

# MULTIVARIATE BAYESIAN HIERARCHICAL MODELS WITH COPULAS-BASED ASSUMPTIONS ON SPATIAL EFFECT

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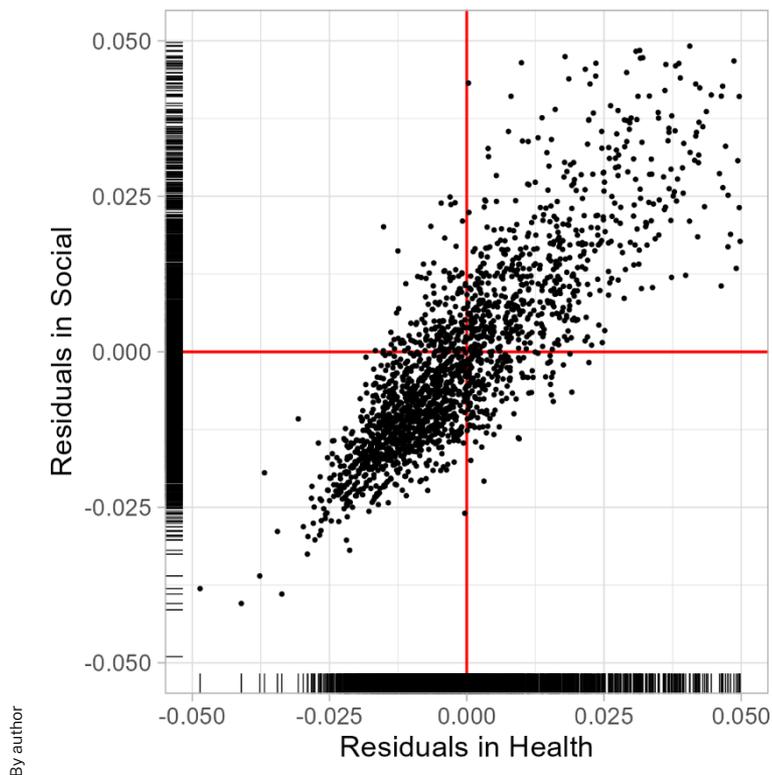
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# Background

## Bayesian hierarchical models

- A well-used small area estimation methods. To get a more accurate estimation when the sample size is small in each small area, the model borrow the strength from
  - Other data with much more samples (Census data for example)
  - Spatial information – area that near to each other are tend to perform the same
    - » Conditional autoregressive (CAR) models [1]
- Multivariate models can capture the relations between two response together
  - Issue: Correlation between two response (or residuals of each response) may not be constant and symmetric – this would be usually happened between two risks – *“It never rains, but it pours”*
    - » Key Questions: Construct a new method that can capture this non-linear correlation in small area estimation

Residuals of Bivariate Model  
Based on AEDC 2021 at SA2 level



## Dependence Structure on Residuals

Based on AEDC 2021 at SA2 level

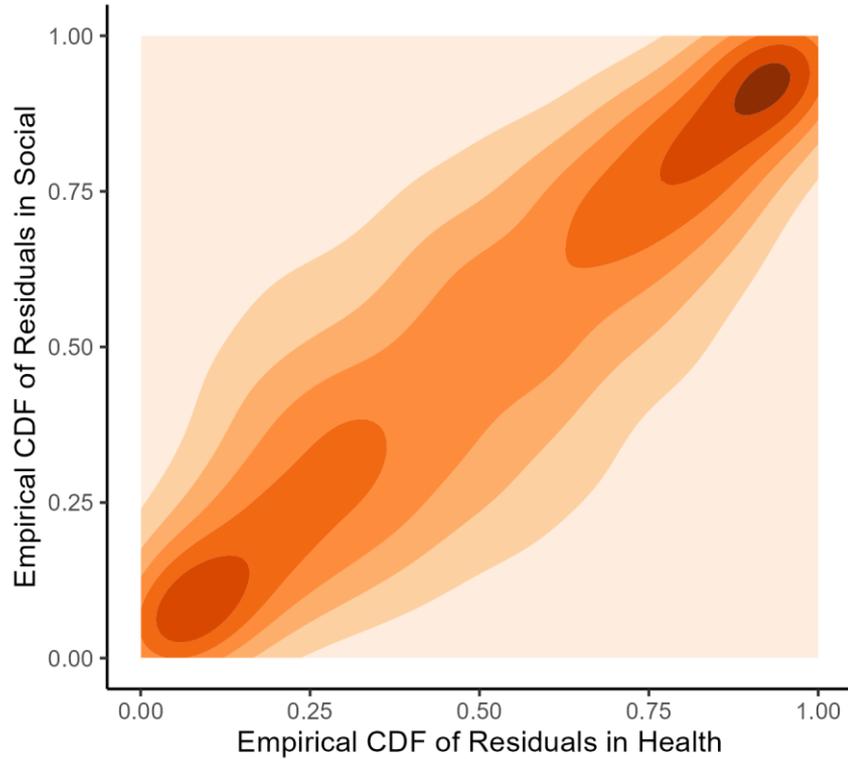


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## Non-constant Correlation between Residuals

