained the data from the Queensland Department of Health on numbers of notified RRV cases by LGA for the period January 1, 1999–December 31, 2001. Because RRV is a notifiable disease, it is a legal requirement that positive test results are reported by laboratories to the Queensland Department of Health, where data are archived by the Communicable Diseases Unit. The requirement for notification of RRV disease is based on a demonstration of a 4-fold or greater change in serum antibody titers between acute and convalescent phase serum, isolation of RRV or demonstration of arboviral antigen or genome in the blood.¹⁸ However, in practice; most notifications are based on single tests showing immunoglobulin M (IgM) using an enzyme-linked immunosorbent assay (ELISA) technique. These case notification data were linked to a digital base-map of LGAs in a geographical information system (GIS). Weather and Socio-economic Index for Areas (SEIFA) data were obtained for the same period from the Australian Bureau of Meteorology and the Australian Bureau of Statistics, respectively. The SEIFA is a continuum of socio-economic advantage (high values) to disadvantage (low values) and takes into account variables relating to education, occupation, wealth, and living conditions. The SEIFA allows ranking of regions/areas, providing a method of determining the level of social and economic well being in each region. Weather data contained interpolated monthly mean maximum temperature (°C) and

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monthly precipitation (mm), which were available at a 0.25×0.25 degree grid resolution (about 30×30 km at the equator). Average temperature and rainfall values for each LGA and month were extracted using the GIS software package Vertical Map.¹⁹ Relevant population data and electronic boundaries of LGAs were retrieved from the national census database managed by the Australia Bureau of Statistics.

Data analysis. An initial descriptive analysis of RRV was performed. Crude standardized morbidity ratios (SMRs) for each LGA for the entire study period were calculated using standard methods,²⁰ where $SMR = (\text{the observed number of RRV cases})/(\text{the expected number of RRV cases})$. Five Poisson regression models were developed in a Bayesian framework, using the WinBUGS software version 1.4.²¹ Model I, including only rainfall, temperature, and SEIFA as explanatory variables; Model II, adding an interaction term for temperature and rainfall; Model III, incorporating a random effect for LGA; Model IV adding a LGA spatial random effect and LGA-specific temporal trends; and Model V, adding a seasonally oscillating temporal random effect. The mathematical notation for Model V is presented below, and contains all of the components of the preceding four models. This model assumed that the observed counts of cases (O_{kt}) for the k th LGA ($k = 1 \dots 125$) in the t th month (1999–2001) follow a Poisson distribution with mean (μ_{kt}), that is,

$$O_{kt} \sim \text{Poisson}(\mu_{kt}) \quad (1)$$

and

$$\log(\mu_{kt}) = \log(E_{kt}) + \theta_{kt} \quad (2)$$

where E_{kt} (the expected number of cases in LGA k , month t) is an offset to control for population size. The logarithm of the mean rate of RRV per LGA per month was modeled as

$$\begin{aligned} \log(\mu_{kt}) = & \alpha + (\text{Temp}_{kt}^T - 30)\beta_1 + (\text{Rain}_{kt}^T - 50)\beta_2 \\ & + (\text{SEIFA}_{kt}^T - 1,000)\beta_3 + (\text{Temp}_{kt}^T - 30) \\ & * (\text{Rain}_{kt}^T - 50)\beta_4 + \gamma_k + u_k + v_k + \delta \end{aligned} \quad (3)$$

where α is the intercept, β_1 is the coefficient for temperature, β_2 is the coefficient for rainfall, β_3 is the coefficient for SEIFA, β_4 is the interaction coefficient of temperature and rainfall, γ is the LGA-level temporal trend coefficient, u is LGA-level variation that is spatially structured (i.e., spatially-structured

factors not explained by the model covariates), and v is spatially unstructured LGA-level variation; δ is the amplitude of seasonal oscillation in the month-specific random effects, which was modeled by a sinusoidal term $\cos(2\pi \cdot t/12)$. Spatial structuring in u was modeled using CAR prior structure, with spatial relationships between LGAs modeled using an adjacency weights matrix.²⁰ This approach allows for formal assessment of spatial clustering in the number of reported cases of RRV by LGA. The centering method was used to cope with the multicollinearity between the interaction term and predictors. Centering involves subtracting a constant (the constant is often a mean, but it can be any value) from every observation's value of a predictor variable and then running the model on the centered data.²² In this study, we used the near mean-centering method, which can provide a more meaningful interpretation.

Parameter estimation was obtained by Markov Chain Monte Carlo simulation (MCMC) employing a single chain algorithm. We undertook an initial burn-in of 5,000 iterations, which were subsequently discarded. Convergence was assessed by examining posterior density plots, history plots, and autocorrelation of selected parameters. A subsequent set of 20,000 iterations was used for estimation. Model selection was conducted using the deviance information criterion (DIC), where a lower DIC suggests a better trade-off between model fit and parsimony.

