Introduction

A number of R packages are available for implementing spatio-temporal Bayesian modelling such as spBayes, R-INLA, CARBayesST and spTDyn. The main advantage of the Bayesian approach for modelling spatio-temporal structures resides in its ability to account uncertainty in the estimates or predictions, and its ease in specifying spatial and temporal structure in priors distributions. Here, we will focus on four R packages, namely R-INLA (Integrated Nested Laplace Approximation) and CARBayesST, and apply these packages through a case study of dengue fever in Makassar, Indonesia. The number of dengue cases in Makassar fluctuates between locations and years. Since dengue cases vary in location and time, the spatial and temporal component must be taken into consideration. Here, we investigate dengue spatial and spatio-temporal model specification.

Methods

Annual dengue fever incidence data for Makassar, Sulawesi, Indonesia (14 geographic areas) during 2002-2015 were obtained from the City Health Department of Makassar South Sulawesi Province. The following range of Bayesian model specifications were considered. All models used a Poisson distribution for the count data.

Model-1: Spatio-temporal CAR linear
\[ \text{logit}(\logit) = \alpha + \gamma_j + \delta_{ij} \]
where \( \gamma_j \) and \( \delta_{ij} \) are spatially varying intercept and slope respectively.

Model-2: Spatio-temporal CAR ANOVA
\[ \text{logit}(\logit) = \alpha + \gamma_j + \delta_{ij} \]
where \( \logit(\logit) \) is the overall temporal trend effect. \( \gamma_j \) is overall temporal trend random effect, \( \delta_{ij} \) is independent space-time interactions

Model-3: Spatio-temporal CAR separate spatial
\[ \text{logit}(\logit) = \alpha + \gamma_j + \delta_{ij} \]
\( \alpha \) and \( \gamma_j \) are separate for each time period

Model-4: Spatio-temporal CAR AR1
\[ \text{logit}(\logit) = \alpha + \gamma_j \]

Model-5: Spatio-temporal CAR adaptive
Overall model structure is the same as for ST CAR AR model, but more suitable when the residual spatial autocorrelation in the response is consistent over time but has a localised structure.

Model-6: Spatio-temporal CAR localised
\[ \text{logit}(\logit) = \alpha + \gamma_j + \delta_{ij} \]
\( \alpha \) and \( \gamma_j \) are piecewise constant clustering component

Model-7: Linear temporal trend model
\[ \text{logit}(\logit) = \alpha + \gamma_j + \delta_{ij} \]
the linear trend effect and the area-specific trend

Model-8: Nonparametric dynamic trend(EW) model
\[ \text{logit}(\logit) = \alpha + \gamma_j + \delta_{ij} \]
where \( \delta_{ij} \) are temporally structured random effects

Model-9: Nonparametric dynamic trend(EW) model
\[ \text{logit}(\logit) = \alpha + \gamma_j + \delta_{ij} \]
Model is the same as Model 8, except temporally structured random effect \( \gamma_j \) uses a first order of autoregressive (AR1)

Model-10: Nonparametric dynamic trend(AR1) model
\[ \text{logit}(\logit) = \alpha + \gamma_j + \delta_{ij} \]
Model is the same as Model 8, except temporally structured random effect \( \gamma_j \) uses a second order of autoregressive (AR2)

Model-11: Nonparametric dynamic trend(AR2) model
\[ \text{logit}(\logit) = \alpha + \gamma_j + \delta_{ij} \]
Model is the same as Model 8, except temporally structured random effect using a second order of autoregressive (AR2)

Models were run using R-INLA and CARBayes packages and compared using goodness-of-fit measures, such as Deviance Information Criterion (DIC) and Wahinebra-Akaike Information Criterion (WAIC), as well as comparing the obtained estimates and their precision for each area. For models run under CARBayes package, we used burnin=20000 and nsample=10000.

Results

Table 1. DIC, WAIC and Time used for every model

<table>
<thead>
<tr>
<th>Model</th>
<th>DIC</th>
<th>WAIC</th>
<th>Time (seconds)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>2012.91</td>
<td>2330.25</td>
<td>44.40</td>
</tr>
<tr>
<td>Model 2</td>
<td>9374.02</td>
<td>45374.63</td>
<td>34.70</td>
</tr>
<tr>
<td>Model 3</td>
<td>9499.17</td>
<td>Inf</td>
<td>71.80</td>
</tr>
<tr>
<td>Model 4</td>
<td>1632.36</td>
<td>1884.21</td>
<td>33.00</td>
</tr>
<tr>
<td>Model 5</td>
<td>1923.21</td>
<td>2111.74</td>
<td>162.90</td>
</tr>
<tr>
<td>Model 6: G1</td>
<td>1347.07</td>
<td>1927.29</td>
<td>117.10</td>
</tr>
<tr>
<td>Model 6: G2</td>
<td>1438.99</td>
<td>1892.07</td>
<td>128.80</td>
</tr>
<tr>
<td>Model 7</td>
<td>2075.85</td>
<td>2164.67</td>
<td>4.10</td>
</tr>
<tr>
<td>Model 8</td>
<td>1526.40</td>
<td>1614.81</td>
<td>4.27</td>
</tr>
<tr>
<td>Model 9</td>
<td>1526.63</td>
<td>1615.17</td>
<td>8.23</td>
</tr>
<tr>
<td>Model 10</td>
<td>1526.31</td>
<td>1614.75</td>
<td>4.51</td>
</tr>
<tr>
<td>Model 11</td>
<td>1526.35</td>
<td>1614.93</td>
<td>5.12</td>
</tr>
</tbody>
</table>

The spatio-temporal CAR localised model with G=2 had substantially better model fit (has the lowest DIC). However, Spatio-temporal CAR separate spatial model had the highest DIC.

Comparison of different Bayesian spatio-temporal models using R packages

Conclusion

This work was supported by the ARC Centre of Excellence for Mathematical and Statistical Frontiers and the Statistical Society of Australia (SSA).

Acknowledgements

Authors: Aswi Aswi, Kerrie Mengersen, Susanna Cramb, Wenbiao Hu, Genny White

1 ARC Centre of Excellence for Mathematical and Statistical Frontiers, Queensland University of Technology, Australia; 2 School of Public Health and Social Work, Queensland University of Technology, Australia; 3 School of Mathematical Science, Queensland University of Technology, Australia.

References