TURKISH NATURAL CATASTROPHE INSURANCE POOL

International Workshop on Advances in Assessment and Modelling of Earthquake Loss
TCIP Workshop, Istanbul, November 4-5, 2019

Imperial College London

Risk Oriented Earthquake Hazard Assessment

Peter J Stafford

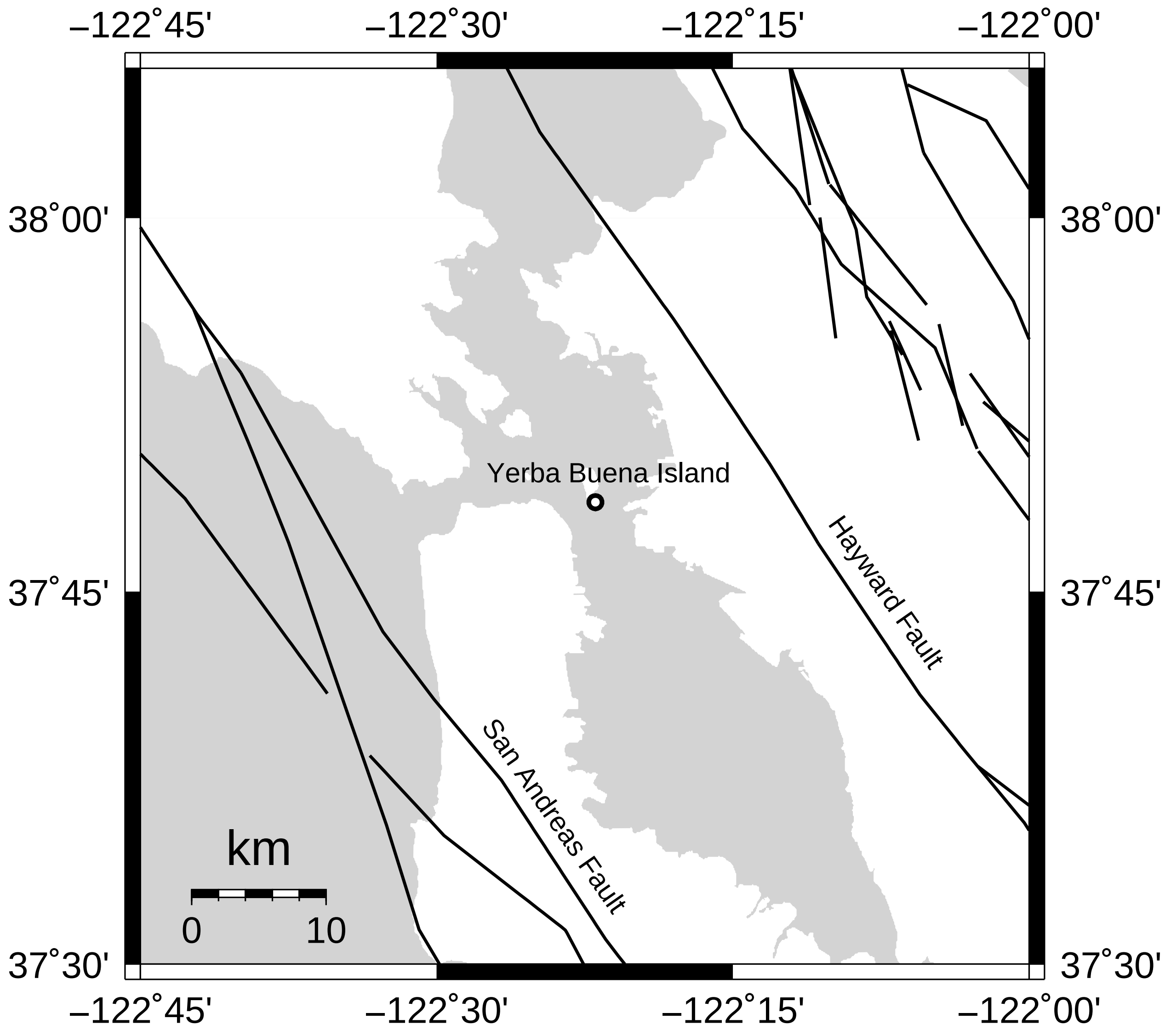
Imperial College London
p.stafford@imperial.ac.uk

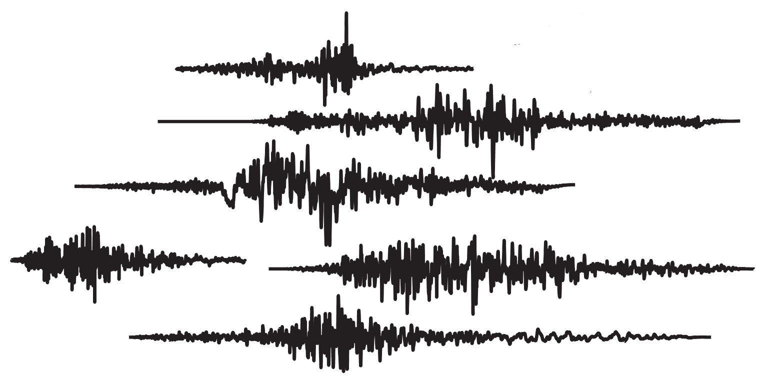
Outline

- Seismic hazard within risk applications
- Requirements of ground-motion and correlation models
- Implications of the ergodic assumption for seismic risk
- Non-ergodic issues within seismic sequences

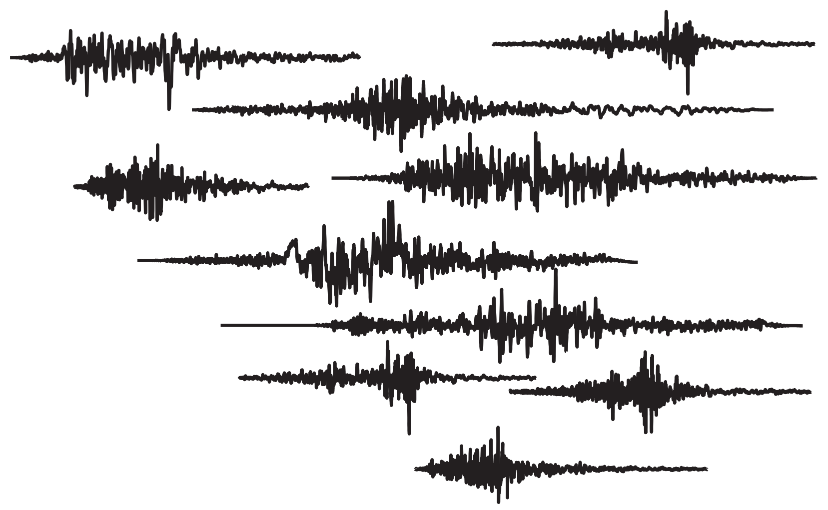
Conceptual risk framework

Seismic sources and rupture scenarios

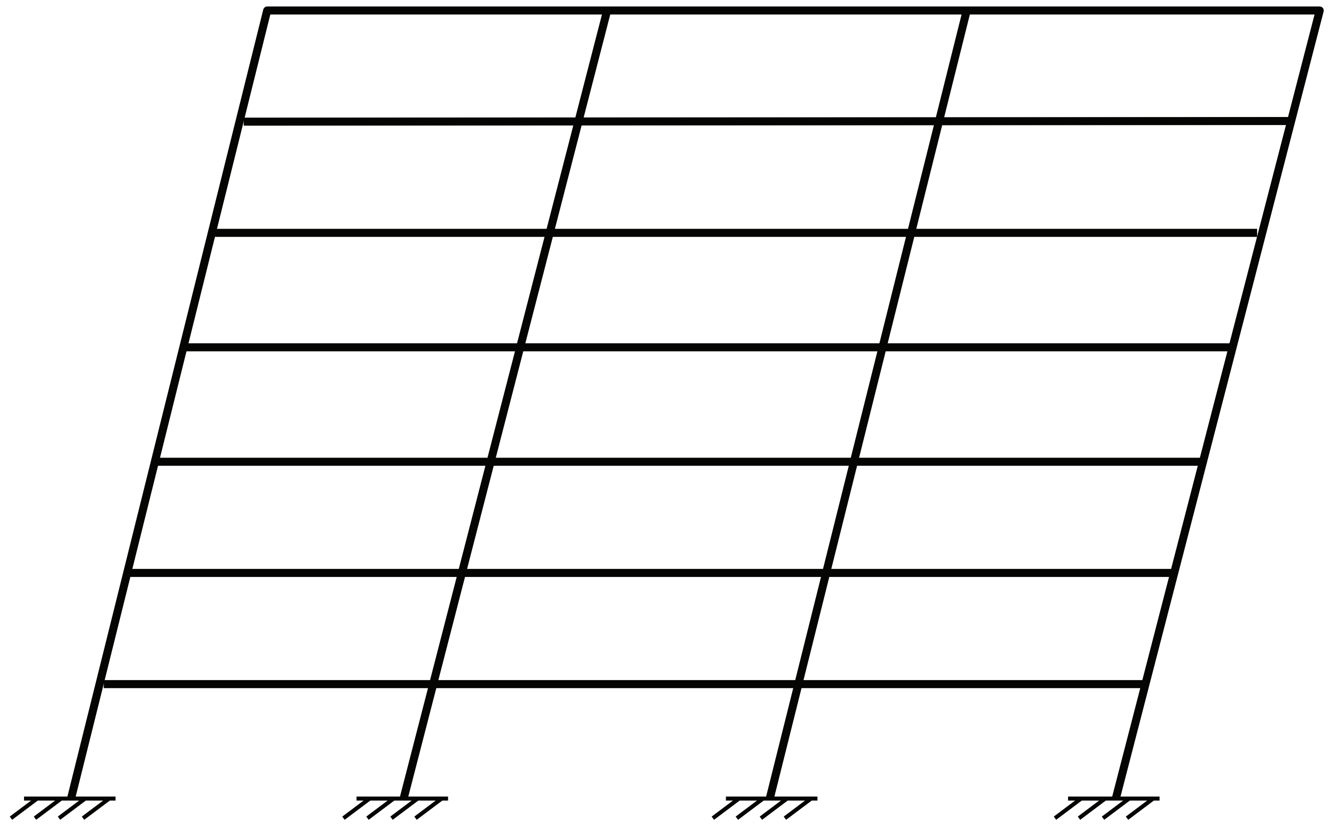




Ground motions for every rupture scenario



Structural performance



- From a seismic source model we define $\lambda(rup)$, the $P(rup)$ in some time window, or some stochastic sequence of rup scenarios

- For each rup we could pass compatible ground motions directly through the structural model and obtain the response distribution $f_{\boldsymbol{EDP}}(\boldsymbol{edp}; rup)$

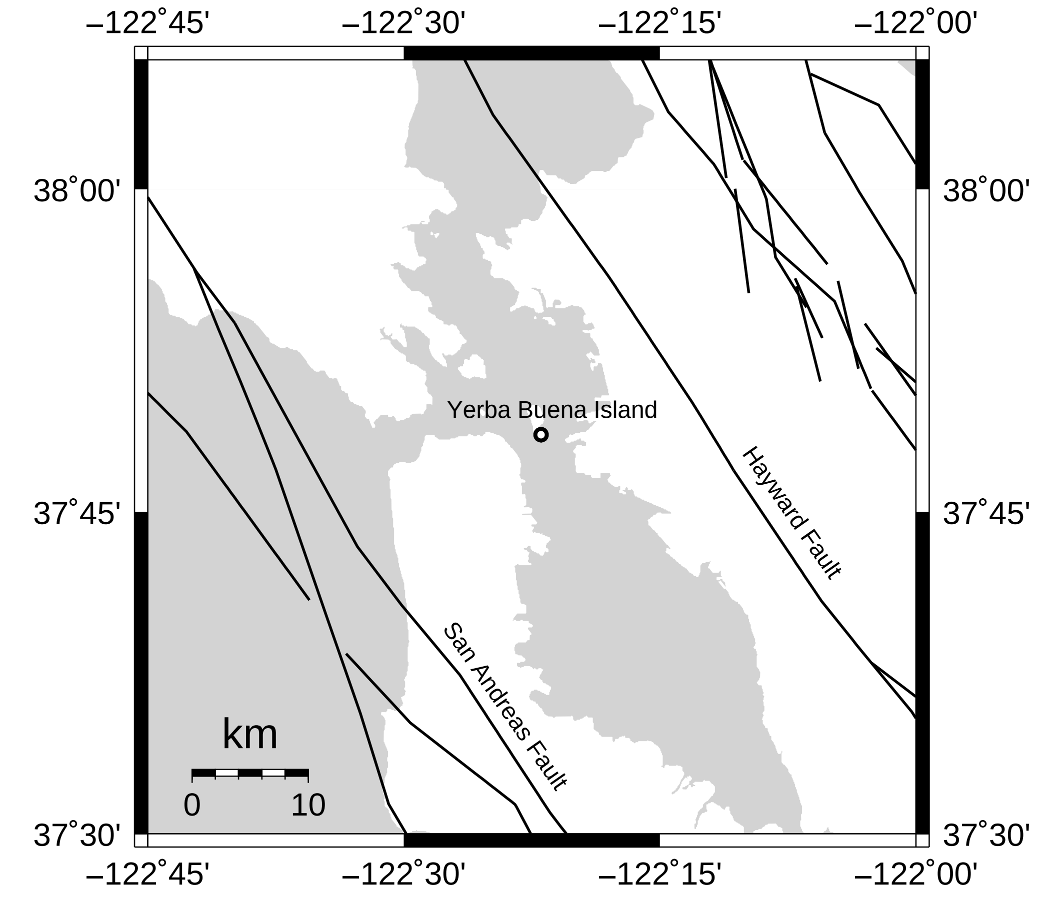
- Loss estimates are derived from the conditional distribution of $\boldsymbol{EDP} \mid rup$

Typical risk framework (single site)

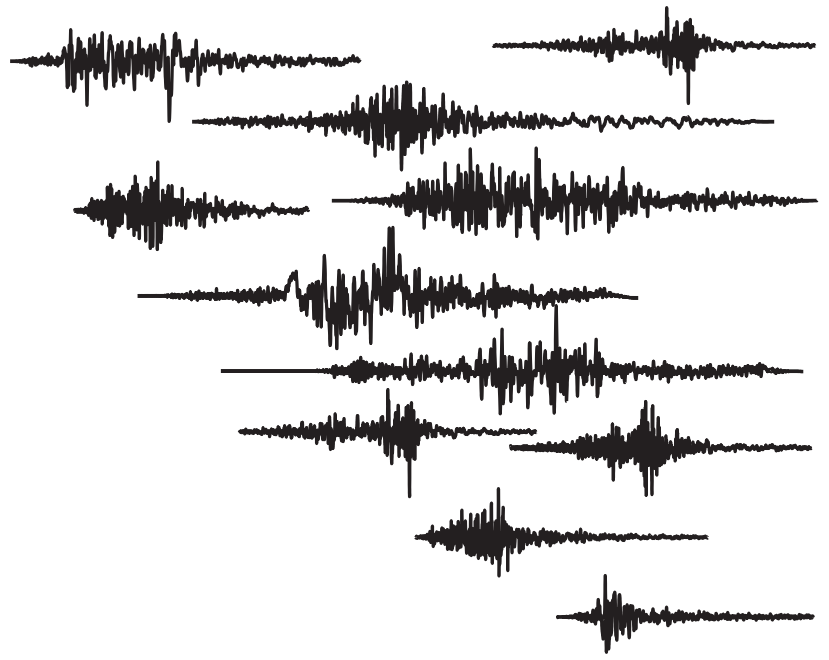
- A seismic source model defines $\lambda(rup)$, the $P(rup)$ in a time window, or some stochastic sequence of rup scenarios
- Ground-motion models and correlation models are used to predict the distribution of intensity measures $f_{\boldsymbol{IM}}(\boldsymbol{im}; rup)$ for each rupture
- A relatively small suite of ground motions are selected to be representative of $f_{\boldsymbol{IM}}(\boldsymbol{im}; rup)$, and upon passing these through the structural model we estimate $f_{\boldsymbol{EDP}|\boldsymbol{IM}}(\boldsymbol{edp} \mid \boldsymbol{im}; rup)$
- Loss estimates are derived from the conditional distribution of $\boldsymbol{EDP} \mid \boldsymbol{IM}$

Typical risk framework (single site)