Based on AEDC 2021 at SA2 level

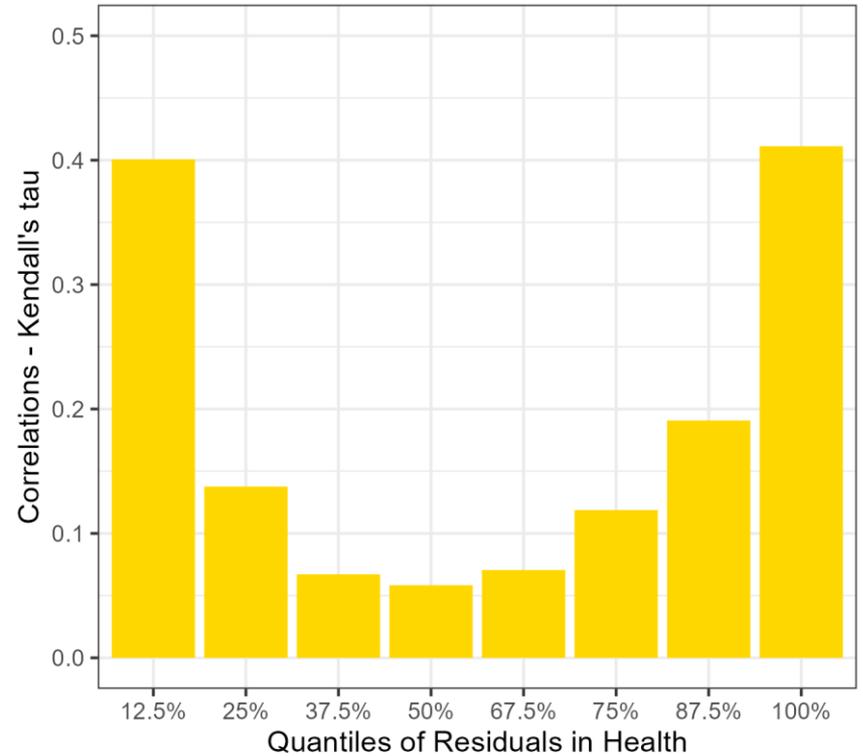


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# Non-symmetric Correlation

Where does the non-symmetric correlation come from?

## Simulations for Non-symmetric Correlation

We would like to investigate the possible theoretical source of non-symmetric correlation by simulation in a simple way.

- Generate bivariate  $Y$

$$Y_1 = X_1 + X_2 + \epsilon_1$$
$$Y_2 = X_1 + X_2 + X_3 + 0.3X_2X_3 + \epsilon_2$$

Unobservable,  
Caught in Res

- Where we just simply assume that the fixed effect  $X_1, X_2, X_3$  and random effects  $\epsilon_1$  and  $\epsilon_2$  are all generated from standard normal distributions
  - We also assume that when run simple linear regression models, the only observed value would be  $X_1$ , i.e.  $Y \sim X_1$ , where the rest of the fixed value are “latent variables” that can only be captured by residuals.
  - What would residuals  $Res(Y_1)$  and  $Res(Y_2)$  consist of?
    - $X_2$  both contained in  $Res(Y_1)$  and  $Res(Y_2)$ , which is the source of correlation level
    - $\epsilon_1$  and  $\epsilon_2$  are independent
    - $Res(Y_2)$  contains additional values  $X_3 + \frac{1}{4}X_2X_3$  which represent that effects from the hidden variable  $X_3$  and the interaction terms between  $X_2$  and  $X_3$
- » *Let's check the residuals!*