RESULTS

Table 1 shows the summary statistics for each variable. The monthly mean of number of RRV cases, maximum temperature, rainfall, and SEIFA was 12.59, 28.26°C, 689.01 mm, and 935.61, respectively, from January 1999 to December 2001.

Figure 1 depicts the variation over time in RRV numbers in relation to rainfall and temperature. The curves indicate a consistent inter-relation between climate variability and RRV cases.

A pairwise scatter-plot reveals relationships between all the variables (Figure 2). Incidence of RRV was positively associated with rainfall and temperature.

Figure 3A shows the SMRs of RRV incidence in Queensland by LGA. Although the maps show a high degree of spatial variability, there are also some clear patterns: RRV incidence rates appear to be high in western regions of the state and generally lower toward the coast. Figure 3B–D shows the spatial patterns of rainfall, temperature, and SEIFA in Queensland by LGA. These maps confirm that all these variables varied with geographical location.

TABLE 1

Descriptive statistics of Ross river virus (RRV) and socio-ecologic factors by local government areas (LGA) in Queensland, January 1999–December 2001

	Mean	Minimum	Maximum	Percentile		
				25%	50%	75%
Number of RRV cases*	12.59	0	324	1	3	10.5
Spring	0.71	0	10	0	0	1
Summer	4.08	0	72	0	1	3
Autumn	6.62	0	213	0	1	4
Winter	1.18	0	29	0	0	1
Temperature (°C)	28.26	23.51	34.06	26.37	28.12	29.67
Rainfall (mm)	689.01	169.81	2602.3	457.14	620.58	786.47
SEIFA	935.61	831.36	1059.84	909.92	930.64	962.88
Population	29226	312	888449	2486.5	5421	17994

*Numbers refer to the distribution of values across all LGAs for the entire study period.

FIGURE 1. Maximum temperature, rainfall, and incidence of Ross River virus (RRV) by local government areas (LGA) in Queensland, Australia between January 1999 and December 2001.

Bayesian analyses show that the spatiotemporal model (model V) had the smallest DIC value (9,869) and therefore appeared to be the best among all the models examined (Table 2).

Table 3 shows that the average increase in monthly RRV incidence rates was 2.4% (95% credible interval (CrI): 0.1–4.5%) and 2.0% (95% CrI: 1.6–2.3%) for a 1°C increase in monthly average maximum temperature, whereas average

FIGURE 2. Pairwise scatter plot of smoothed Ross River virus (RRV) incidence rates and explanatory variables.

FIGURE 3. Raw standardized morbidity ratios for Ross River virus (RRV), maximum temperature, rainfall, and Socio-economic Index for Areas (SEIFA) by local government areas (LGA) in Queensland.

rainfall equals 50 mm and a 10 mm increase in monthly average rainfall while maximum temperature equals 30°C, respectively. An interactive effect between temperature and rainfall on RRV incidence was found (changes: 0.4%; 95% CrI: 0.3–0.5%). The Bayesian spatiotemporal model shows that spatial variation (u) (changes: 27.2%; 95% CrI: 13–42%) and spatially smoothed LGA-level temporal trend (γ) (changes: 5.4%;

95% CrI: 2.4–8.5%) were significantly associated with RRV transmission (Table 3). However, there was no association between SEIFA and RRV incidence (changes: –0.8%; 95% CrI: –0.3–0.2%).

Figure 4A shows residual variation after taking into account the socio-ecologic variables. Clusters of high-incidence LGAs were located in inland, western Queensland, whereas clusters of low-incidence LGAs were located in southeast coastal Queensland. Figure 4B shows that clusters of LGAs with higher than average temporal trend were also located in inland areas. Clusters of LGAs in western and north-eastern Queensland show an increasing trend in RRV incidence. The clusters of LGAs with lower than average temporal trend were interspersed throughout the state.

Figure 5 indicates that relative risks of RRV were clearly associated with the interaction between maximum temperature and rainfall.

TABLE 2

Model comparisons using the deviance information criterion (DIC)		
Models	Types	DIC
Model I	Rainfall, temperature, and SEIFA	12752
Model II	Model I plus a climatic interaction term	12690
Model III	Model II plus a non-spatial random effect	11949
Model IV	Model III plus a spatial random effect	11941
Model V	Model IV plus a seasonal oscillation	9869

TABLE 3

Changes (%) in relative risks with 95% credible intervals from Bayesian spatiotemporal models of Ross River virus (RRV) in Queensland, Australia*

Variables	Changes (%)	95% Credible intervals
SEIFA	-0.8	-0.3-0.2
Rainfall (10 mm increase)	2.0	1.6-2.3
Temperature (°C increase)	2.4	0.1-4.5
Rainfall: temperature	0.4	0.3-0.5
Spatial variation (u)	27.2	13-42
Spatially-smoothed LGA-level temporal trend (γ)	5.4	2.4-8.5

*SEIFA = Socio-Economic Index for Areas; LGA = local government areas.