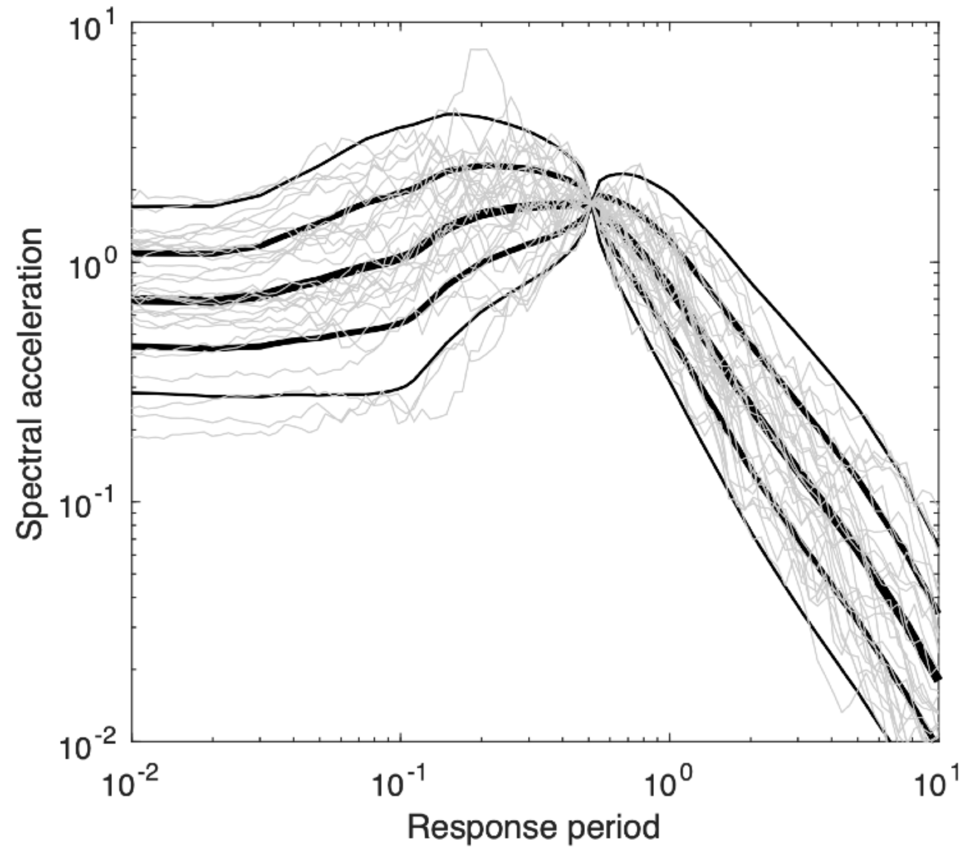
Seismic sources and rupture scenarios

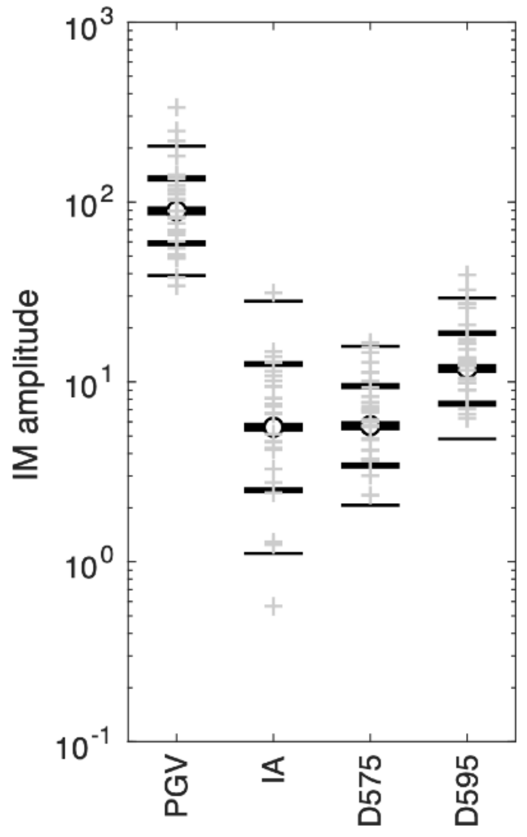


Ground motions used in GMM development

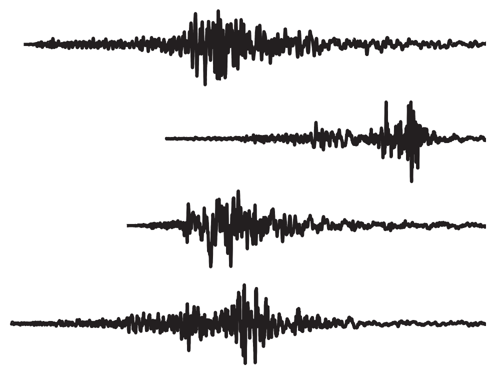


Target intensity measures

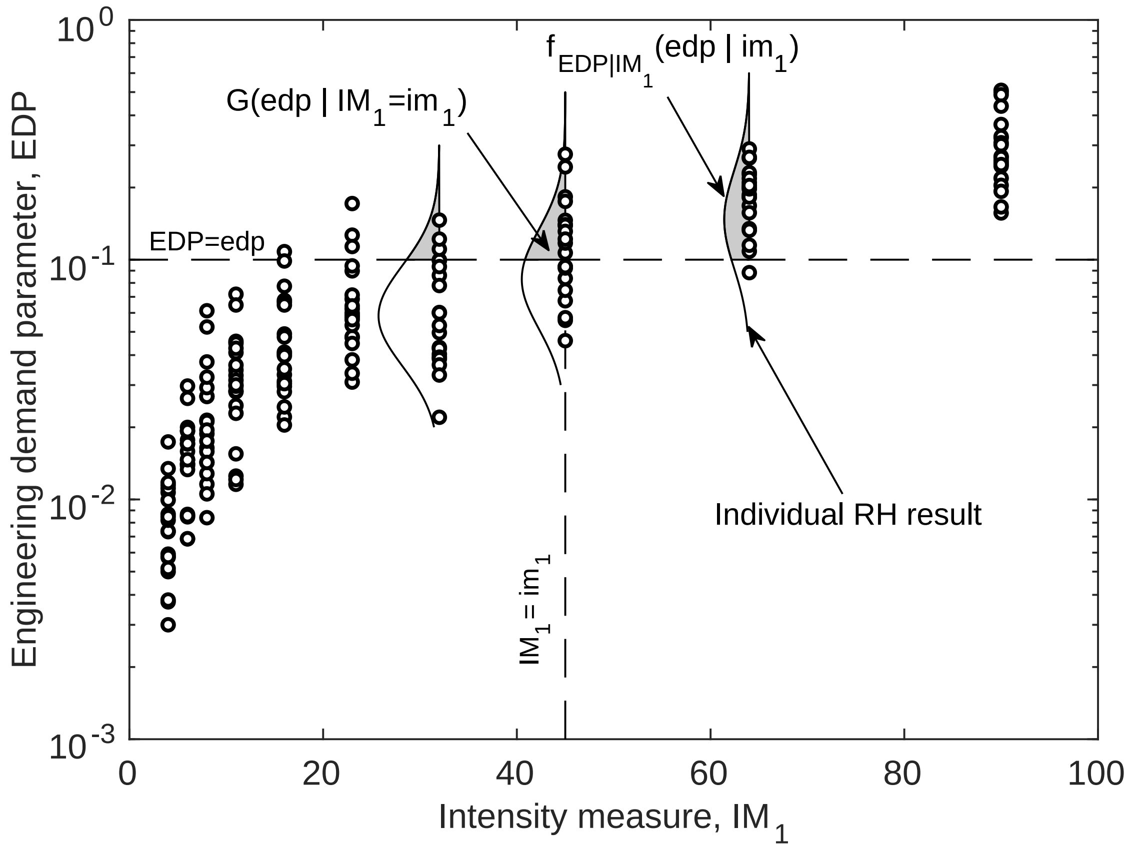




Selected ground motions



Structural performance



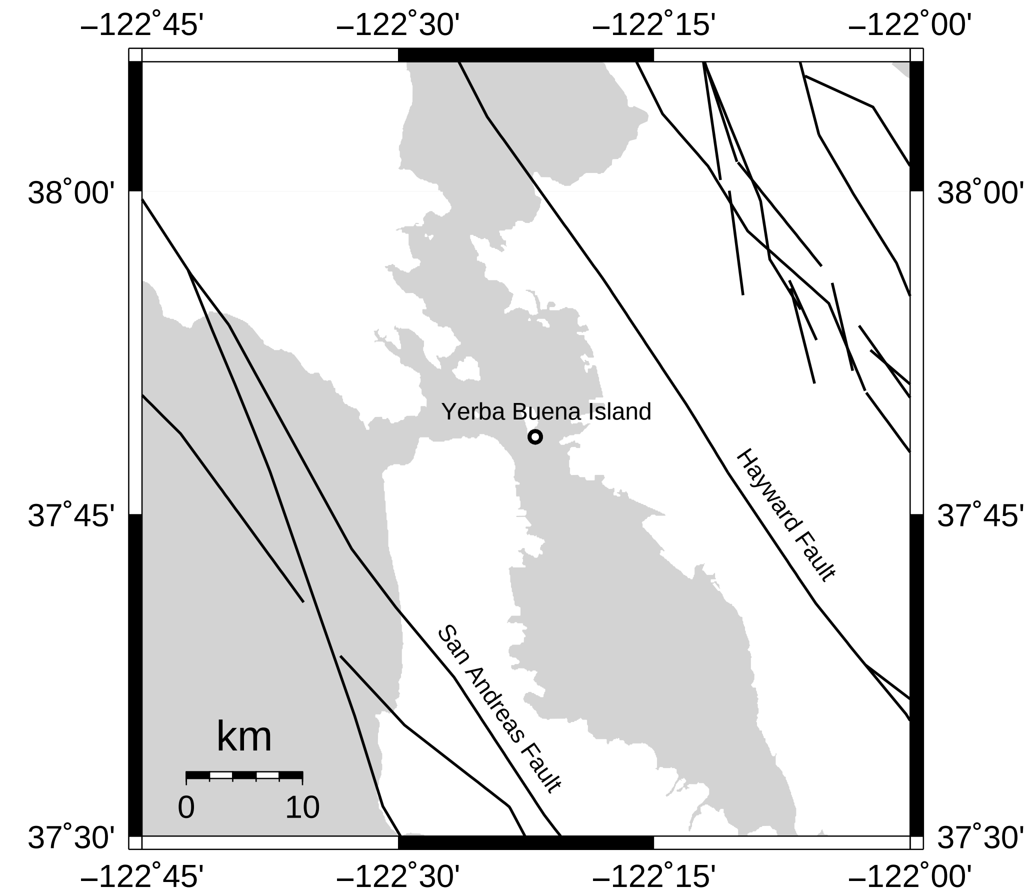
- A seismic source model defines $\lambda(rup)$, the $P(rup)$ in a time window, or some stochastic sequence of rup scenarios
- Ground-motion models and correlation models are used to predict the distribution of a single intensity measure $f_{IM_1}(im_1; rup)$ for each rupture
- A relatively small suite of ground motions are selected to be representative of $f_{\boldsymbol{IM}|IM_1}(\boldsymbol{im} \mid im_1; rup)$, and upon passing these through the structural model we estimate $f_{\boldsymbol{EDP}|IM_1}(\boldsymbol{edp} \mid im_1; rup)$
- Loss estimates are derived from the conditional distribution of $\boldsymbol{EDP} \mid IM_1$

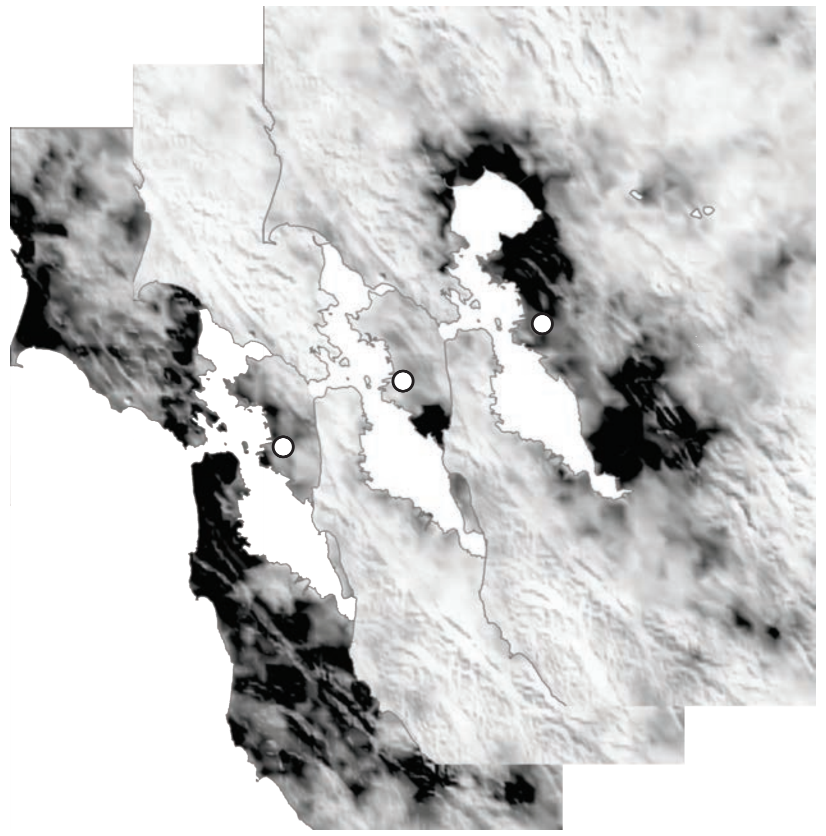
Typical risk framework (portfolio)

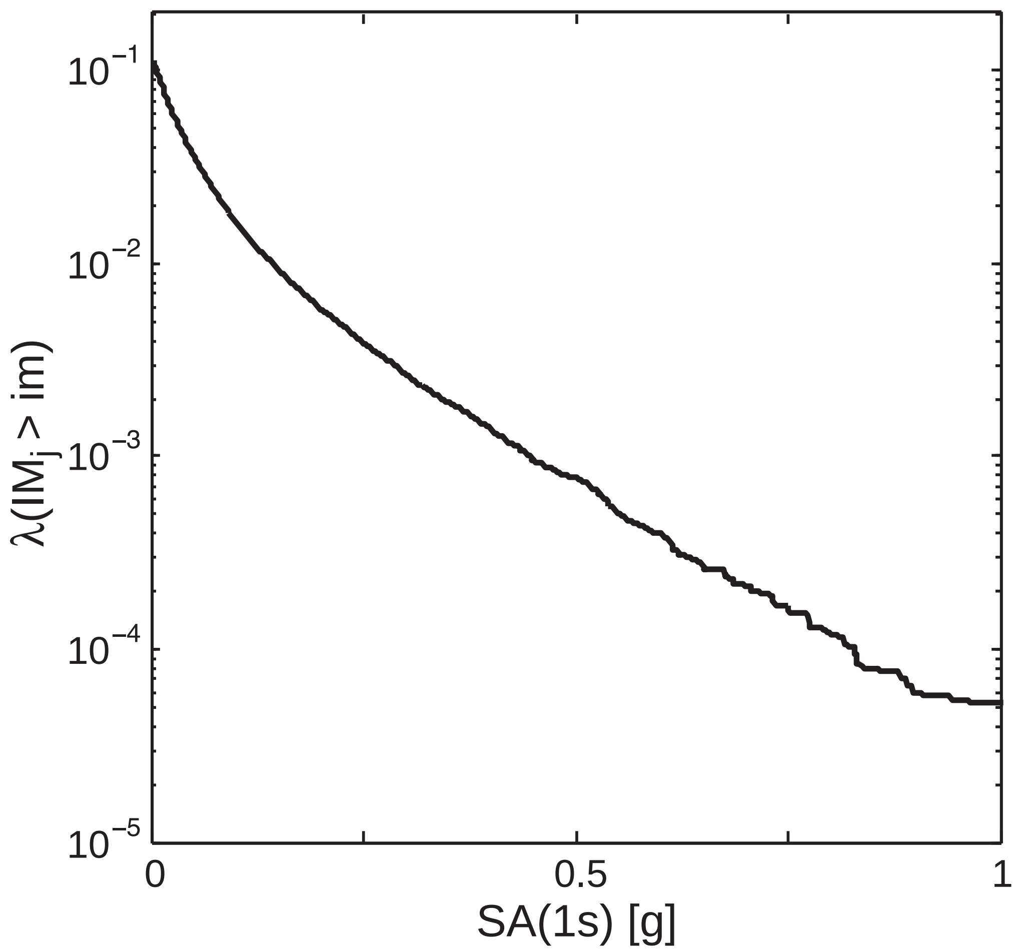
Seismic sources and rupture scenarios

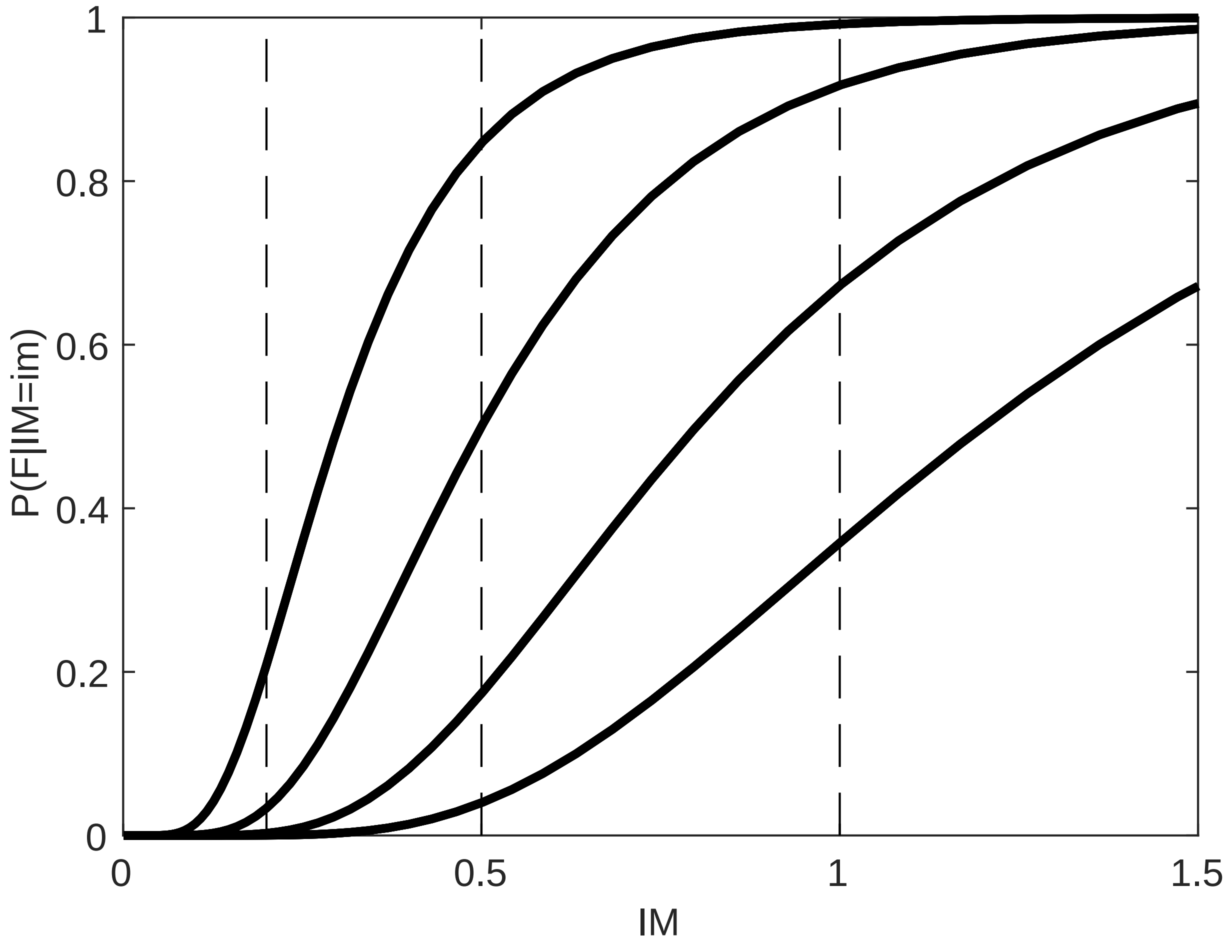
Simulations of ground-motion fields

Structural performance via fragility curves representing building classes









- From a seismic source model we define $\lambda(rup)$, the $P(rup)$ in some time window, or some stochastic sequence of rup scenarios

- Ground-motion models and correlation models are used to simulate fields of intensity measures according to $\boldsymbol{im} \sim MVN\left[(\boldsymbol{\mu}(rup), \boldsymbol{\Sigma}(rup)\right]$

- Loss estimates are derived from fragility curves $\boldsymbol{DM} \,|\, IM$

Typical risk framework

- Our objective is to calibrate these various different approaches to solving the same problem such that they provide similar results
- For portfolio risk applications it is clear that simplifications must be made in light of the computational and data requirements
- However, it is still important that we attempt to ensure that the various characteristics of the ground-motion fields and structural portfolio are represented in our simplified methods
- The focus of this presentation is to discuss the requirements for ground-motion models used within portfolio risk applications and to highlight potential inconsistencies that exist in current approaches

Requirements for ground-motion models

Model assumptions

- The focus of the ground-motion model is solely upon $f(\boldsymbol{IM}; rup)$, but it is important ensure that the $\boldsymbol{IM}$s that our model generates are consistent with what is used for the fragility modelling

- We assume that the distribution $f(\boldsymbol{IM}; rup)$ is well-represented by a multivariate normal distribution (for logarithmic intensity measures)

$$f(\boldsymbol{IM}; rup) \equiv MVN\left[\boldsymbol{\mu}(rup), \boldsymbol{\Sigma}(rup)\right]$$

- We therefore require:
  - $\boldsymbol{\mu}(rup)$ - which is provided by the ground motion model; and
  - $\boldsymbol{\Sigma}(rup)$ - which is the covariance matrix of the intensity measures for each rupture

- The current presentation focus upon $\boldsymbol{\Sigma}(rup)$, its constituent components, and its uncertainty

Traditional components of ground motion variability

General representation of variability components in ground-motion models for portfolio risk applications

Simulated surface motion (linear case)

Between-event variate

$$im(\boldsymbol{x}) = \mu(\boldsymbol{x}; rup) + \delta_B + \delta_W(\boldsymbol{x})$$