## Residuals of Bivariate Model

Based on Simulation Data

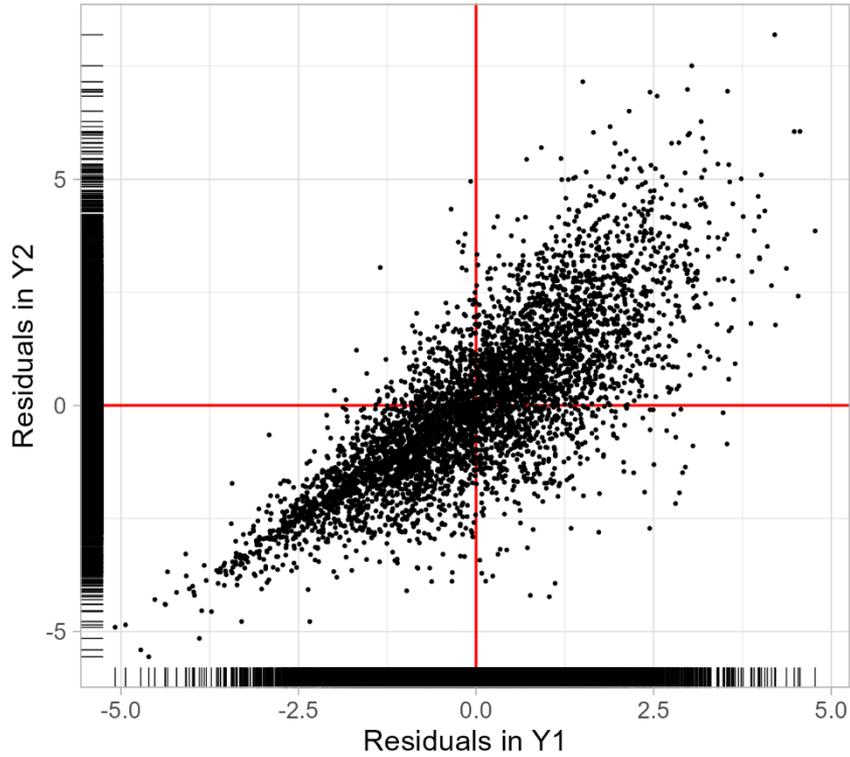


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## Dependence Structure on Residuals

Based on Simulation Data

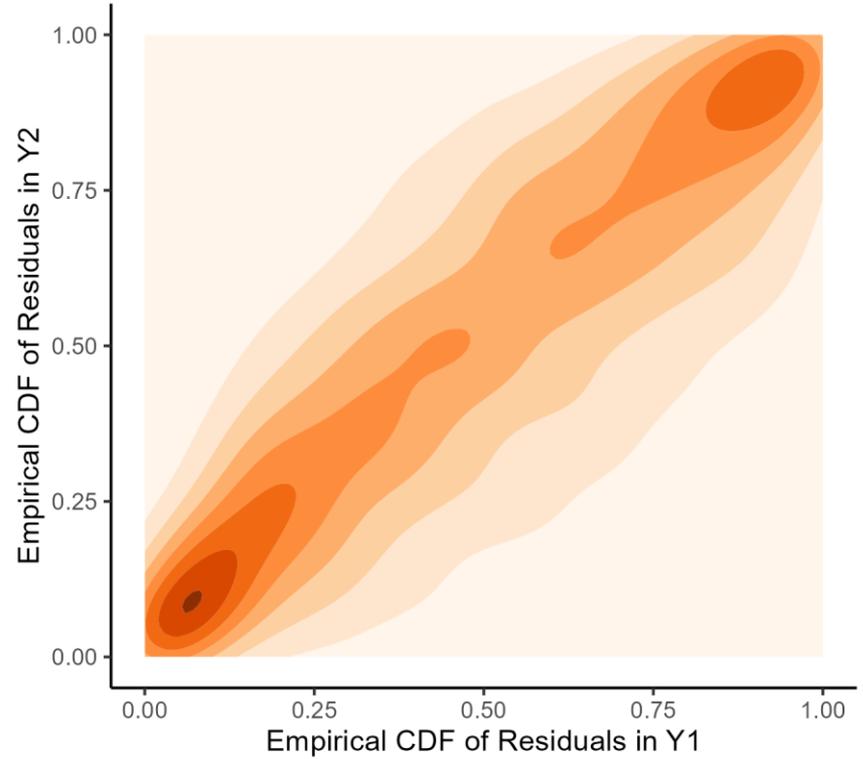


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## Dependence Structure of each Copulas Based on different parameter alpha