DISCUSSION

Our results show that temperature and rainfall were consistently and positively associated with RRV incidence at LGA level. These ecological factors seemed to have played an important role in RRV transmission cycles. Our models provide some novel information about RRV epidemiology in Queensland.

Rainfall is a key driver in the transmission of mosquito-borne diseases including RRV infection.^{12,23} All mosquitoes have aquatic larval and pupal stages and therefore require water for breeding.²⁴ Considerable evidence has accrued to show that rainfall and flooding can lead to increased mosquito breeding and outbreaks of arboviral disease,^{23,24} including RRV in various parts of Australia.^{11,23} The finding of this detailed spatiotemporal analysis corroborates previous observations that rainfall is one of the key predictors of RRV transmission.¹¹

Temperature changes affect RRV transmission and epidemic potential by altering the vector's reproduction or biting rate; by shifting a vector's geographic range or distribution; by altering the extrinsic incubation periods (EIPs) of the pathogen; and by increasing or decreasing vector-pathogen-host interaction and thereby affecting host susceptibility.²⁵ Warmer temperatures may allow mosquitoes such as *Cx. annulirostris* and *Ochlerotatus* (formerly *Aedes*) *vigilax* to reach maturity

much faster than at lower temperatures.²⁶ Our previous study has clearly shown that *Ochlerotatus vigilax* and *Culex annulirostris* are two major mosquito species associated with RRV transmission.²⁷

People with lower levels of education and/or income often have poor health knowledge about disease transmission and personal protection from a mosquito biting.²⁸ However, in this study, we found that the average SEIFA in LGA had no substantive association with RRV disease in Queensland, suggesting that SEIFA levels may be more heterogenous and/or may not be an important factor at the LGA level. The SEIFA scores can be used to rank geographic areas across Australia in terms of their socio-economic characteristics. Some research shows that SEIFA scores correlate with the proportion of people living in an area who report poor health and other health risk factors.^{29,30} However, SEIFA scores are area-level indices that should not be presumed to apply to individuals living within the area. The SEIFA scores are calculated at the census district level and great care is required when interpreting scores that have been aggregated to larger geographical areas.³⁰ People living in low-SEIFA areas have similar medical services by general practitioners with a high level of SEIFA.³¹

This study has three major strengths. First, a sophisticated Bayesian spatiotemporal model was used to examine the potential impact of socio-ecologic factors on the transmission of RRV infection in Queensland, Australia. This model assessed both spatial and temporal trends, and some previous research suggests that failure to account for spatiotemporal correlation in the data can lead to biased estimates.³² Second, comprehensive and detailed information on socio-ecologic factors by LGA was linked across the entire state, and incorporated into the statistical models. This may provide a novel approach to assessing disease risk factors.^{33,34} Finally, research outcomes from this study and other researches may have important implications for public health decision making in the control and prevention of RRV infection.^{12,14,15,27,35-38}

The limitations of this study must also be acknowledged. First, under the Notifiable Diseases Surveillance System,

FIGURE 4. Spatial random effects and spatial smoothed trend for Ross River virus (RRV) incidence rates.

FIGURE 5. The interactive effect between rainfall and maximum temperature on Ross River virus (RRV).

the LGA of onset is assumed as the place where acquisition of infection occurred. Although the reported place of onset (mostly home address) for each case is often used for determining the geographic origin of RRV infection,³⁹ this assumption may not hold for all cases, particularly during holiday periods. Second, this is a spatiotemporal assessment of the relationship between socio-ecologic variability and the transmission of RRV at the LGA level and the findings cannot be related to an individual's risk of infection. More detailed information at the community and individual level (e.g., mosquito population densities, human behaviors, population immunity, and housing characteristics) could eventually be included to further improve the models. However, such data were unavailable for most LGAs at the current time.

In conclusion, because RRV has already had marked impacts on population health, industry, and tourism, it is important to develop an epidemic forecast system for this disease. The results of this study reveal significant and positive effects of temperature and rainfall and their synergistic impact on the spatiotemporal patterns of RRV transmission. The disease surveillance data can be integrated with social, biological, and environmental databases to explain and potentially predict disease risks. These data can provide additional input into the development of epidemic forecasting models.^{40,41} These attempts may have significant implications in environmental health decision making and practices, and may help health authorities to use limited resources more effectively and efficiently.

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