Median surface prediction (linear case)

Within-event variate

Nonlinear site response complicates this a little as we first predict an motion at some reference velocity horizon (at depth), and then compute the amplification as a function of this motion

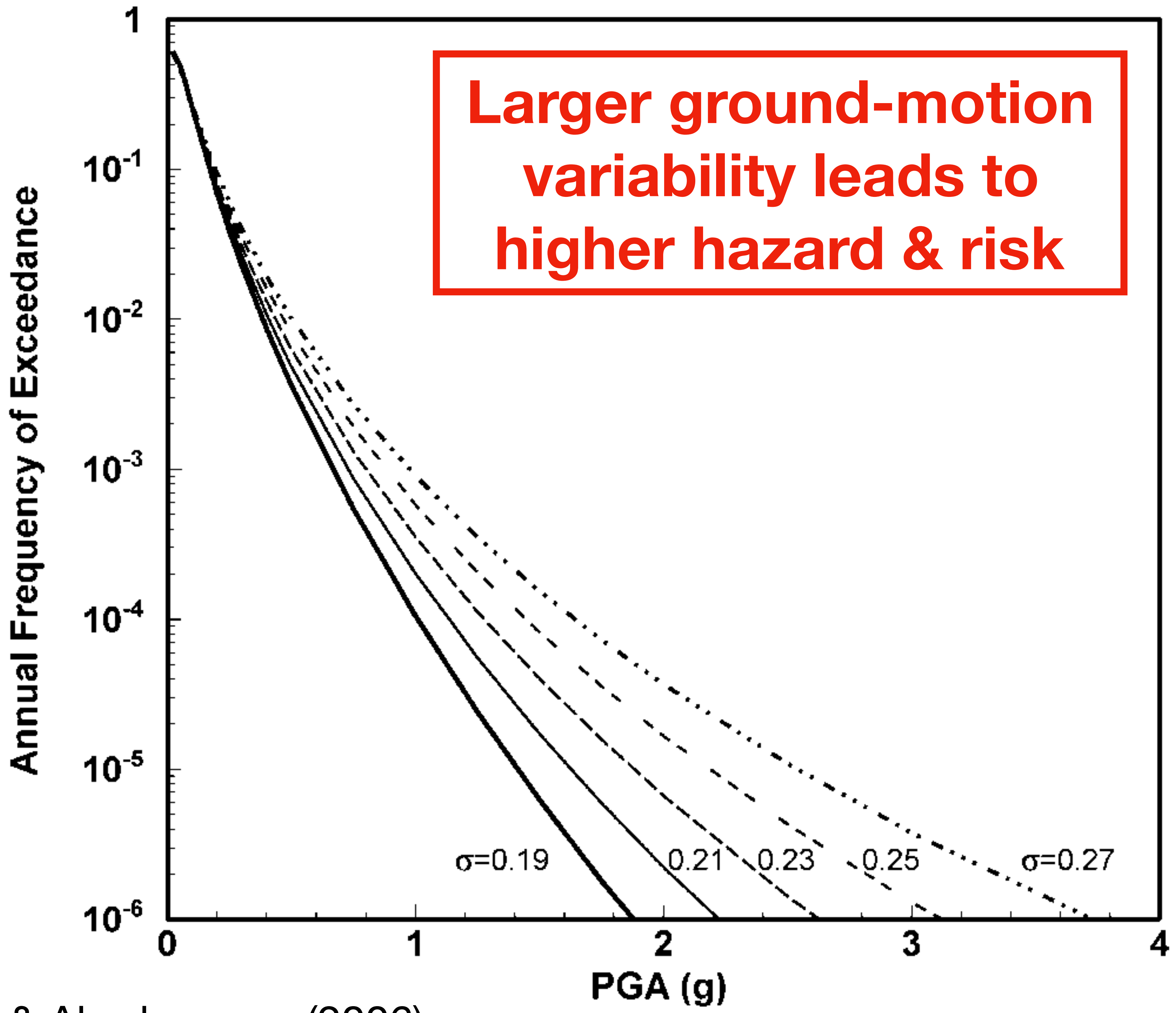
Motion at depth: $$im_{ref}(\boldsymbol{x}) = \mu_{ref}(\boldsymbol{x}; rup) + \delta_{B,0} + \delta_{W,0}(\boldsymbol{x})$$

Motion at surface: $$im(\boldsymbol{x}) = im_{ref}(\boldsymbol{x}) + \mu_{\ln AF}\left[\boldsymbol{x}, im_{ref}(\boldsymbol{x})\right] + \varepsilon_{\ln AF}\left[\boldsymbol{x}; im_{ref}(\boldsymbol{x})\right]$$

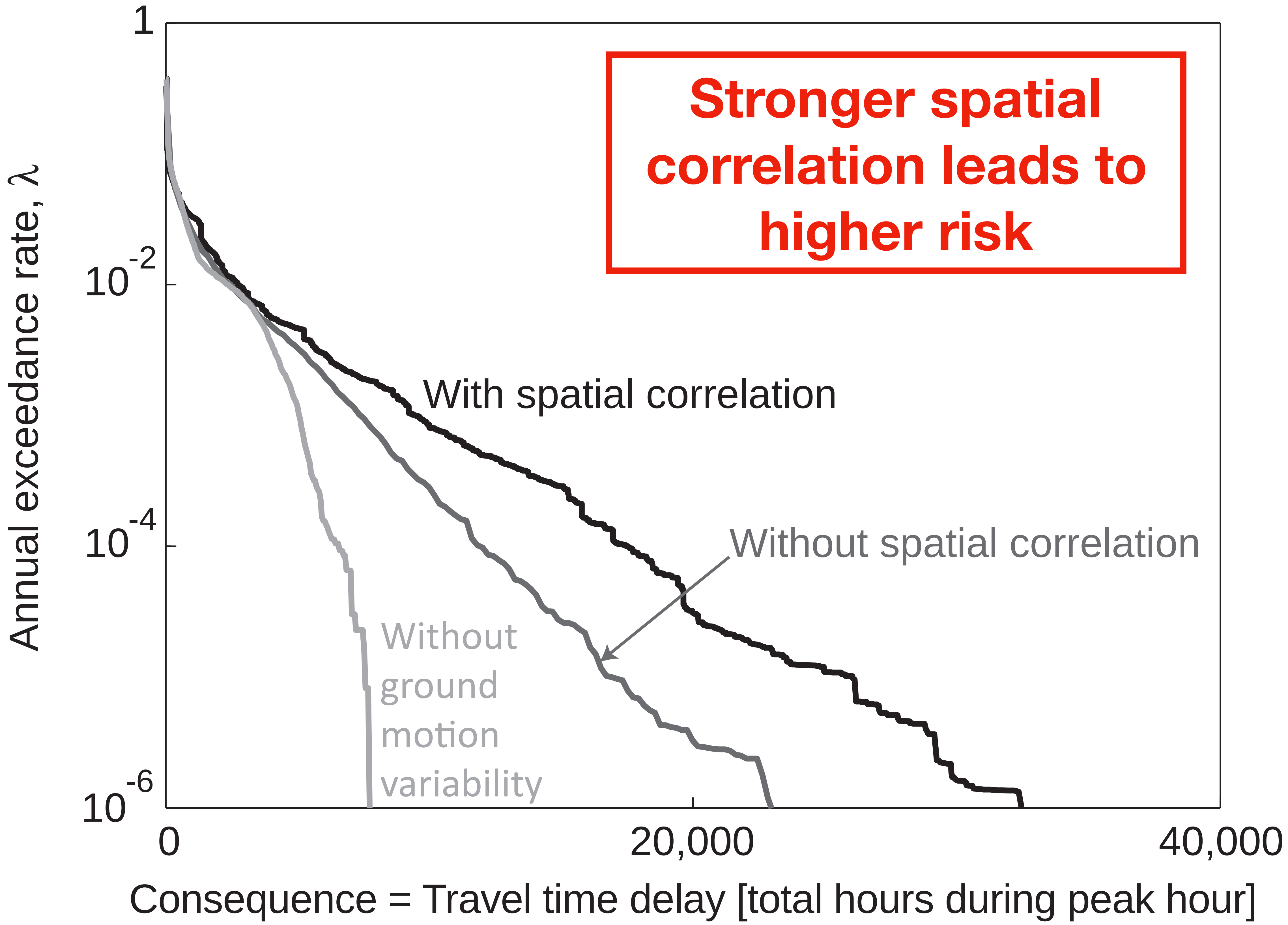
Traditional variance structure

Event variates are normal with variance τ^2, within-event variates are multi-variate normal with marginal variance ϕ^2 and a spatial correlation matrix $\boldsymbol{R}(\boldsymbol{x})$

$$im(\boldsymbol{x}) = \mu(\boldsymbol{x}; rup) + \delta_B + \delta_W(\boldsymbol{x}) \qquad \delta_B \sim N(0,\tau^2) \qquad \delta_W(\boldsymbol{x}) \sim MVN\left[\boldsymbol{0}, \phi^2(\boldsymbol{x})\boldsymbol{R}(\boldsymbol{x})\right] \qquad \sigma(\boldsymbol{x}) = \sqrt{\tau^2 + \phi^2(\boldsymbol{x})}$$



Bommer & Abrahamson (2006)



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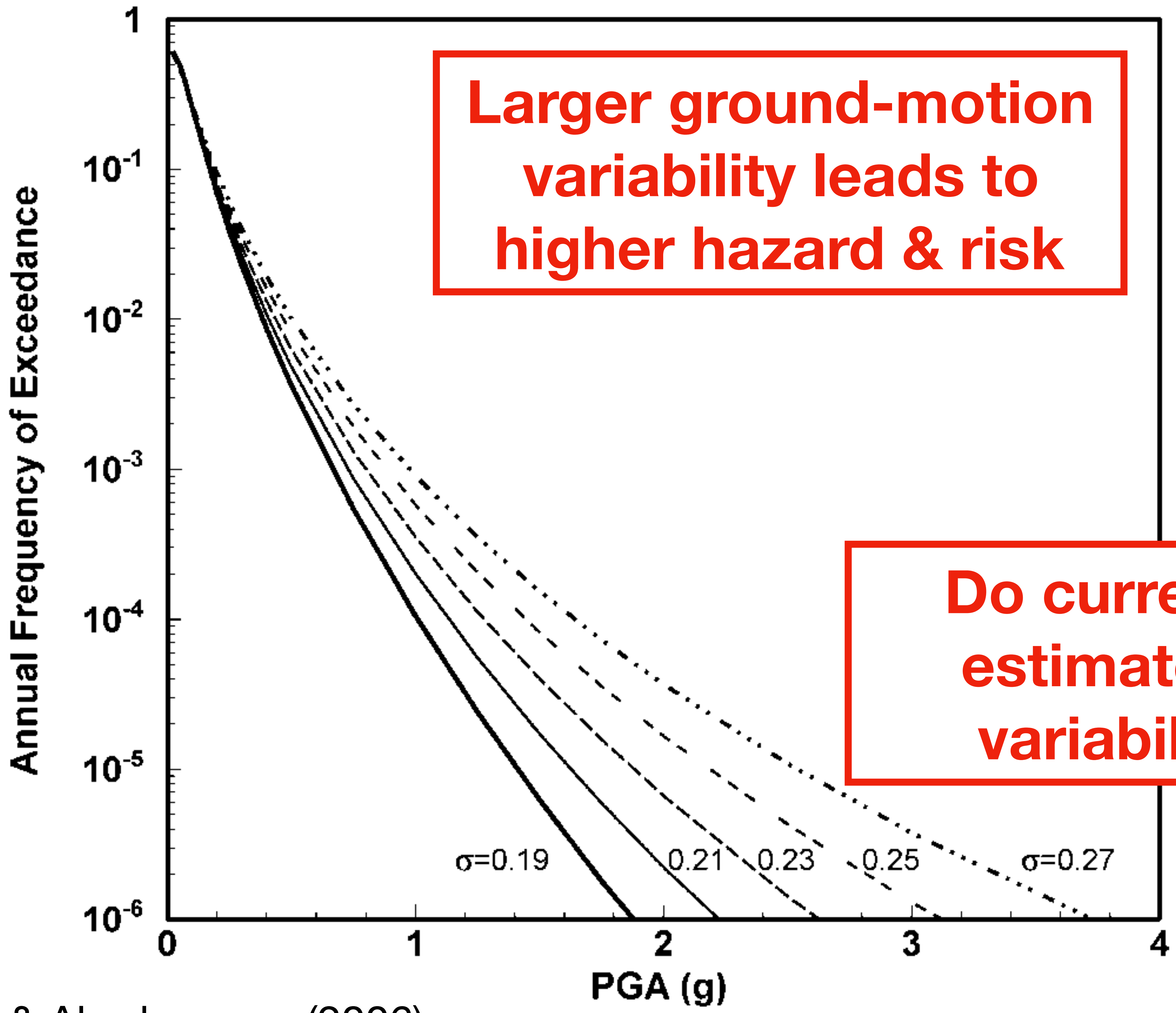
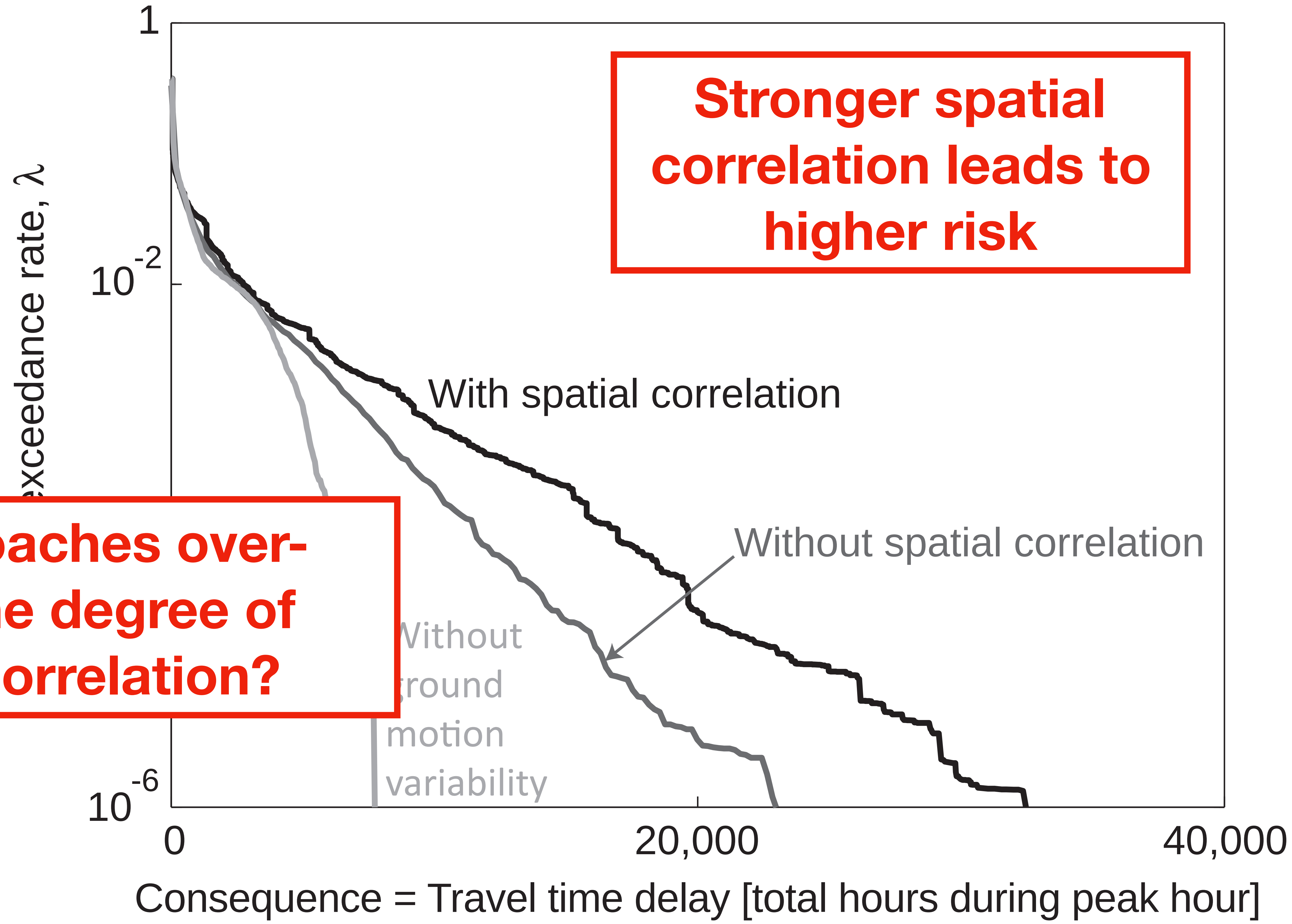


Bommer & Abrahamson (2006)



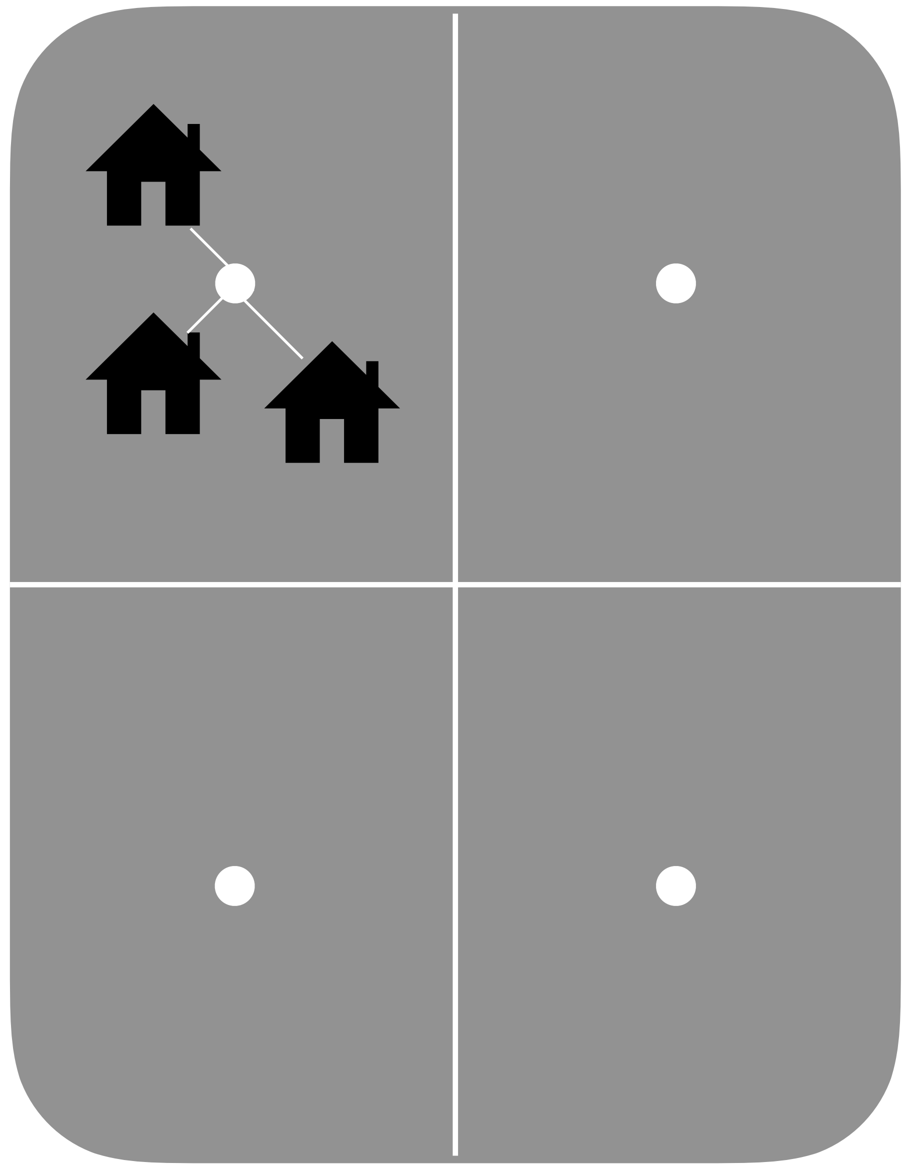
Do current approaches over-estimate both the degree of variability and correlation?