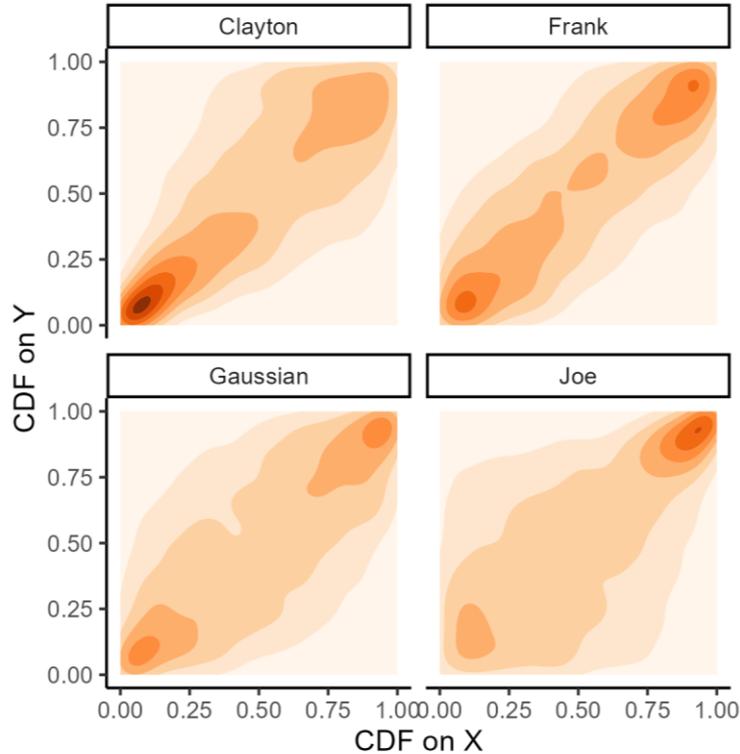


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# Methods

## Idea of Copulas

A powerful tool for decompose the joint distribution into marginal distribution and the dependence structure [2].

$$F_{XY}(x, y) = C(F_X^{-1}(x), F_Y^{-1}(y))$$

$C(., .)$  denotes for a copula function that could capture the dependence structure

- We could choose a copula function that could give a non-linear correlation performance shown by data
  - Clayton copula
    - » High correlation in one-side tail, with only one parameter to adjust the shape of the dependence structure

$$C(u, v) = (u^{-\alpha} + v^{-\alpha} - 1)^{-\frac{1}{\alpha}}$$



# Methods

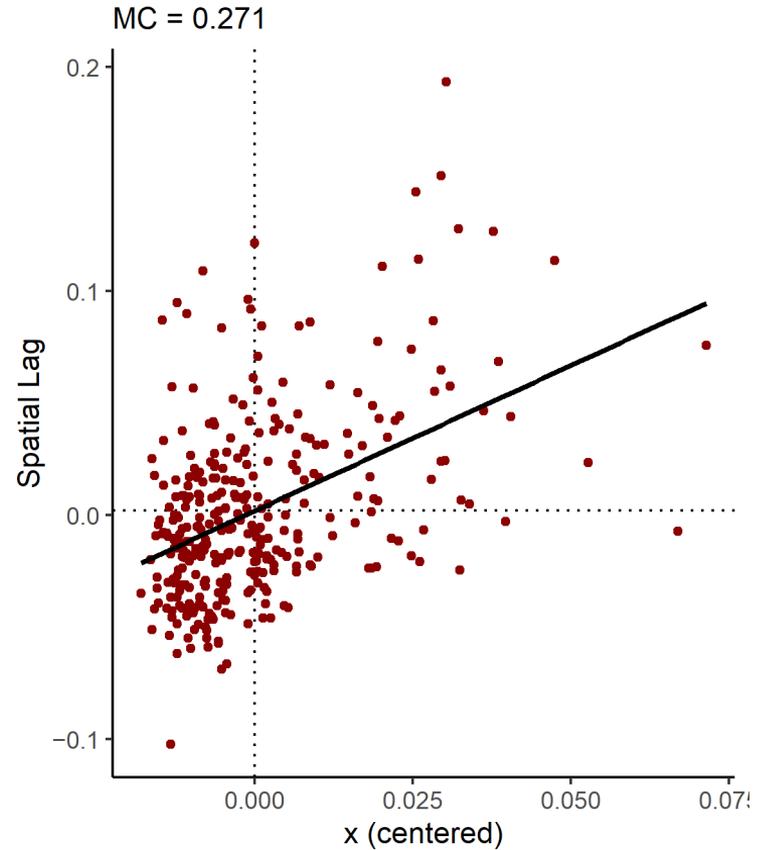
## Idea of Conditional Autoregressive Model

