# Spatial Modeling for Areal Data: Spatial Autoregression

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## Hierarchical GLM for Spatial disease mapping

- ightharpoonup At unit (region) i, we observe response  $y_i$  and covariate  $x_i$
- $g(E(y_i)) = x_i^{\top} \beta + w_i$  where  $g(\cdot)$  denotes a suitable link function

$$p_2(\beta, \tau_w, \rho) \times N(w \mid 0, \tau_w(D - \rho A)) \times \prod_{i=1}^n p_1(y_i \mid x_i^{\top} \beta + w_i)$$

 $ightharpoonup p_1$  denotes the density corresponding to the link  $g(\cdot)$ 

#### **CAR** models

CAR model:

$$w_i \mid w_{-i} \sim N \left( \frac{\rho}{n_i} \sum_{j \mid i \sim j} w_j, \tau_w n_i \right)$$

- ► Apply Brook's Lemma to obtain joint density for w
- $w = (w_1, w_2, \dots, w_k)^\top \sim N(0, \tau_w(D \rho A)) \text{ where } D = \operatorname{diag}(n_1, n_2, \dots, n_k)$
- $\rho = 1 \Rightarrow$  Improper distribution as (D A)1 = 0 (ICAR)
  - ► Can be still used as a prior for random effects
  - Cannot be used directly as a data generating model

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- $ho = 1 \Rightarrow$  Improper distribution as (D A)1 = 0 (ICAR)
  - ► Can be still used as a prior for random effects
  - Cannot be used directly as a data generating model
- $ho < 1 \Rightarrow$  Proper distribution with added parameter flexibility

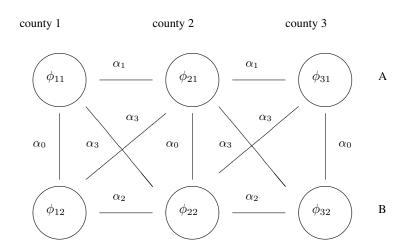
## **Multivariate Disease Mapping**

- $\triangleright$   $y_{ij}$  is the disease count for disease j in county i.
- $\triangleright$   $x_{ij}$  are explanatory, region-level spatial covariates for disease j.

$$p_2(\beta, \theta) \times N(\phi \mid 0, \Sigma_{\theta}) \times \prod_{i=1}^{n} \prod_{j=1}^{p} p_1(y_{ij} \mid x_{ij}^{\top} \beta_j + \phi_{ij})$$

▶ How do we model the  $\phi_{ij}$ 's?

## Multivariate disease mapping using graphs



### Conditional bivariate CAR: Jin et al. (2005)

ightharpoonup Build a hierarchical bivariate spatial model for p=2 outcomes:

$$N(\phi_1 | 0, \tau_1(D - \rho_1 A)) \times N(\phi_2 | C\phi_1, \tau_2(D - \rho_2 A))$$

ightharpoonup  $E[\phi_2 \mid \phi_1] = C\phi_1$ . Assume that the elements of C are

$$c_{ij} = \begin{cases} \eta_0 & \text{if } j = i \\ \eta_1 & \text{if } j \sim i \text{ (i.e., if region } j \text{ is a neighbor of region } i) \\ 0 & \text{otherwise} \end{cases}.$$

- $C = \eta_0 I + \eta_1 A$ , where  $\eta_0$  and  $\eta_1$  control spatial smoothing for cross-covariances.
- ► Call this CBCAR( $\rho_1, \rho_2, \eta_0, \eta_1, \tau_1, \tau_2$ ). Some special cases emerge:
  - Separable MCAR
  - Kim, Sun and Tsutakawa (2001): Two-fold CAR model with smoothing of cross-correlations
- Generalizations:  $C = \sum_{j} \eta_{j} A^{j}$