Correlation cases

For a general risk model there are various correlations among IMs that need to be considered

‘Same’ buildings, ‘same’ position

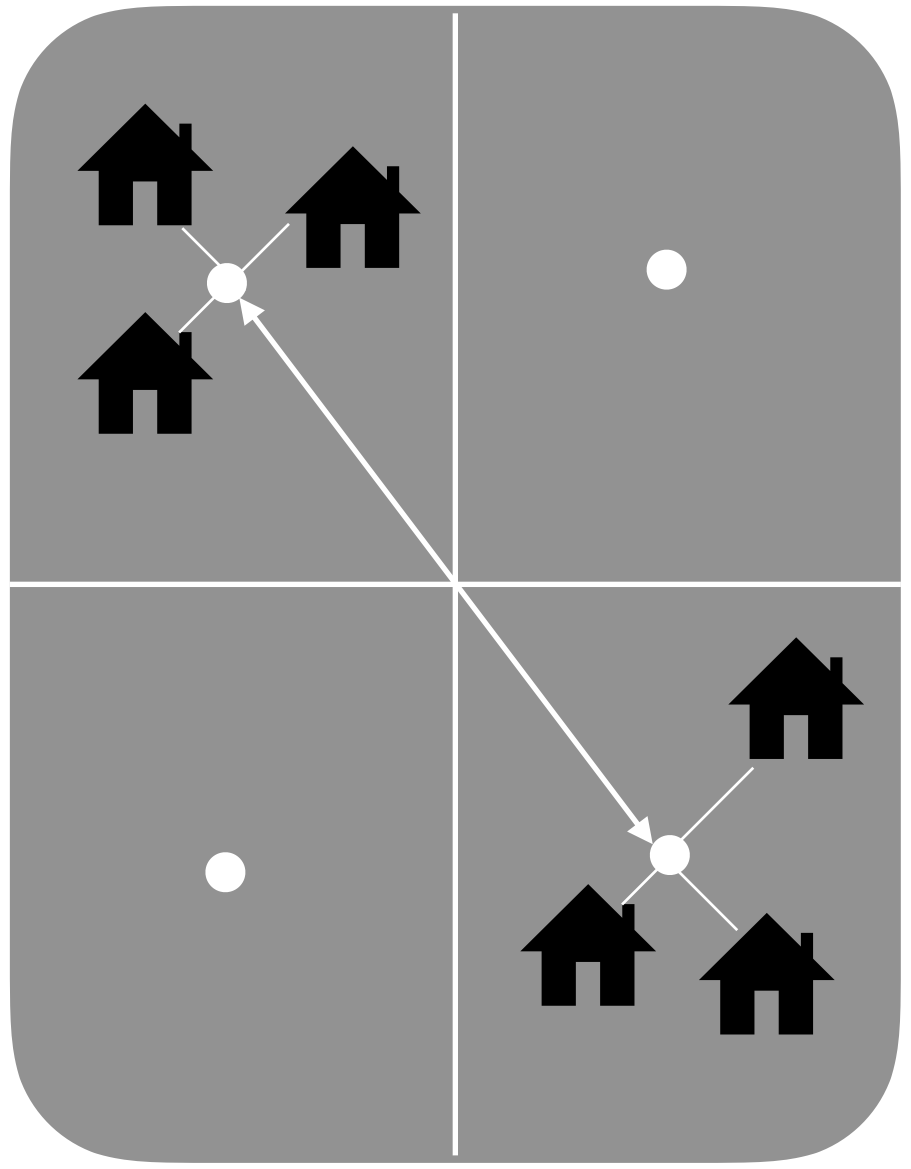
$\rho\left(\{T_1, \boldsymbol{x}_1\}, \{T_1, \boldsymbol{x}_1\}\right) = 1$



No correlation required

‘Same’ buildings, different positions

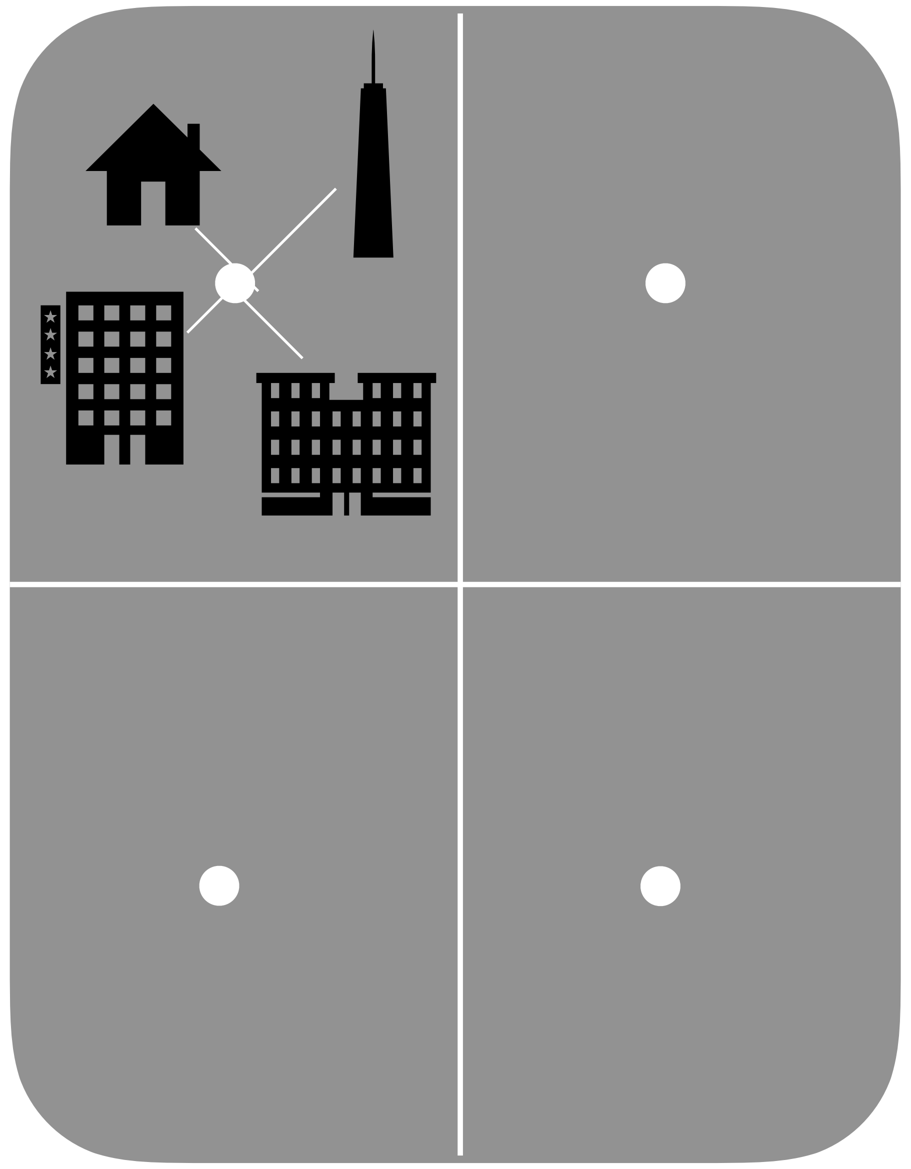
$\rho\left(\{T_1, \boldsymbol{x}_1\}, \{T_1, \boldsymbol{x}_2\}\right) < 1$



Only spatial correlation

Different buildings, ‘same’ position

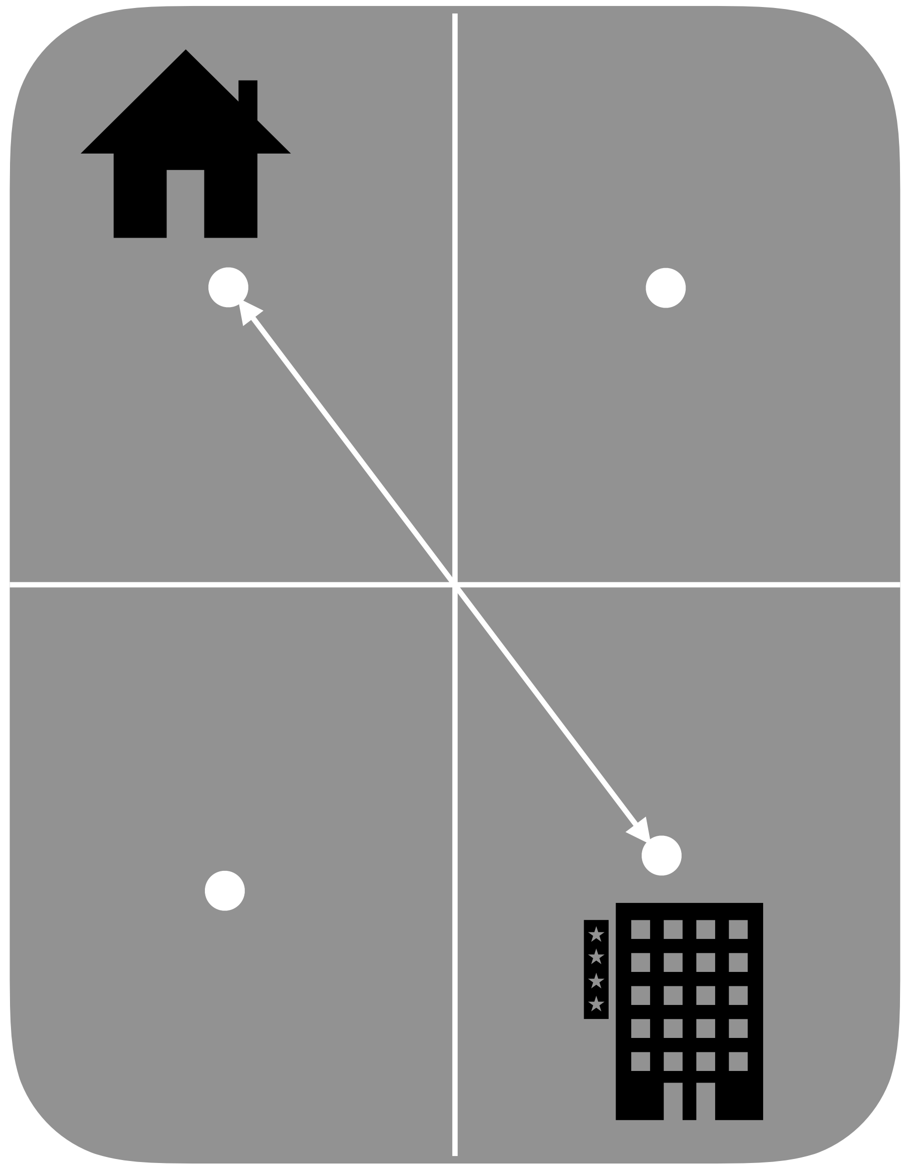
$\rho\left(\{T_1, \boldsymbol{x}_1\}, \{T_2, \boldsymbol{x}_1\}\right) < 1$



Only inter-IM correlation

Different buildings, different positions

$\rho\left(\{T_1, \boldsymbol{x}_1\}, \{T_2, \boldsymbol{x}_2\}\right) < 1$



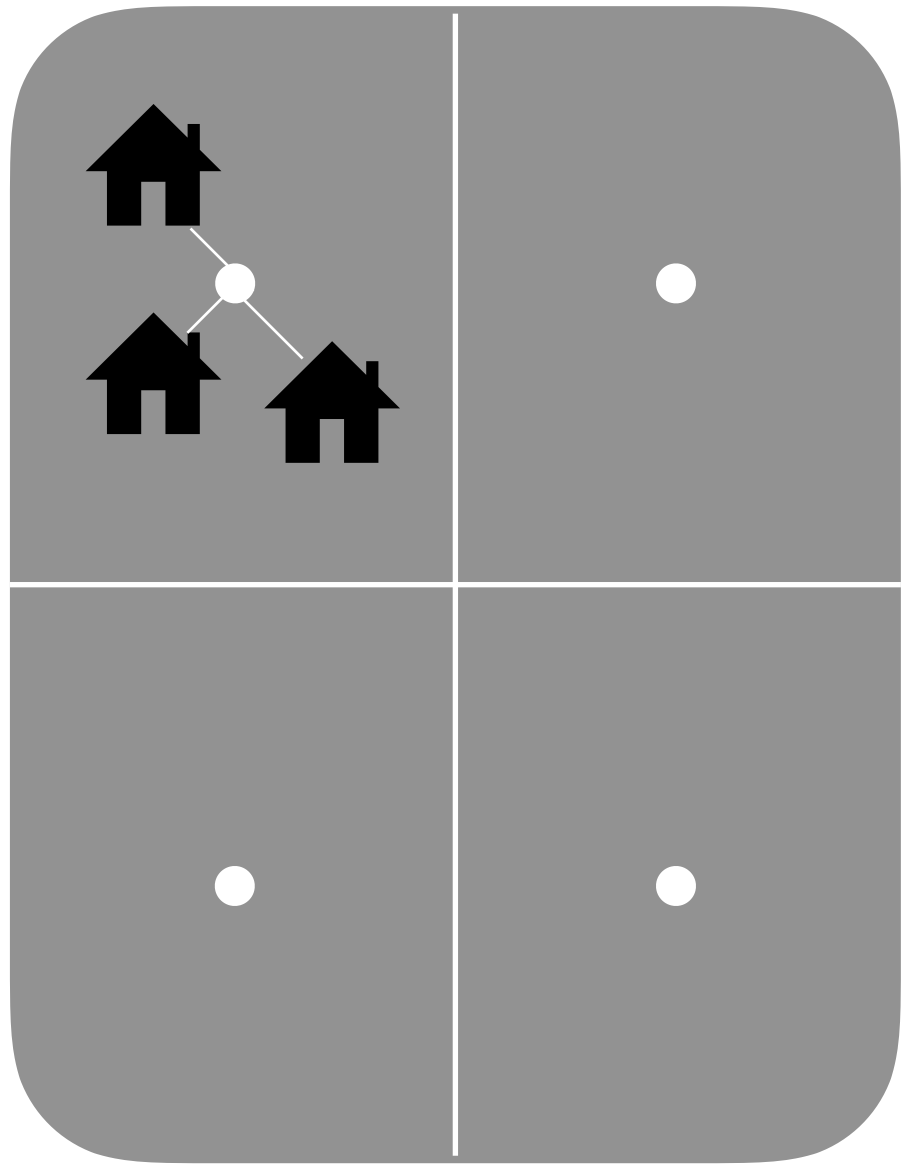
Spatial and inter-IM correlation

Issues with treatment of correlation cases

For a general risk model there are various correlations among IMs that need to be considered

'Same' buildings, 'same' position

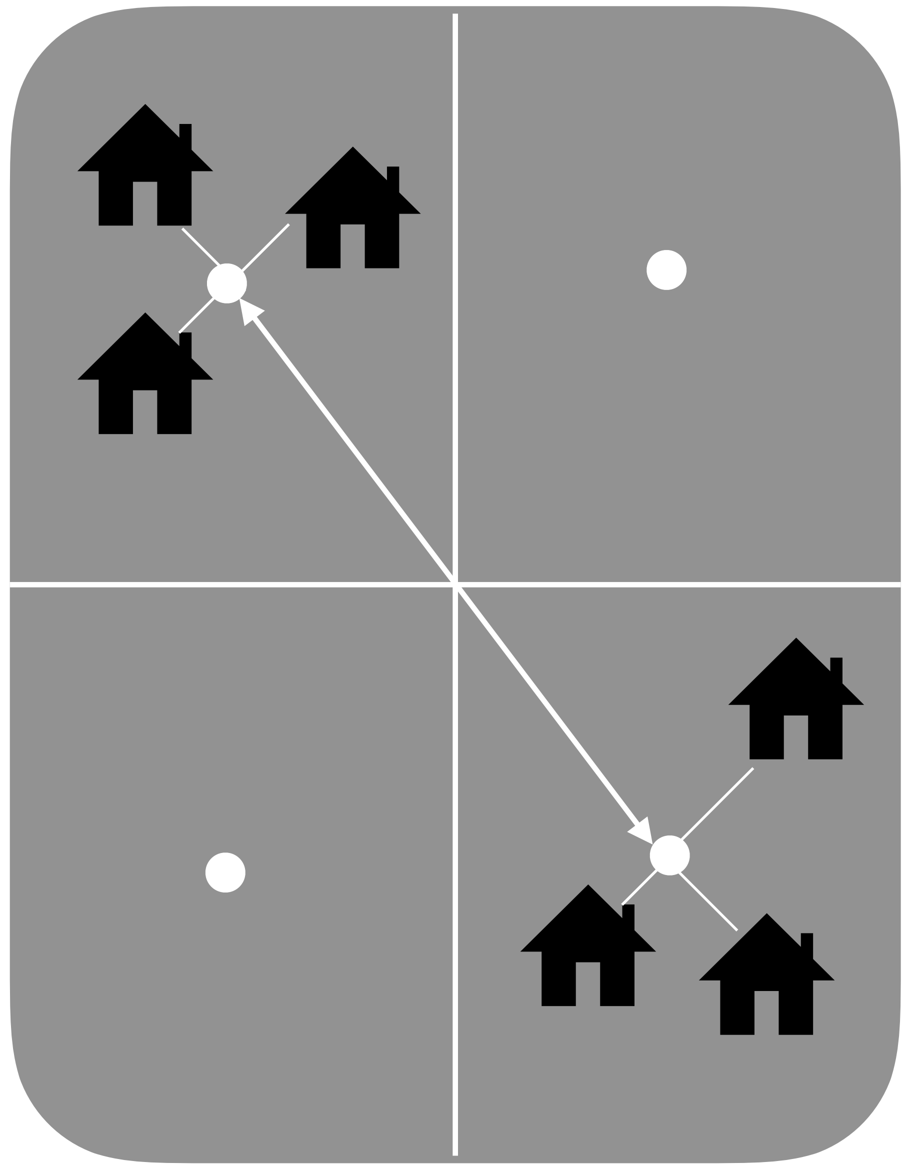
$\rho\left(\{T_1, \boldsymbol{x}_1\}, \{T_1, \boldsymbol{x}_1\}\right) = 1$



All buildings obviously not at the same location - cannot really have perfect correlation within cell