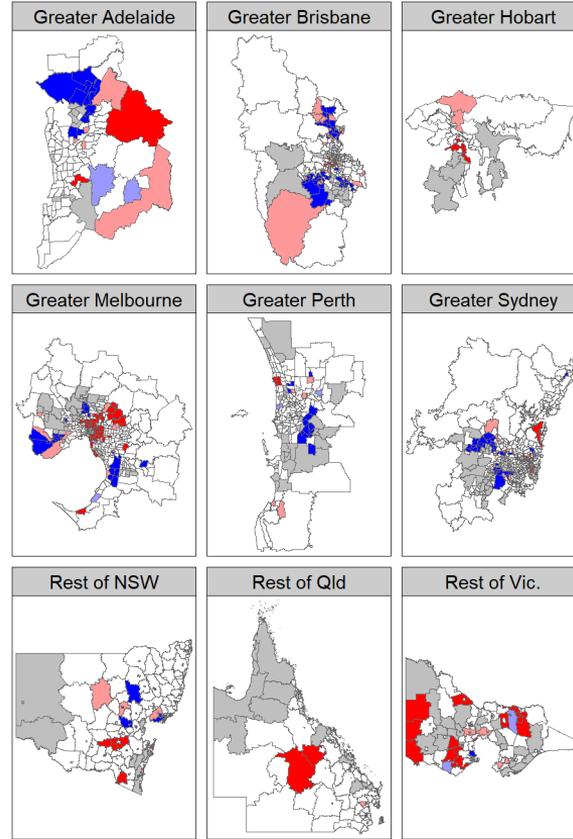
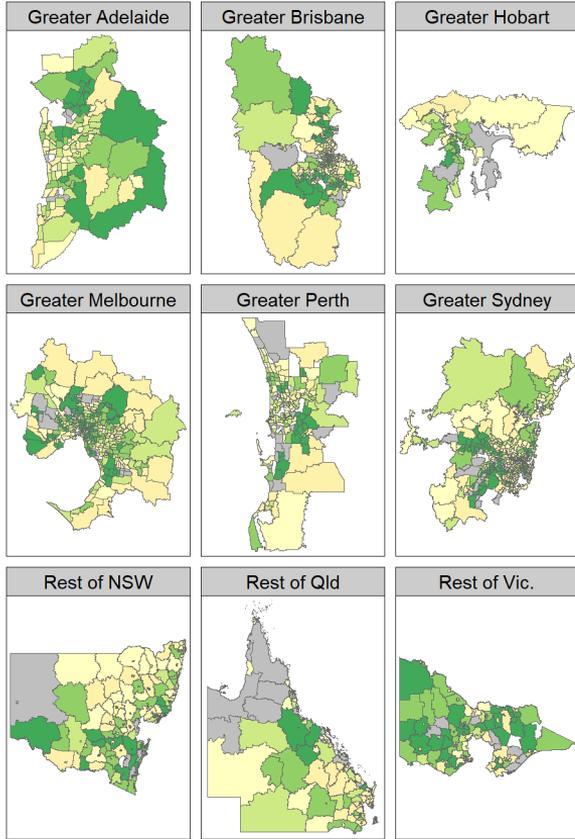
Areas that near to each others tends to perform in the same pattern

- Could be tested by Local Moran or Local Indicators Spatial Associations (LISA)
- The mean of the random effects were conditionally determined by the value of random effects of the neighbours; And the variance of random effects were conditionally determined by the number of the neighbours – It is a Gaussian Field
- Value of  $\rho$  represents the strength of spatial effects

$$(\psi_i | \psi_{-i}, W) \sim N\left(\frac{\rho \sum_{j=1}^R w_{ij} \psi_j}{1 + \rho \sum_{j=1}^R w_{ij} - \rho}, \frac{\tau}{1 + \rho \sum_{j=1}^R w_{ij} - \rho}\right)$$

Image credit here





# Methods

## Copula-based CAR

### Combine Copula with multivariate CAR

Now, we apply the CAR models on marginal distributions and generate the joint distribution with the Copulas when fitting the Bayesian hierarchical model

$$y_{ir} \sim \text{Binomial}(N_{ir}, p_{ir})$$
$$\log\left(\frac{p_{ir}}{1 - p_{ir}}\right) = \mathbf{X}\boldsymbol{\beta}_i + \boldsymbol{\psi}_{ir}$$
$$\boldsymbol{\psi}_r \sim \mathcal{C}_\alpha(\psi_{1r}, \psi_{2r})$$

- Specifications of the Binomial Case:
  - $y_{ir}$  denotes the responses of  $i$ th domain in  $r$ th area;
  - $N_{ir}$  denotes size of total valid observations of  $i$ th domain in  $r$ th area;
  - $\boldsymbol{\psi}_r$  denotes the bivariate random effect that follows the joint distribution constructed by copula function  $\mathcal{C}(\cdot, \cdot)$  with parameter  $\alpha$ , and the marginal distribution of the random effects from the first and the second domain  $\psi_{1r}$  and  $\psi_{2r}$
  - $\psi_{1r}$  and  $\psi_{2r}$  are generated from the CAR model
- » This capture both spatial effects and the non-symmetric correlations



