Evaluating the interplay between clusters, climatic covariates and spatial priors in spatio-temporal modelling of dengue in Makassar, Indonesia

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Background: Dengue fever is one of the most important vector borne diseases. A range of Bayesian models have been used to describe spatial and temporal patterns of disease in areal unit data. Here we apply two Bayesian spatio-temporal conditional autoregressive (ST CAR) models, one of which allows discontinuities in risk between neighbouring areas.

Aims: To determine the most appropriate spatial priors to investigate the patterns of dengue fever and evaluate the impact of covariates on the identified groups and model fit.

Methods: ST CAR modelling was used to assess the relationship between annual (2002-2017) and monthly (January 2013 - December 2017) dengue fever cases and climatic factors (temperature, rainfall and humidity) over 14 geographic areas of Makassar. Different combinations of covariates and spatio-temporal model formulations are compared with respect to three metrics: 95% posterior credible interval (CI) for the climatic covariate coefficient does not contain zero, the overall goodness of fit (Watanabe-Akaike Information Criterion, WAIC), and the proportion of areas included in the groups.

Results: Inclusion of climatic predictors causes group size and structure to alter in the localised model. For annual dengue data, an ST CAR localised model (Lee and Lawson, 2016) with three groups and incorporation of average humidity provided the best fit. However, without covariates included, there were only two groups. For monthly dengue data, a single-group ST CAR autoregressive (AR) model (Rushworth et al., 2014) with incorporation of rainfall and average humidity provided the best fit. A single-group was still preferred even without covariates.