'Same' buildings, different positions

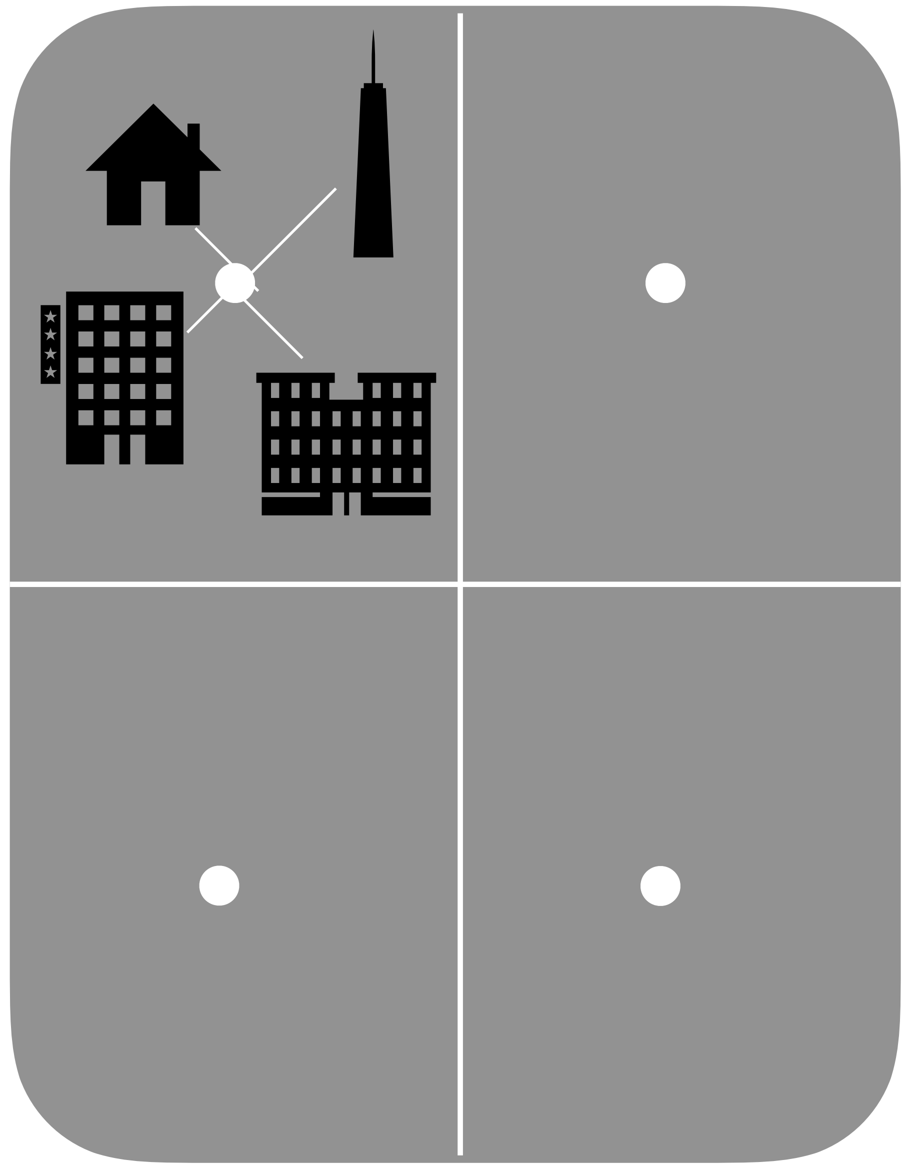
$\rho\left(\{T_1, \boldsymbol{x}_1\}, \{T_1, \boldsymbol{x}_2\}\right) < 1$



Pure spatial correlation from point-to-point ignores spatial distribution of buildings within cells

Different buildings, 'same' position

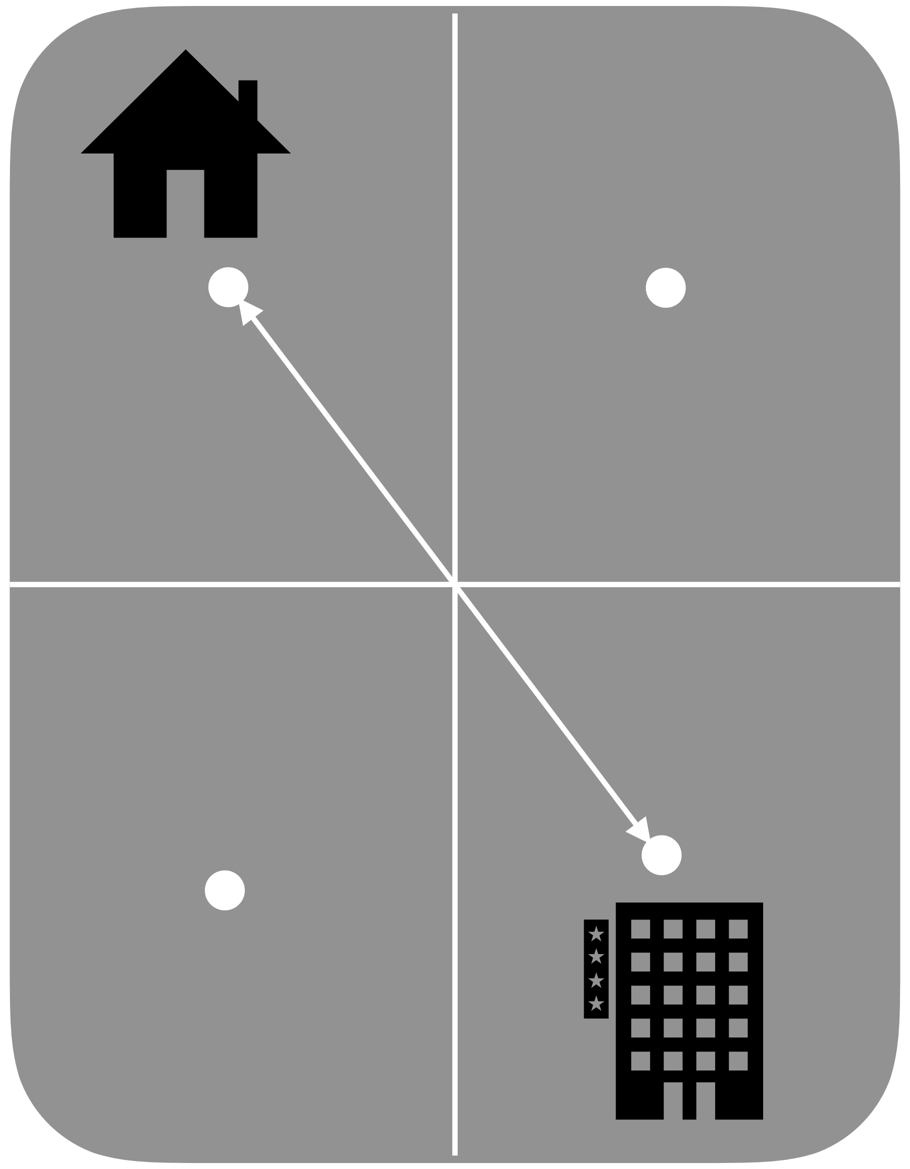
$\rho\left(\{T_1, \boldsymbol{x}_1\}, \{T_2, \boldsymbol{x}_1\}\right) < 1$



Need to down-weight the typical inter-period correlation to reflect spatial distribution

Different buildings, different positions

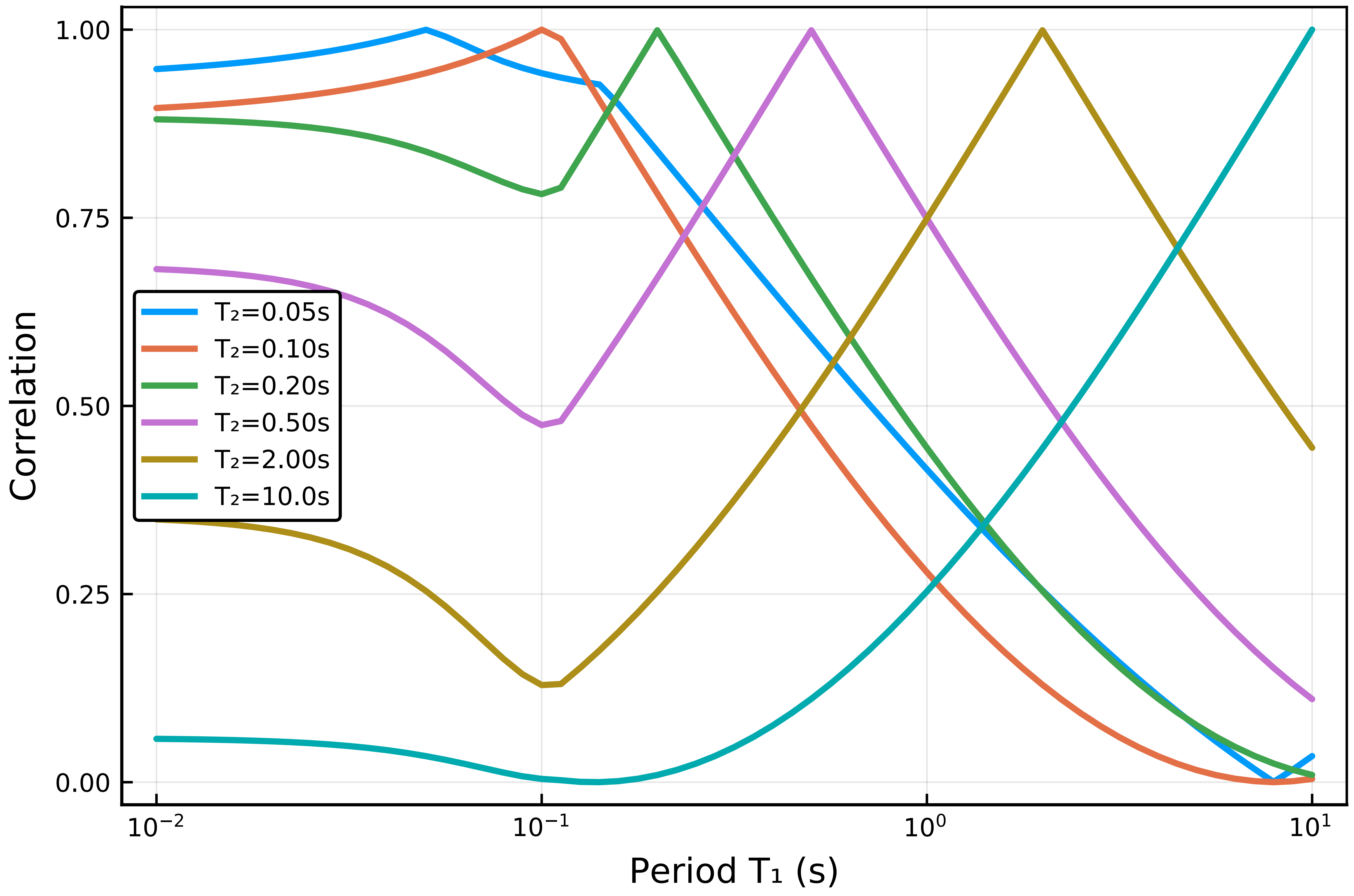
$\rho\left(\{T_1, \boldsymbol{x}_1\}, \{T_2, \boldsymbol{x}_2\}\right) < 1$



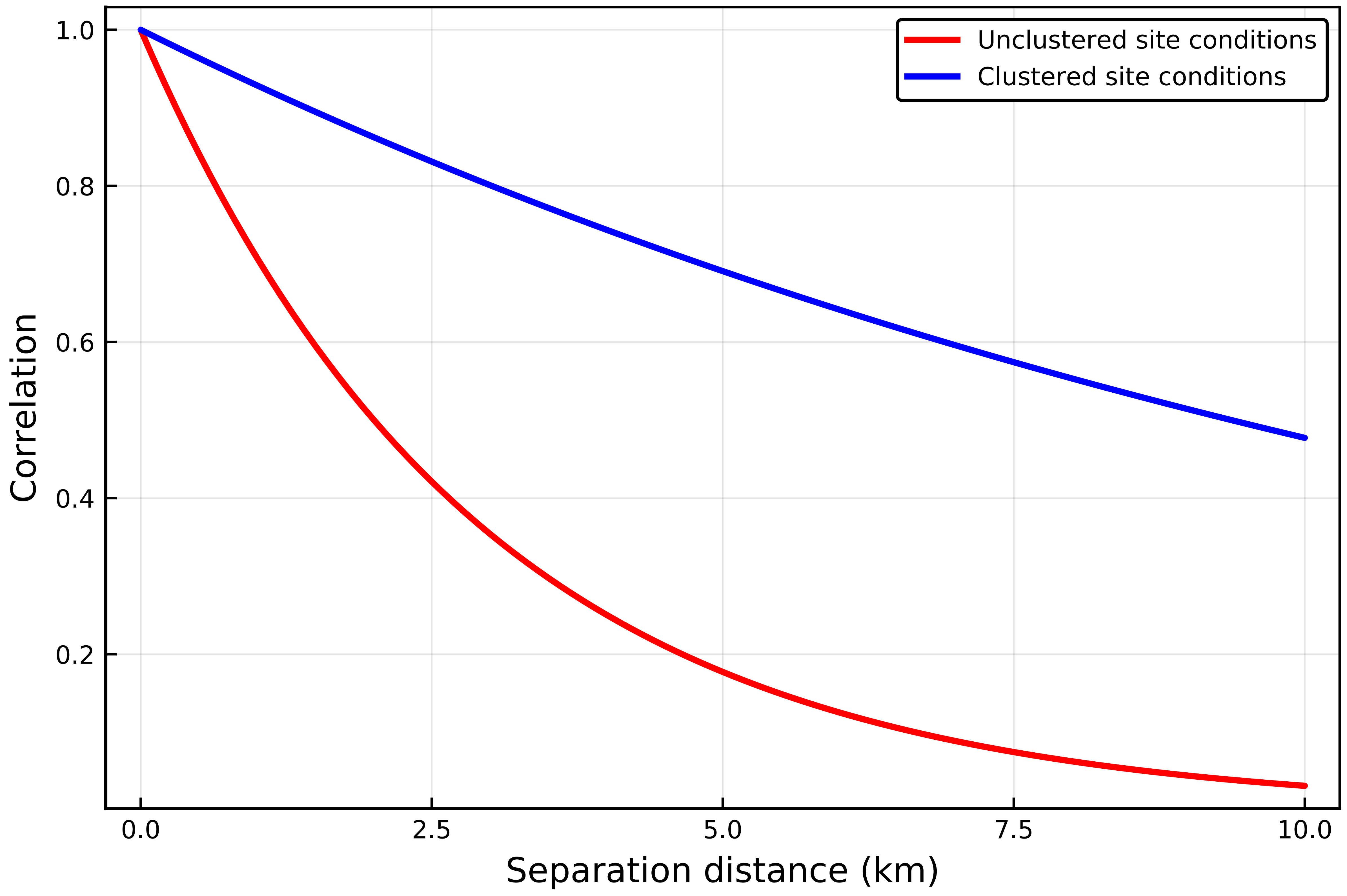
Have to consider possible combinations of actual locations for each building

Markovian approximation

Inter-period correlation from
Baker & Jayaram (2008), $\rho(T_1, T_2)$



Spatial correlation of
Jayaram & Baker (2009), $\rho(\boldsymbol{x}_1, \boldsymbol{x}_2 \,|\, \max(T_1, T_2))$



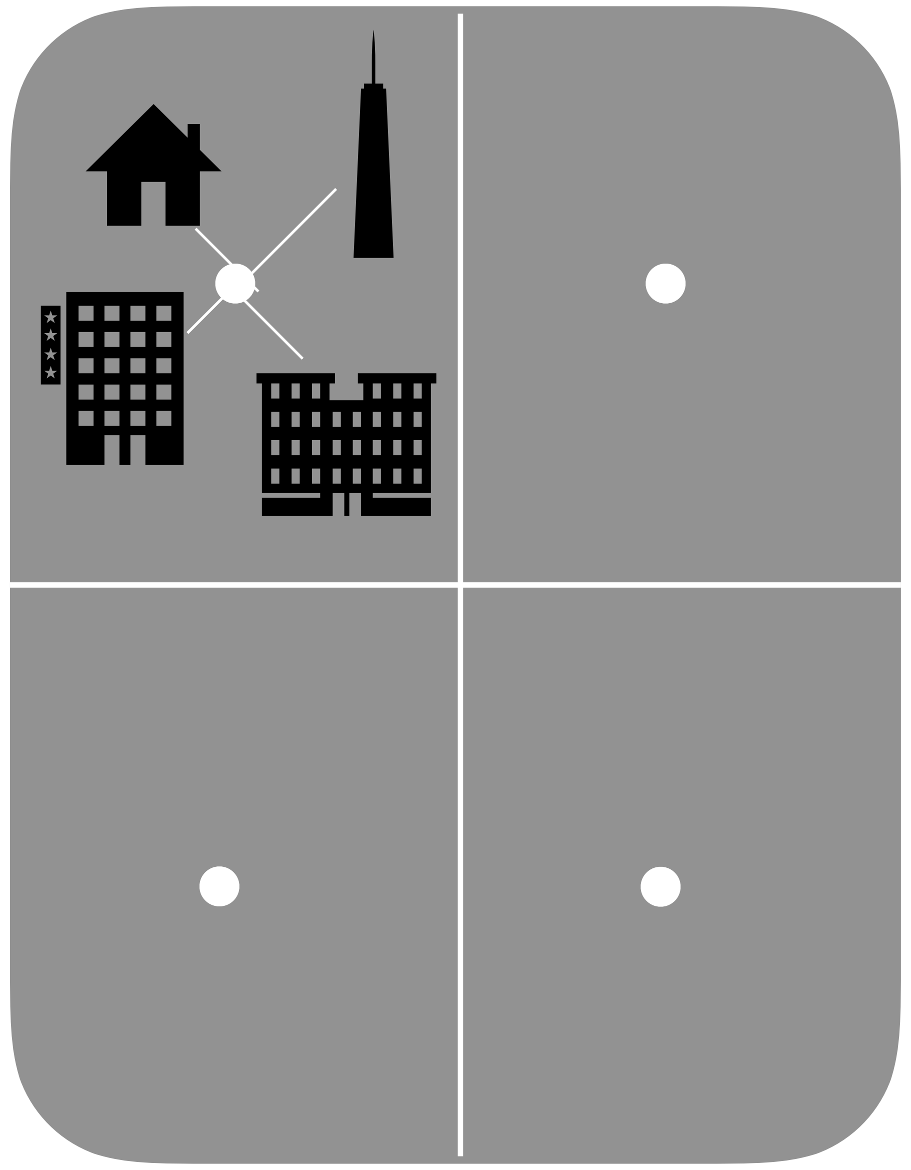
- The correlation between IM_p at location $\boldsymbol{x}_i$ and IM_q at location $\boldsymbol{x}_j$ can be very well approximated by the inter-IM correlation for zero separation distance, and the spatial correlation for the two locations based upon the lowest frequency IM

$$\rho\left(\{T_1, \boldsymbol{x}_1\}, \{T_2, \boldsymbol{x}_2\}\right) \approx \rho(T_1, T_2) \times \rho(\boldsymbol{x}_1, \boldsymbol{x}_2 \,|\, \max(T_1, T_2))$$