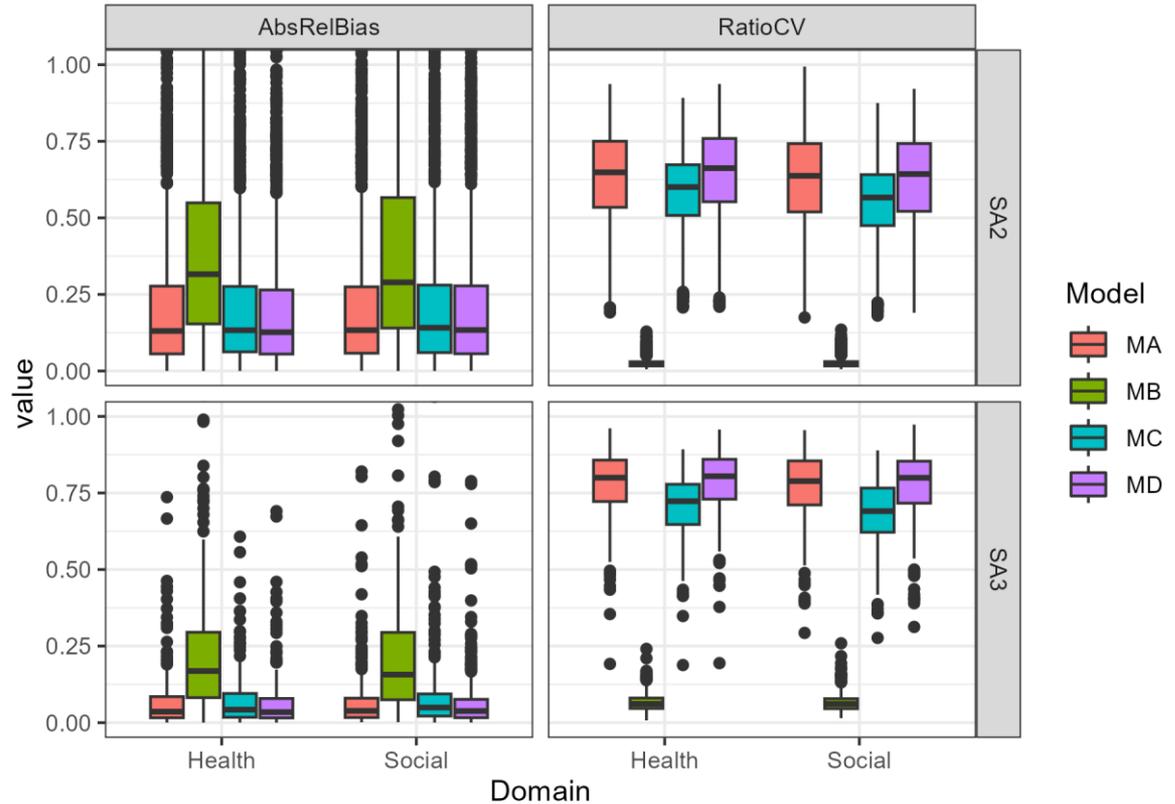
# Results

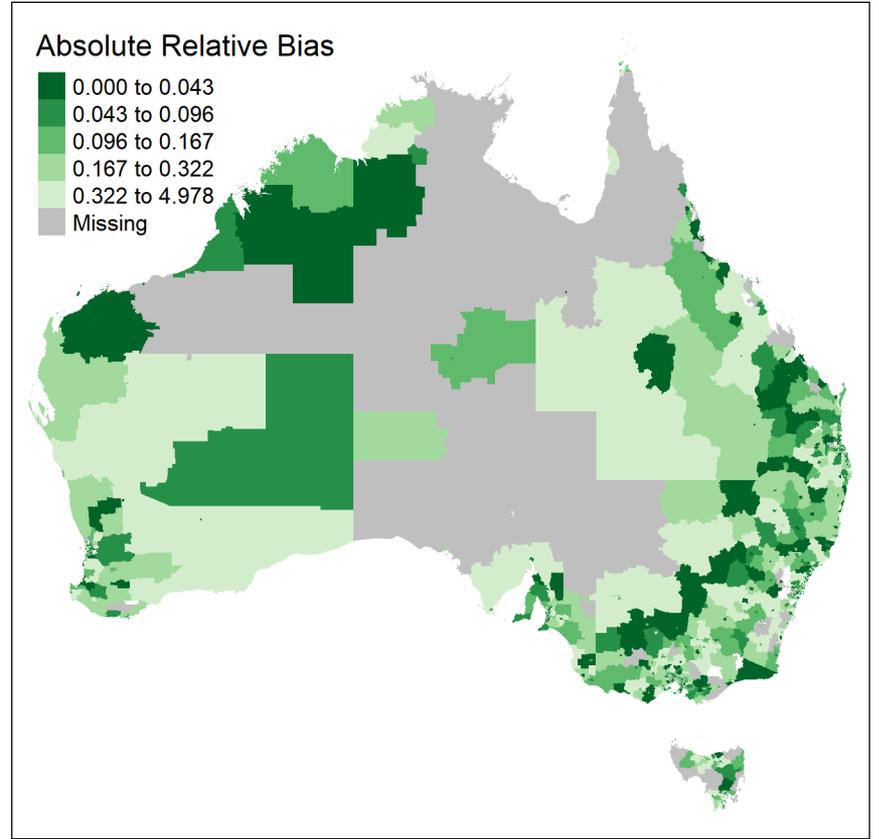