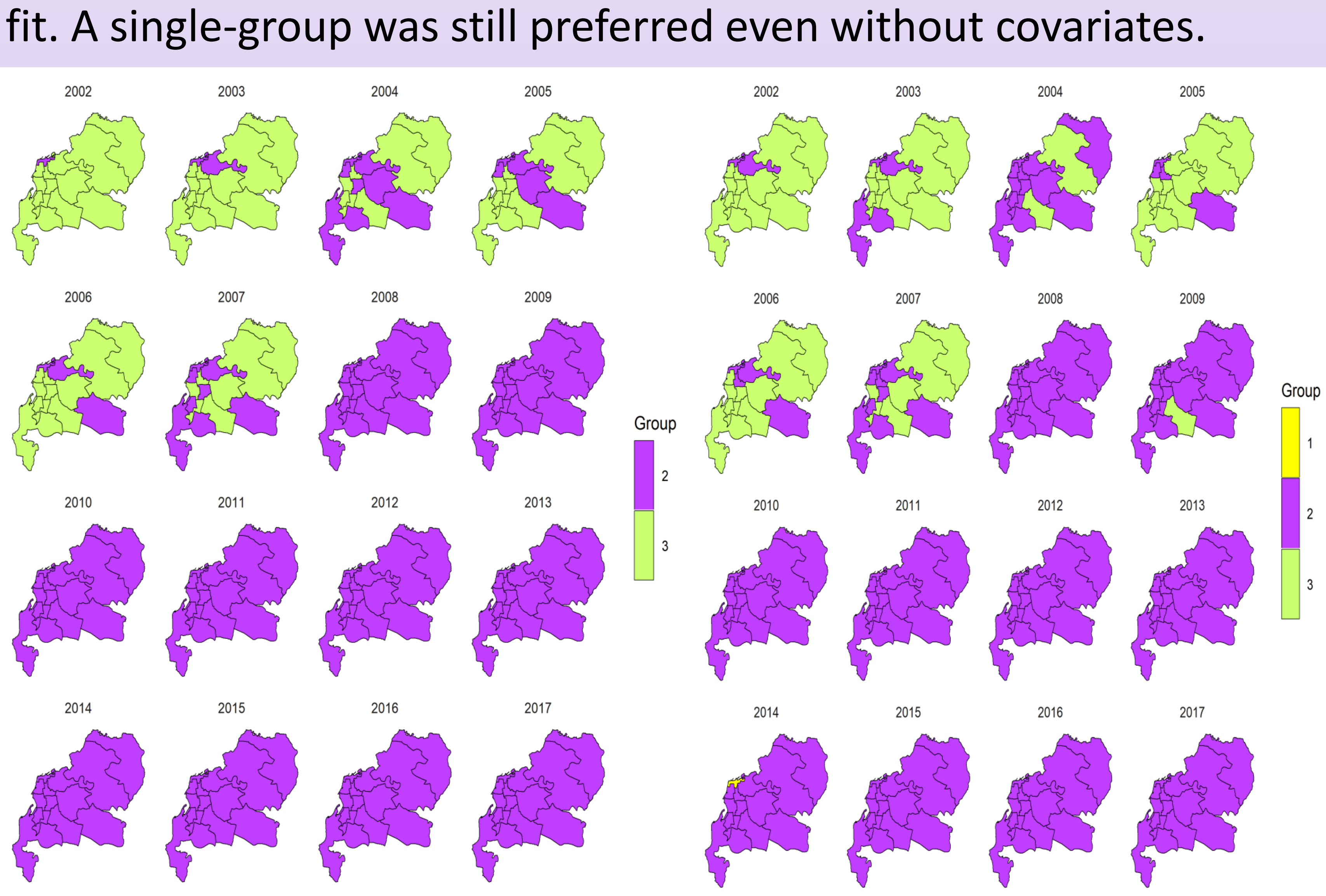

Figure 1. Localised maps obtained under the spatio-temporal CAR localised model for annual data, with G=3 without covariates (left) and with average humidity as a covariate (right).

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TABLE 1. Bayesian ST CAR Localised for G=2 and G=3 with and without climatic covariates for annual dengue cases 2002-2017

	ST CAR Localised with G=2				ST CAR Localised with G=3				
	Models	WAIC	G1	G2	Models	WAIC	G1	G2	G3
1	Without covariates	2045.3	134	90	Without covariates	1915.2	0	165	59
2	R* + AT*+ AH	3613.3	223	1	R* + AT*+ AH*	1979.8	1	180	43
3	R* + AH*	1809.7	224	0	R + AH*	1758.4	0	166	58
4	R	2081.7	139	85	R	1880.2	0	165	59
5	AH*	1828.3	149	75	**AH***	**1837.8**	**1**	**171**	**52**
6	AT	2251.0	139	85	AT*	1862.0	1	179	44
7	R + AT*	2431.4	140	84	R*+ AT*	1878.4	0	182	42
8	R + MinT	2412.2	138	86	R + MinT*	2178.1	1	184	39
9	R + MaxT*	2069.6	136	88	R + MaxT*	1731.0	1	182	41

*95% posterior credible interval (CI) for the coefficient does not contain zero
The values in columns denoted G1, G2, G3 are the number of observations in groups one, two, and three, respectively.
R, AT, AH, MinT, MaxT are rainfall, average temperature, average humidity, minimum temperature and maximum temperature, respectively.
Smaller values of WAIC indicate better model fit.

TABLE 2. Bayesian ST CAR AR with and without climatic covariates for monthly dengue cases 2013-2017

	Models	WAIC	rho.S	rho.T
1	Without covariates	2037.75	0.55	0.59
2	Rainfall*+ average temperature + average humidity*	2010.17	0.35	0.54
3	**Rainfall*+ average humidity***	**2013.13**	**0.35**	**0.54**
4	Rainfall	2028.54	0.55	0.59
5	Average humidity*	2061.28	0.47	0.56
6	Average temperature	2079.45	0.52	0.57
7	Rainfall + average temperature	2019.18	0.55	0.59
8	Rainfall + minimum temperature	2020.13	0.57	0.59
9	Rainfall + maximum temperature	2031.78	0.55	0.59

*95% posterior credible interval (CI) for the coefficient does not contain zero
rho.S and rho.T measure spatial and temporal autocorrelation, respectively.

Conclusion : The interplay between covariates, spatial priors and grouping structure influenced the performance of models for data at different temporal scales. Using appropriate Bayesian spatio-temporal models enables identification of different clusters of areas and the impact of climatic covariates which may help inform policy decisions.

References: Lee D, Lawson A. Quantifying the Spatial Inequality and Temporal Trends in Maternal Smoking Rates in Glasgow. The Annals of Applied Statistics. 2016;10(3):1427-46.
Rushworth A, Lee D, Mitchell R. A spatio-temporal model for estimating the long-term effects of air pollution on respiratory hospital admissions in Greater London. Spatial and Spatio-temporal Epidemiology. 2014;10:29-38.