Effective inter-period correlations

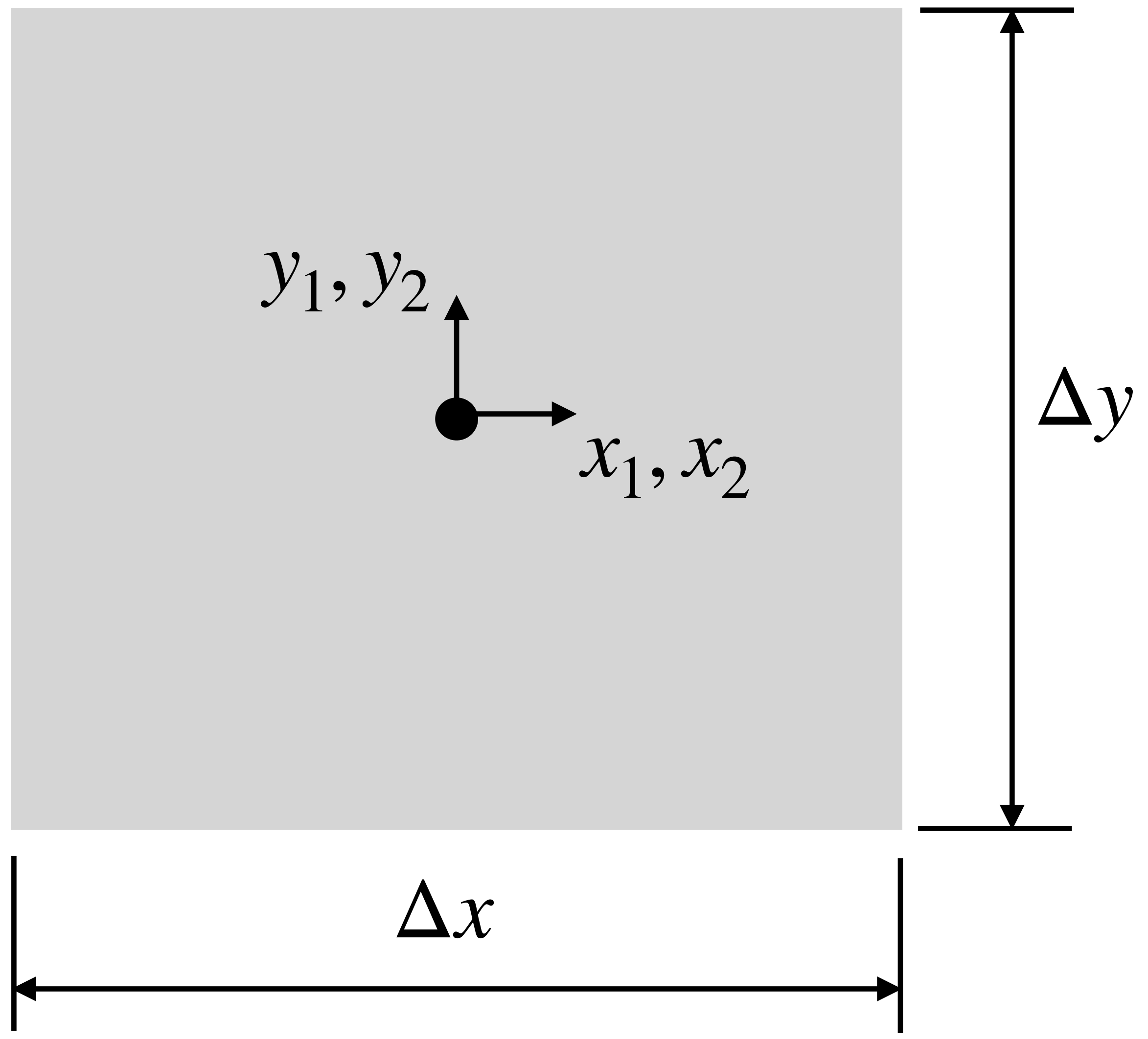
Different buildings, 'same' position

$\rho\left(\{T_1, \boldsymbol{x}_1\}, \{T_2, \boldsymbol{x}_1\}\right) < 1$



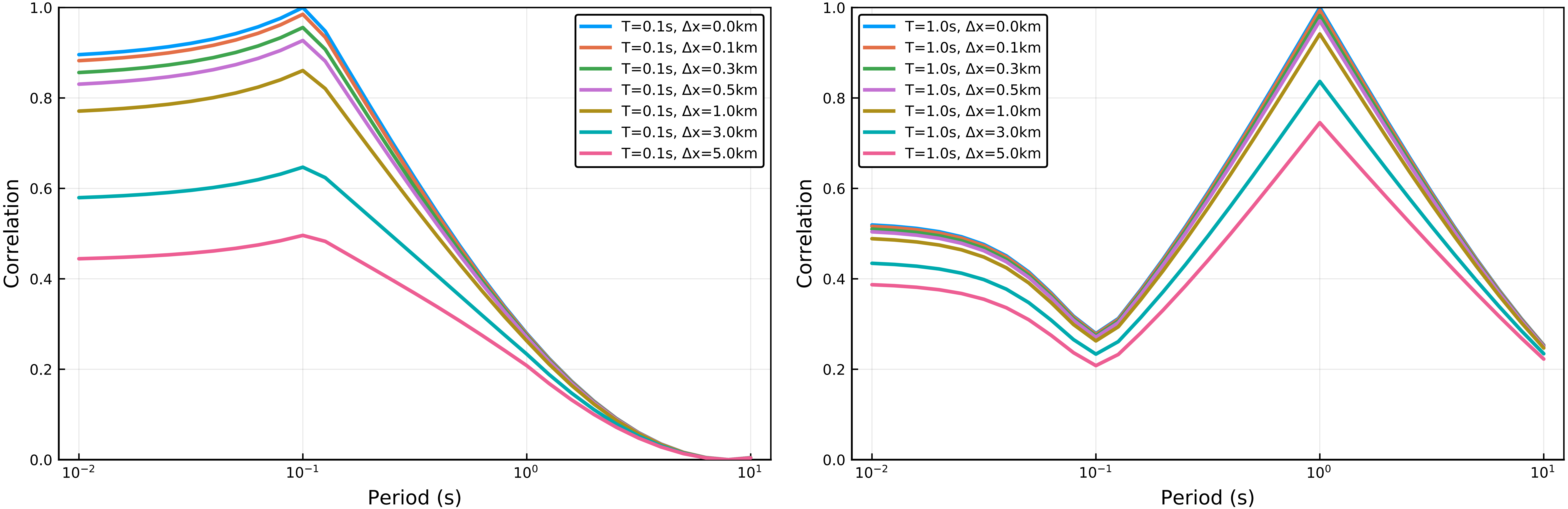
Need to down-weight the typical inter-period correlation to reflect spatial distribution

- Correlation models that are normally used represent correlations among co-located IMs
- However, this isn't really what we want
- Even ignoring the fact that buildings within a class will have different periods (which should be accounted for in the fragility derivation), the spectral demands across buildings within a cell will vary due to their spatial separation



$$\rho_{eff}(T_1, T_2) = \frac{1}{\Delta x^2 \Delta y^2} \iiiint \rho\left(\{x_1, y_1\}, \{x_2, y_2\}, T_1, T_2\right) dx_1 dx_2 dy_1 dy_2$$

Effective inter-period correlations



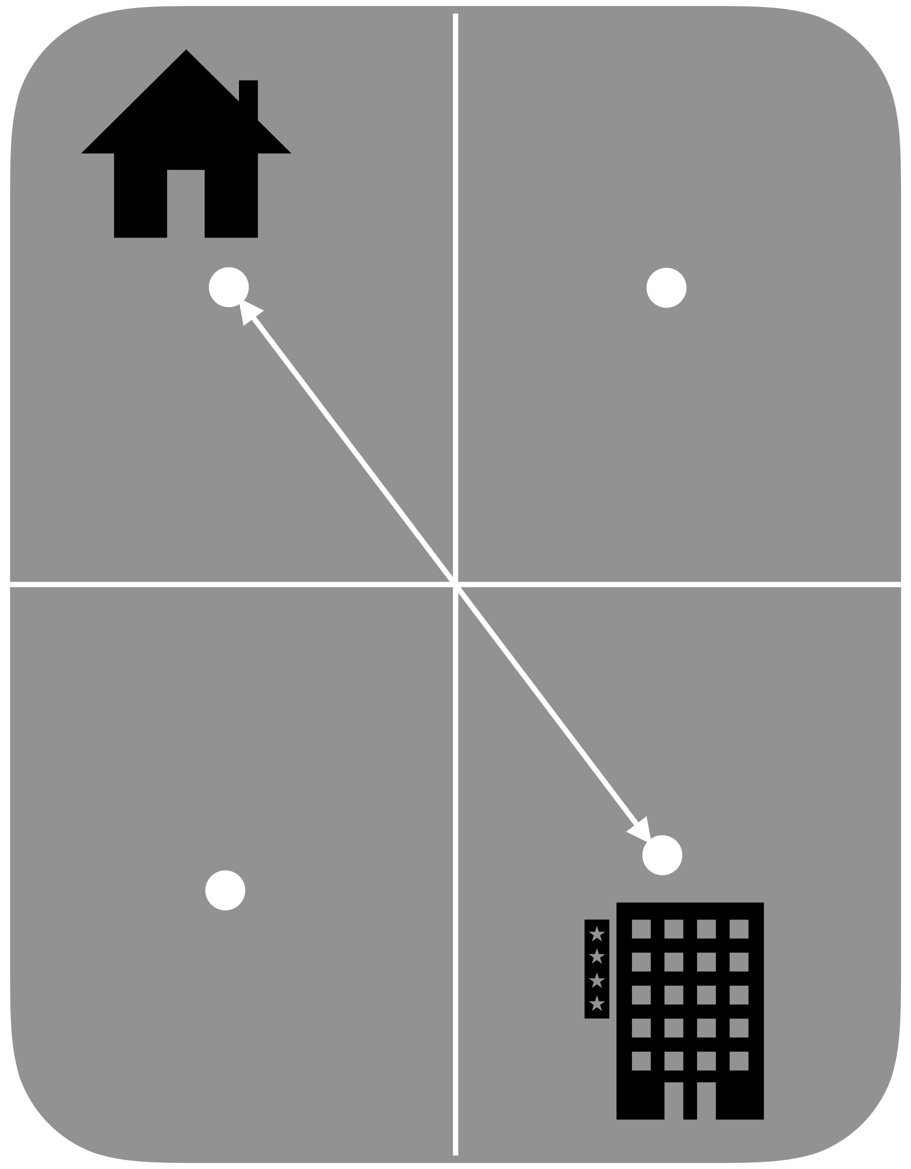
- Naturally, the larger the cell size, the greater the reduction in the inter-period correlation
- One needs to be working at a relatively high resolution in order to ignore this effect
- This reduced inter-period correlation also induces a slight increase in the ground-motion variability for the cell

$$\Delta\sigma(\boldsymbol{x}) \approx \sigma(\boldsymbol{x})\sqrt{1-\rho_{eff}^2}$$

Effective inter-cell correlations

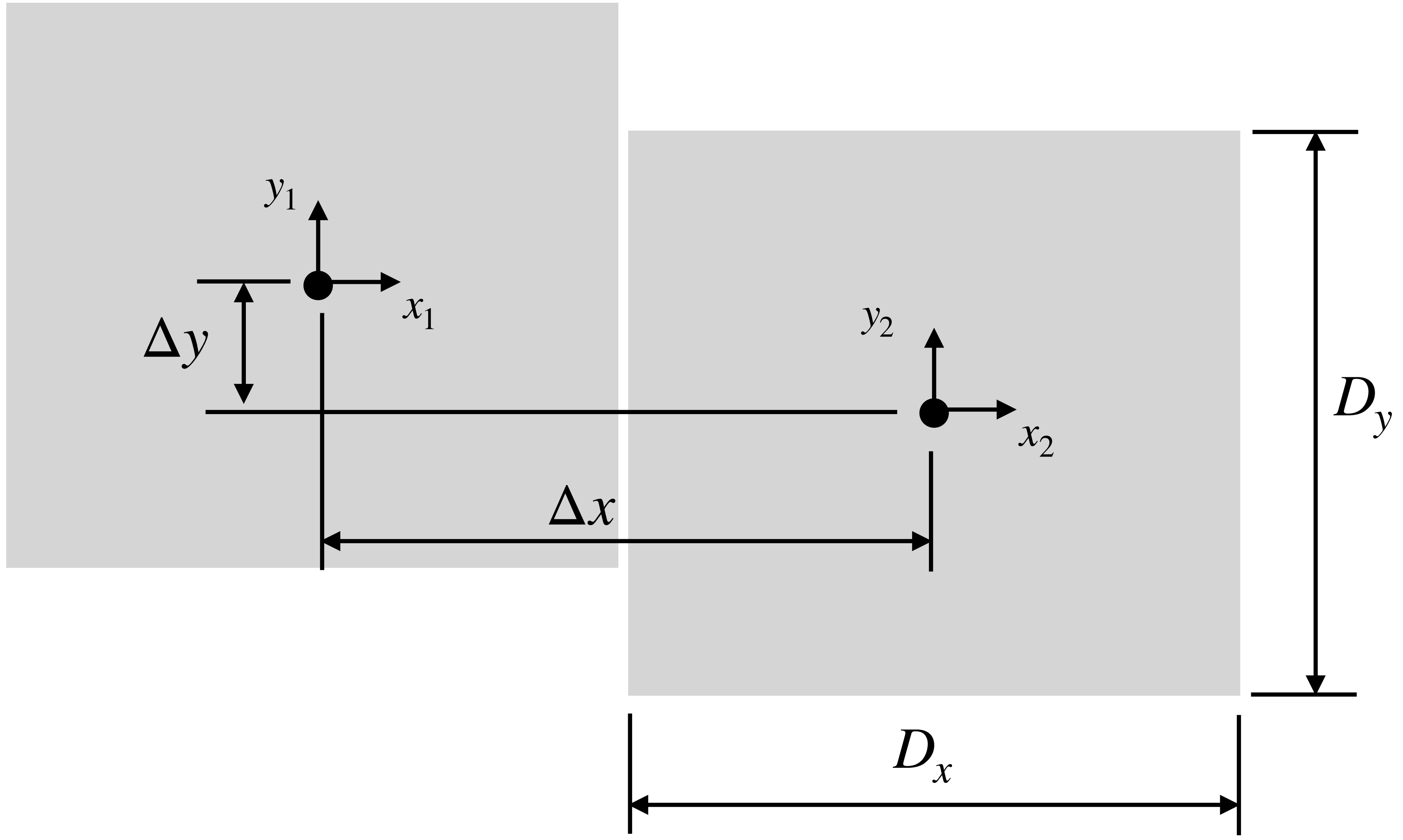
Different buildings, different positions

$\rho\left(\{T_1, \boldsymbol{x}_1\}, \{T_2, \boldsymbol{x}_2\}\right) < 1$



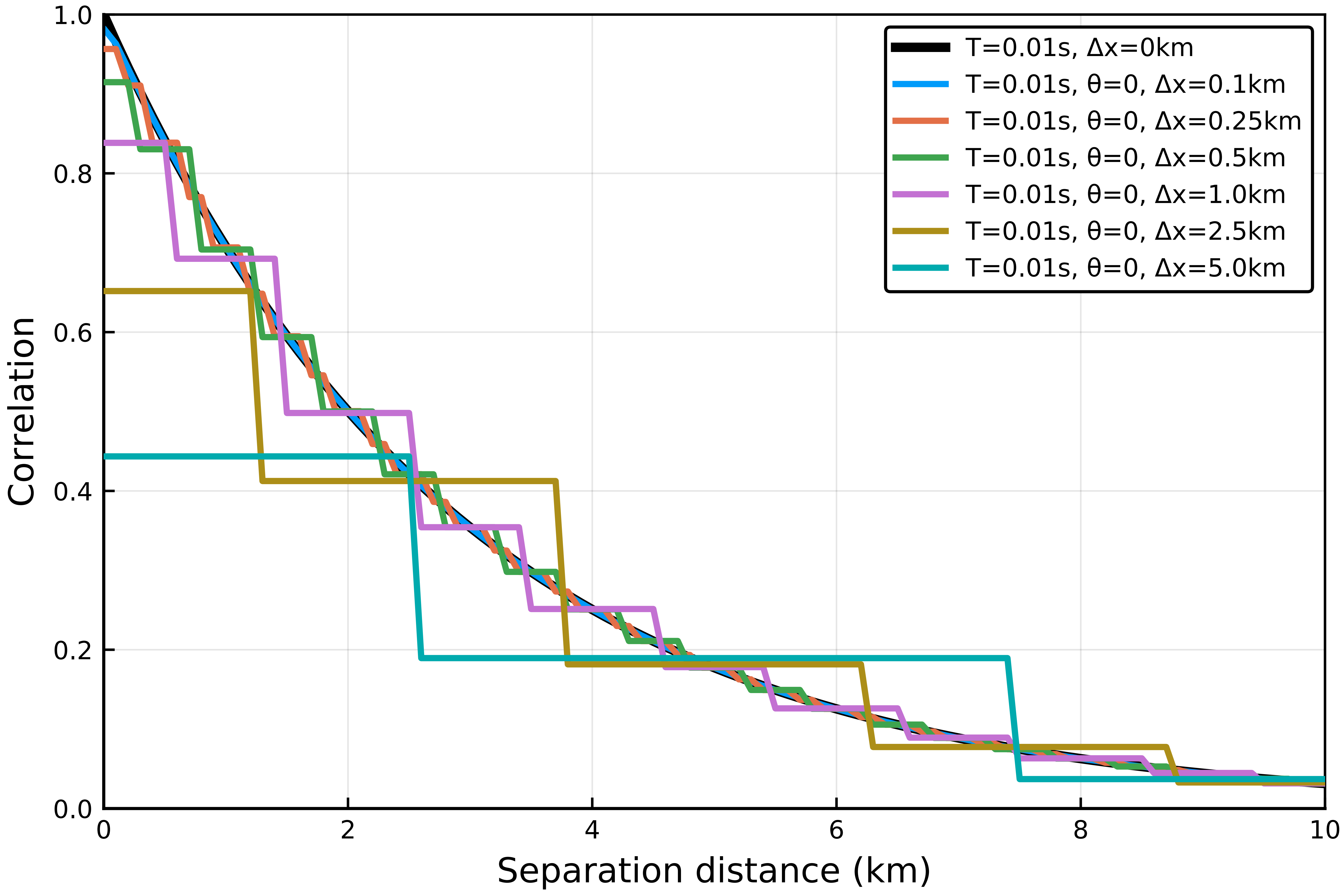
Have to consider possible combinations of actual locations for each building

- Similarly to the effective inter-period correlations, we make the extension of the spatial discretisation over offset cells
- This reflects the unknown location of buildings of different classes throughout the respective cells



$$\rho_{eff}(T_1, T_2) = \frac{1}{D_x^2 D_y^2} \iiiint_{+=\Delta x, +=\Delta y} \rho\left(\{x_1, y_1\}, \{x_2, y_2\}, T_1, T_2\right) dx_1 dx_2 dy_1 dy_2$$