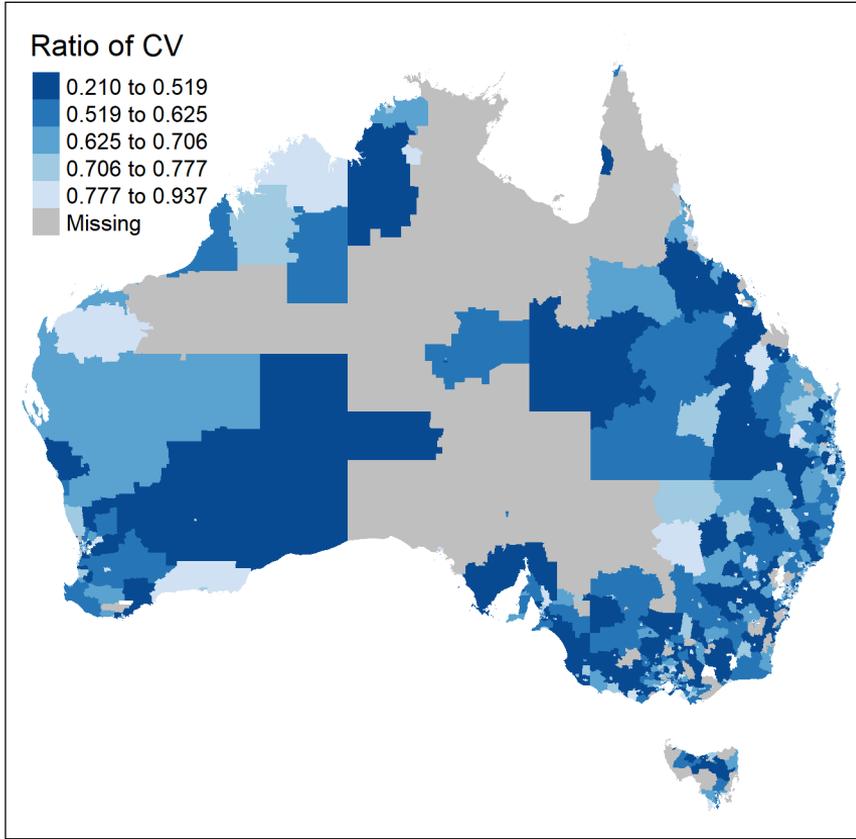
## Models Performances