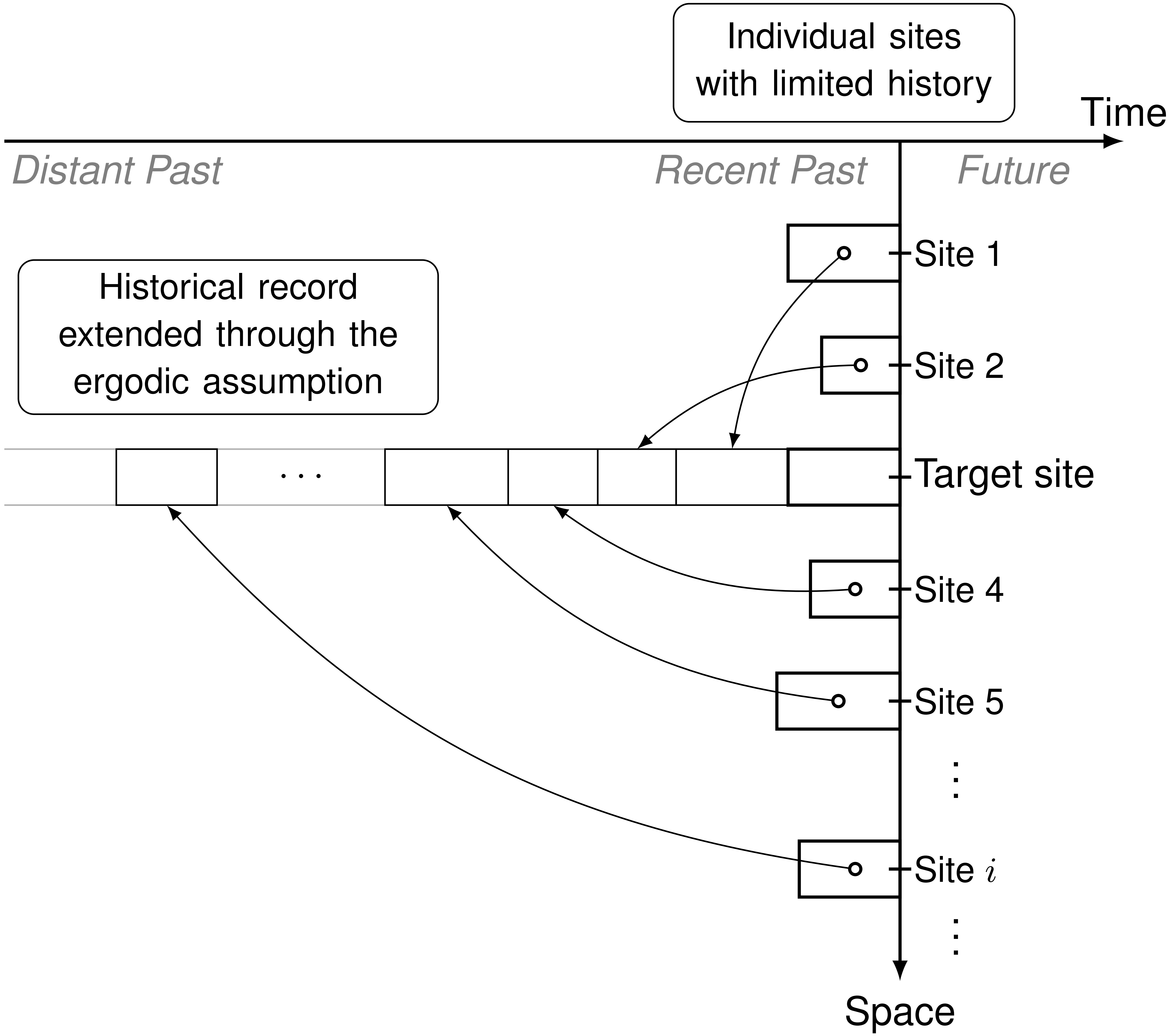
Effective inter-cell correlations



- Largest differences arise at short separation distances where the correlation is most important
- Typically a small reduction in correlation, but it varies with the relative sizes of the cells

The ergodic assumption in ground-motion modelling

Ergodic assumption



- We desire a ground-motion model that reflects the local source, path and site characteristics
- At the same time we want a model that robustly predicts ground-motions for all rupture scenarios of interest in the risk analysis
- We can't have both, so we favour the second point by importing data from other regions
- We assume that this pooled (ergodic) data have the same statistical characteristics as what would be obtained at our target site
- We effectively trade space for time
- In doing so we inflate the variance and over-estimate correlations

Components of ground motion variability

General representation of variability components in ground-motion models for portfolio risk applications

Simulated surface motion (linear case)

Location variate

Between-event variate

Component-to-component variate

$$im(\boldsymbol{x}_s) = \mu(\boldsymbol{x}_s; rup) + \delta_L(\boldsymbol{x}_e) + \delta_B + \delta_{W_{es}}(\boldsymbol{x}_s) + \delta_{S2S}(\boldsymbol{x}_s) + \delta_{C2C}(\boldsymbol{x}_s)$$

Median surface prediction (linear case)

Site & Event corrected within-event variate

Between-site variate

Nonlinear site response complicates this a little as we first predict an motion at some reference velocity horizon (at depth), and then compute the amplification as a function of this motion

Motion at depth: $$im_{ref}(\boldsymbol{x}) = \mu_{ref}(\boldsymbol{x}; rup) + \delta_L(\boldsymbol{x}) + \delta_B + \delta_{W_{es}}(\boldsymbol{x}) + \delta_{C2C}(\boldsymbol{x})$$

Motion at surface: $$im(\boldsymbol{x}) = im_{ref}(\boldsymbol{x}) + \mu_{\ln AF}\left[\boldsymbol{x}, im_{ref}(\boldsymbol{x})\right] + \delta_{S2S}\left[\boldsymbol{x}; im_{ref}(\boldsymbol{x})\right]$$

Components of GM variability

Traditional ergodic approach

$$im(\boldsymbol{x}) = \mu(\boldsymbol{x}; rup) + \delta_B + \delta_W(\boldsymbol{x})$$

$$\boldsymbol{\Sigma}(\boldsymbol{x}; rup) \equiv \tau^2 + \phi^2(\boldsymbol{x})$$

Non-ergodic approach

$$im(\boldsymbol{x}) = \mu(\boldsymbol{x}; rup) + \underbrace{\delta_L(\boldsymbol{x}_e) + \delta_B}_{\delta_B} + \underbrace{\delta_{S2S}(\boldsymbol{x}_s) + \delta_{W_{es}}(\boldsymbol{x}_s)}_{\delta_W(\boldsymbol{x})}$$

ergodic equivalents

$$\boldsymbol{\Sigma}(\boldsymbol{x}; rup) \equiv \underbrace{\tau_L^2(\boldsymbol{x}_e) + \tau_B^2}_{\tau^2} + \underbrace{\phi_{SS}^2(\boldsymbol{x}_s) + \phi_{S2S}^2(\boldsymbol{x}_s)}_{\phi^2(\boldsymbol{x})}$$

ergodic equivalents

The systematic source effect $\delta_L(\boldsymbol{x}_e)$ and systematic site effect $\delta_{S2S}(\boldsymbol{x}_s)$ are actually **epistemic** terms that should be reflected within a logic tree rather than in the aleatory variability

Components of GM variability

Non-ergodic approach

$$im(\boldsymbol{x}) = \mu(\boldsymbol{x}; rup) + \underbrace{\hat{\delta}_L(\boldsymbol{x}_e) + \delta_B}_{\delta_B} + \underbrace{\hat{\delta}_{S2S}(\boldsymbol{x}_s) + \delta_{W_{es}}(\boldsymbol{x}_s)}_{\delta_W(\boldsymbol{x})}$$

ergodic equivalents

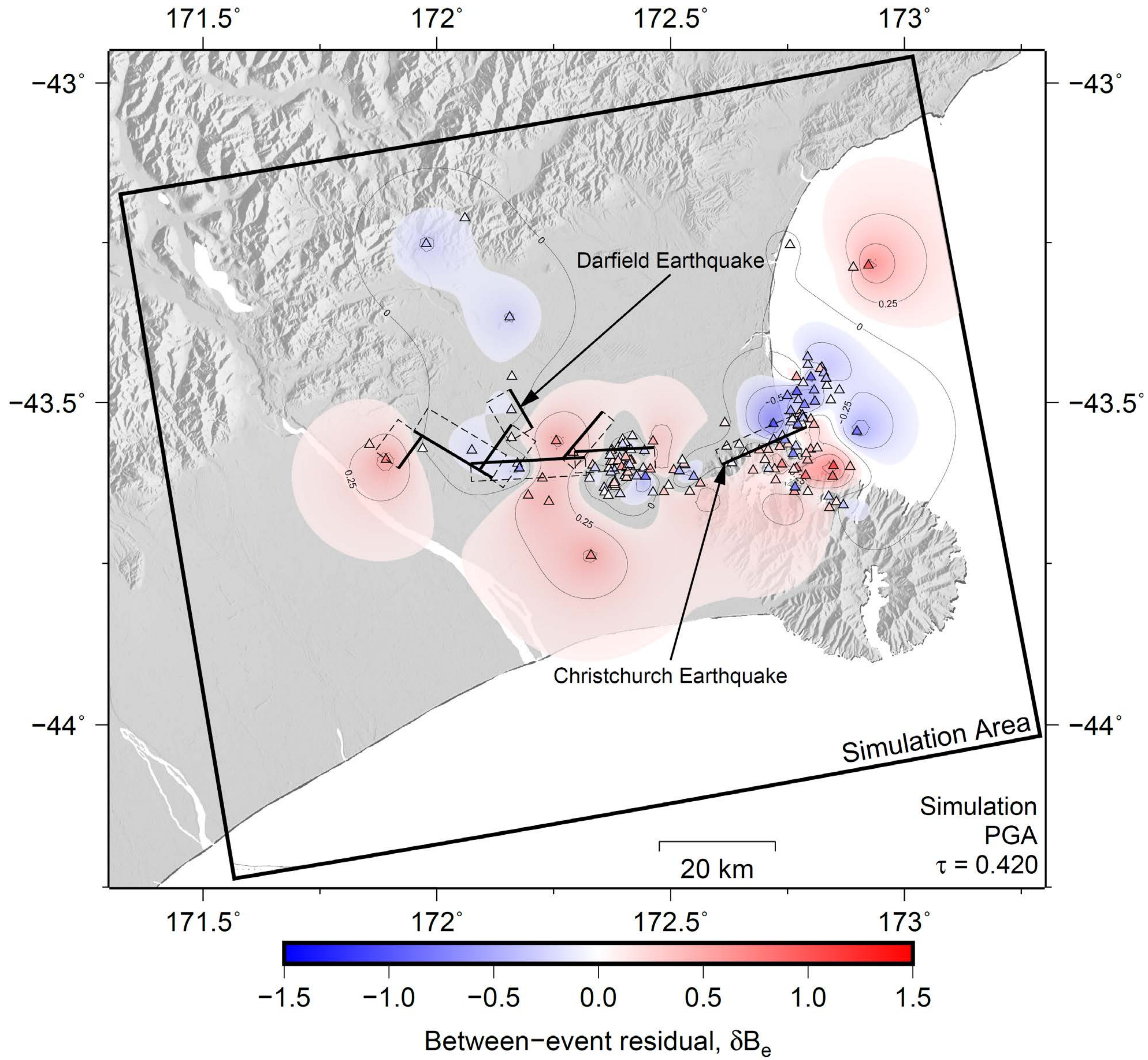
$$\boldsymbol{\Sigma}(\boldsymbol{x}; rup) \equiv \underbrace{\cancel{\tau_L^2(\boldsymbol{x}_e)} + \tau_B^2}_{\tau^2} + \underbrace{\phi_{SS}^2(\boldsymbol{x}_s) + \cancel{\phi_{S2S}^2(\boldsymbol{x}_s)}}_{\phi^2(\boldsymbol{x})}$$

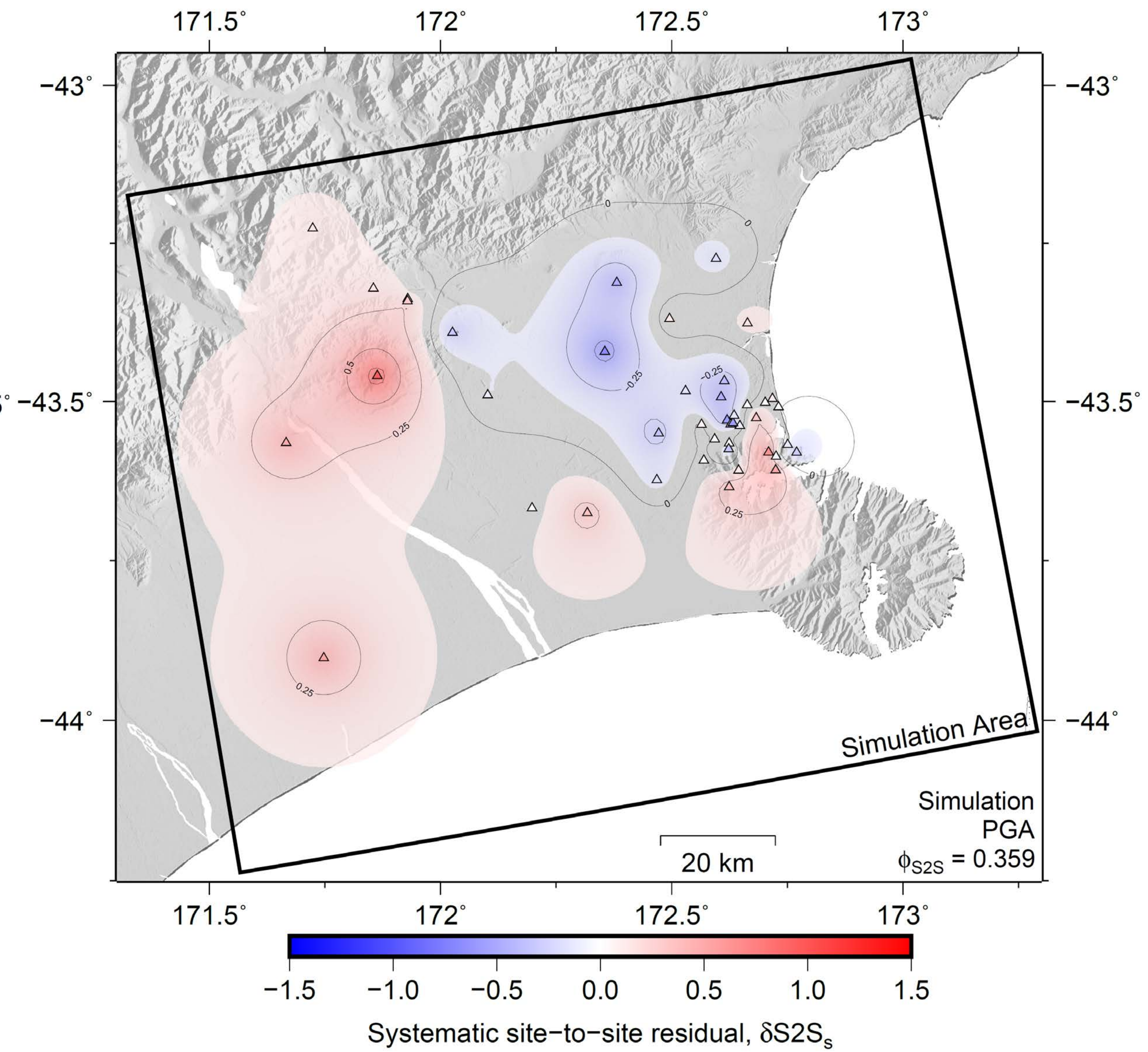
ergodic equivalents

With the systematic source effect $\delta_L(\boldsymbol{x}_e)$ and systematic site effect $\delta_{S2S}(\boldsymbol{x}_s)$ estimated, the covariance terms reduce as $\tau_B^2 < \tau^2$ and $\phi_{SS}^2(\boldsymbol{x}) < \phi^2(\boldsymbol{x})$

As noted yesterday, Istanbul is exposed to a very particular rupture scenario, and relatively good information exists regarding the near-surface geotechnical profiles

Systematic source & site effects

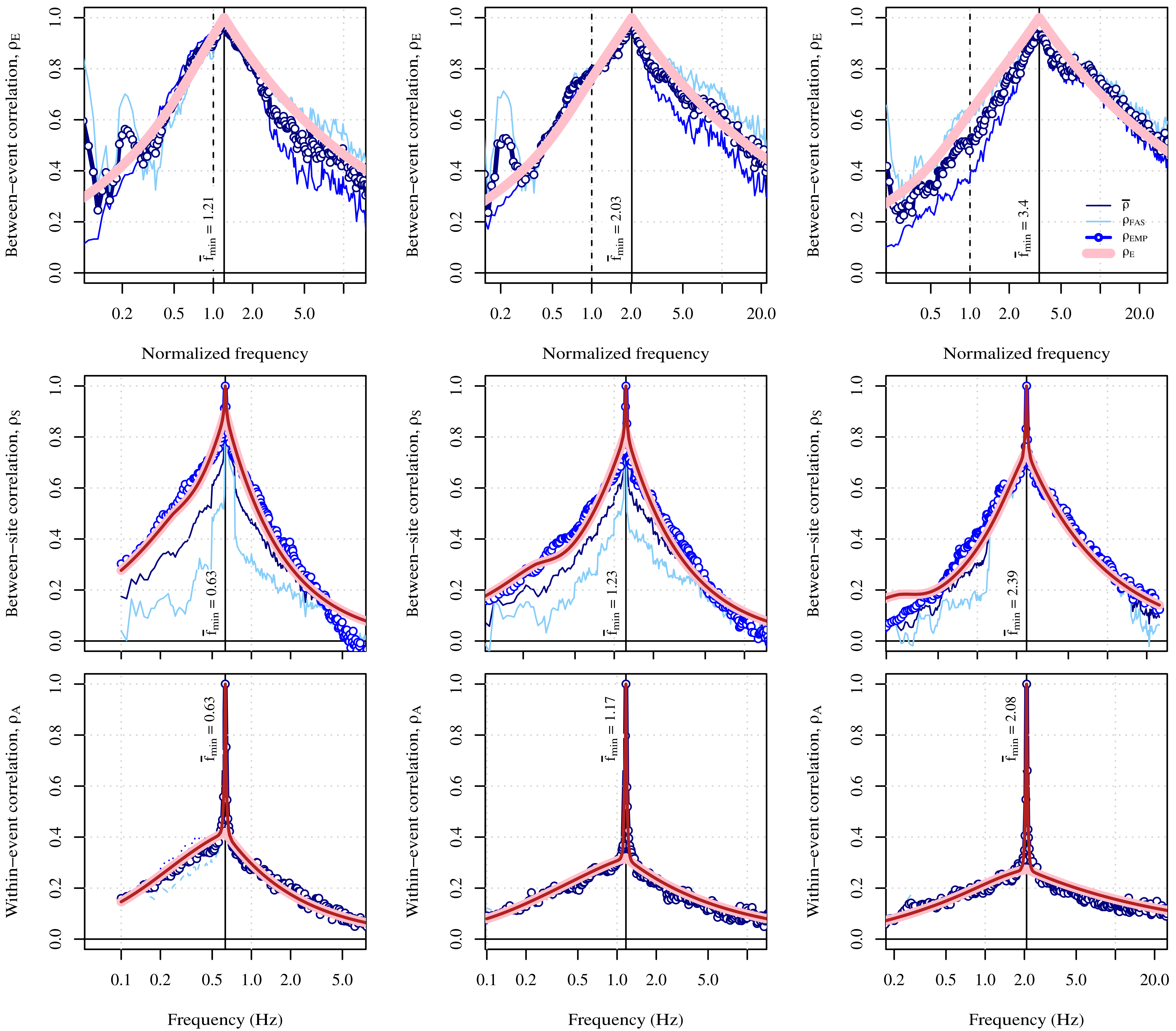




Lee *et al*. (2019)

Impact upon inter-period correlation

- Here inter-frequency correlations among Fourier spectral ordinates are shown
- Correlations among the between-site components is relatively strong and so the removal of these effects reduces the overall correlation
- This maps through to inter-period correlations among response spectral ordinates