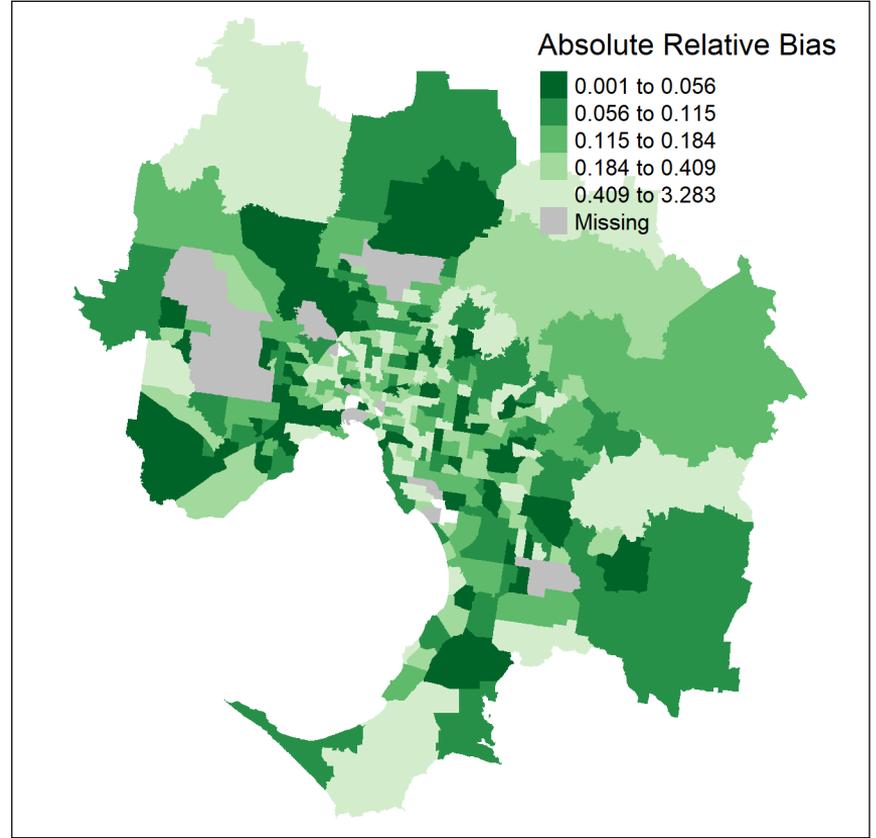
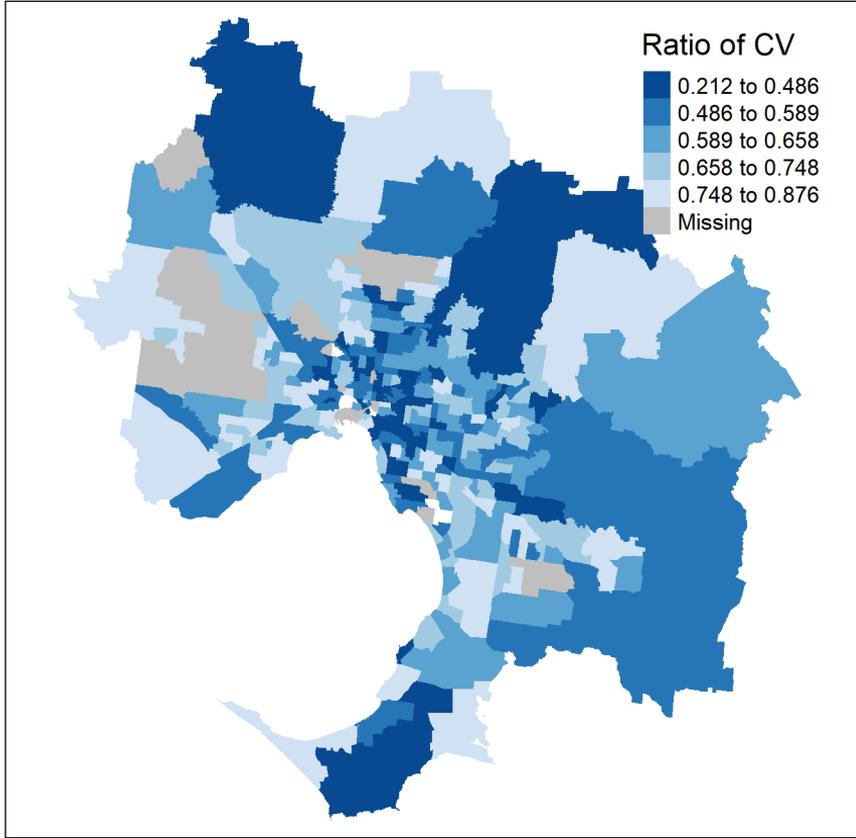
### Model Specifications:

- Model A: univariate CAR model for each domain separately
- Model B: univariate GLM model for each domain separately
- Model C: Bivariate CAR model
- **Model D: Bivariate CAR model with Clayton Inverse Copula assumptions**
- Ratio of Coefficients of Variation (CV)
  - Compare the CV with the direct estimation method, each method reduce the CV obviously
  - **Copula-based model give an acceptable CV improvement**
- Absolute value of Relative Bias (RB)
  - Compare the estimates with the direct estimation
  - Considering Spatial effects reduce the relative bias
  - **Copula-based model give the lowest Relative Bias**

## Comparison of Accuracies of Models







# THANK YOU

## Contact Us

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R Package: <https://github.com/ArmyNoBusiness/CARBayesCopulas.git>

### Reference List:

[1] Lee, D. (2011). A comparison of conditional autoregressive models used in Bayesian disease mapping. *Spatial and spatio-temporal epidemiology*, 2(2), 79-89.

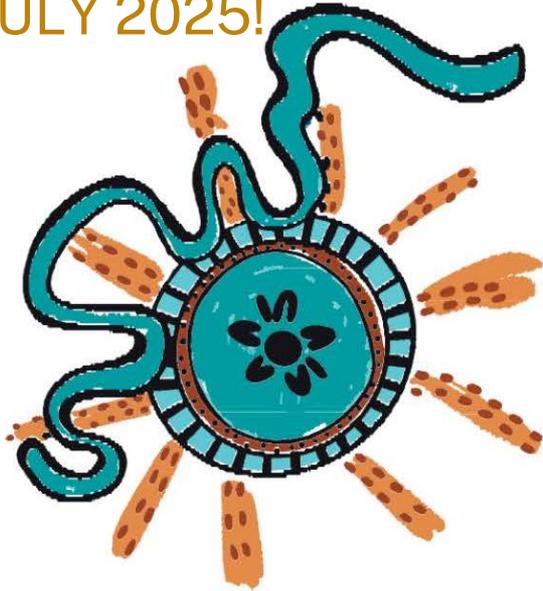
[2] Sklar, A. (1973). Random variables, joint distribution functions, and copulas. *Kybernetika*, 9(6), 449-460.



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