Impact upon spatial correlation

- Jayaram & Baker (2009) presented a now widely-adopted spatial correlation model

- They use an exponential model that has a different correlation length, r, for periods below 1.0 seconds, depending upon whether site conditions are 'clustered' or 'unclustered'

- This approach was motivated by strongly different correlation lengths found in different regions (and soil conditions were held responsible)

- Their model is **ergodic** and can be expressed as:

$$\ln Sa(\boldsymbol{x}) = \mu_{\ln Sa}(\boldsymbol{x}; rup) + \delta_B + \delta_W(\boldsymbol{x}) \qquad \delta_B \sim N\left(0, \tau^2\right) \qquad \delta_W(\boldsymbol{x}) \sim MVN\left(\boldsymbol{0}, \phi^2(\boldsymbol{x})\boldsymbol{R}(\boldsymbol{x})\right)$$

$$\rho\left(\delta_W(\boldsymbol{x}_i), \delta_W(\boldsymbol{x}_j)\right) = \exp\left(-\frac{||\boldsymbol{x}_i - \boldsymbol{x}_j||}{r}\right) = \exp\left(-\frac{\Delta}{r}\right) = \rho(\Delta)$$

Ergodic spatial correlation

Non-ergodic spatial correlation

- If we partition the variance so that we have systematic event and site effects then we rewrite the model as:

$$\ln Sa(\boldsymbol{x}) = \mu_{\ln Sa}(\boldsymbol{x}; rup) + \delta_B + \delta_{S2S}(\boldsymbol{x}) + \delta_{W_{es}}(\boldsymbol{x})$$

$$\delta_B \sim N\left(0, \tau^2\right)$$

$$\delta_{S2S}(\boldsymbol{x}) \sim MVN\left[\mathbf{0}, \phi_{S2S}^2(\boldsymbol{x})\boldsymbol{R}_S(\boldsymbol{x})\right]$$

$$\delta_{W_{es}}(\boldsymbol{x}) \sim MVN\left[\mathbf{0}, \phi_{SS}^2(\boldsymbol{x})\boldsymbol{R}_W(\boldsymbol{x})\right]$$

- The overall within-event spatial correlation in this case is represented by:

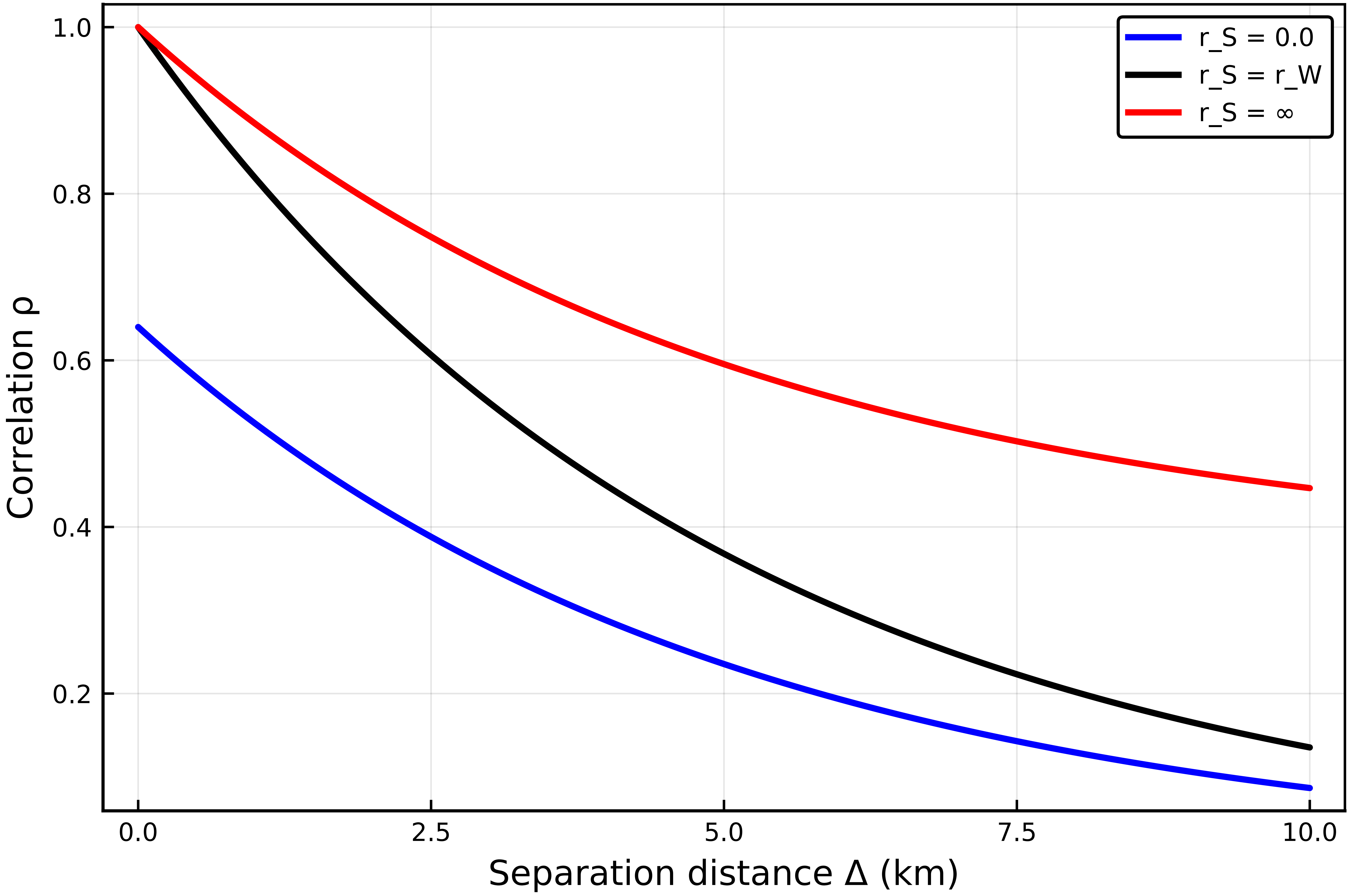
$$\rho\left[\delta_W(\boldsymbol{x}_i), \delta_W(\boldsymbol{x}_j)\right] = \frac{\rho_W(\boldsymbol{x}_i, \boldsymbol{x}_j)\phi_{SS}(\boldsymbol{x}_i)\phi_{SS}(\boldsymbol{x}_j) + \rho_S(\boldsymbol{x}_i, \boldsymbol{x}_j)\phi_{S2S}(\boldsymbol{x}_i)\phi_{S2S}(\boldsymbol{x}_j)}{\phi(\boldsymbol{x}_i)\phi(\boldsymbol{x}_j)}$$

$$\phi^2 = \phi_{SS}^2 + \phi_{S2S}^2$$

- Express the spatial correlations among δ_{S2S} terms and among $\delta_{W_{es}}$ terms as exponential models

$$\rho_S(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp\left(-\frac{\Delta}{r_S}\right) \qquad \rho_W(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp\left(-\frac{\Delta}{r_W}\right)$$

Non-ergodic spatial correlation

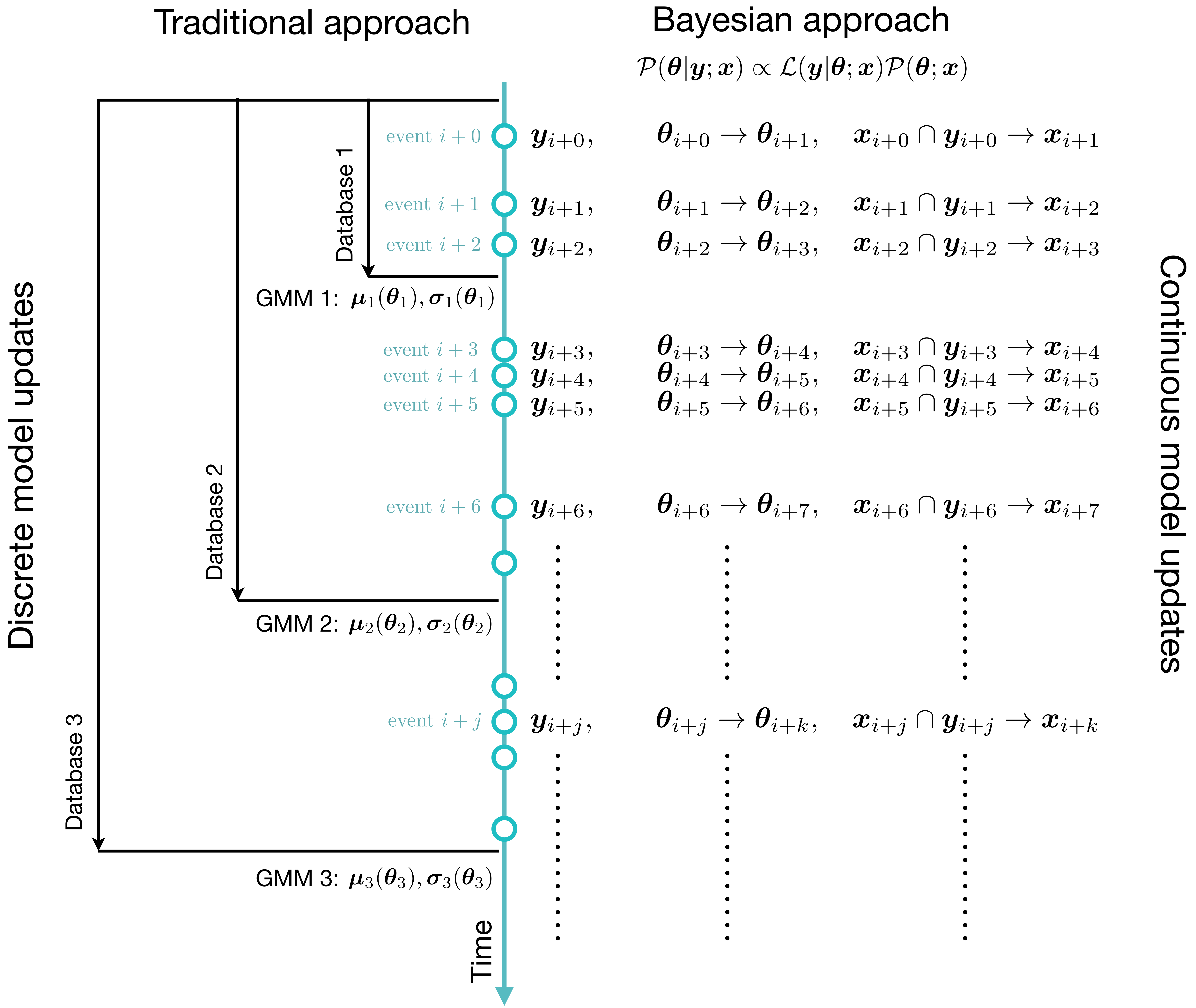


- We can therefore consider the ergodic correlation model as being contaminated by correlations among systematic site effects (epistemic terms) that have some correlation length r_S

$$\rho(\Delta) = \frac{1}{\phi^2}\left[\phi_{SS}^2 e^{-\frac{\Delta}{r_W}} + \phi_{S2S}^2 e^{-\frac{\Delta}{r_S}}\right]$$

- Consider limiting cases of $r_S \to \infty$ (perfectly correlated site conditions) and $r_S \to 0$ (completely random site conditions)
- Jayaram & Baker's clustered vs non-clustered results just reflect implicit r_S values for the regions they investigated

Continuous updating of GMM

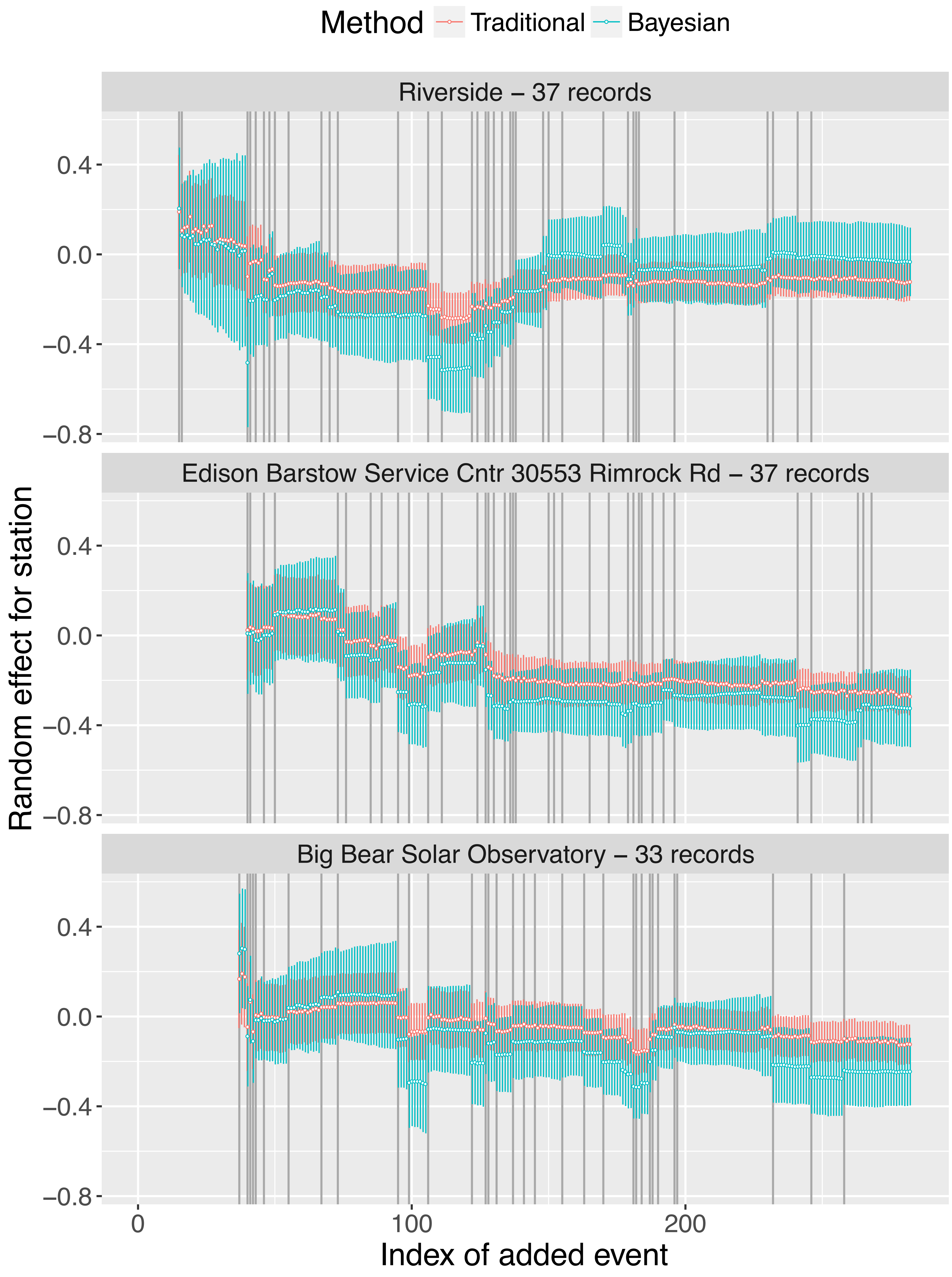


Continuous update of systematic site effects

- In a given region, as every new event is recorded we can revise estimates of the systematic site effect

- For a risk model this would have implications upon the amount of epistemic uncertainty that exists at each site

- This change in uncertainty should also cause updates in the spatial correlations among systematic site effects



Non-ergodic risk analyses for seismic sequences

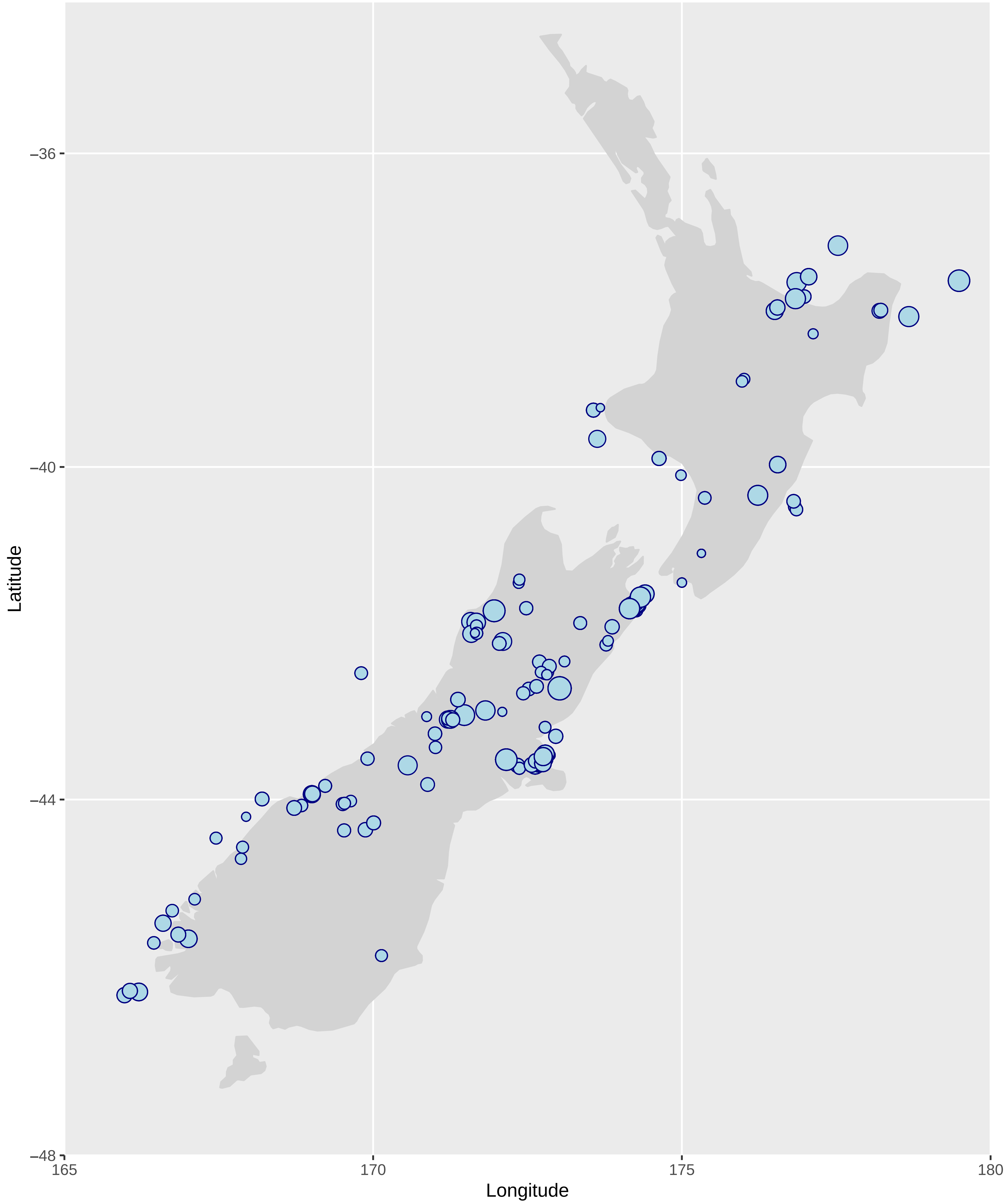
Earthquake sequences

- Consider risk analysis for earthquake sequences - look at a couple of NZ examples

- Usually ongoing risk analyses continue to make use of generic ergodic ground-motion models

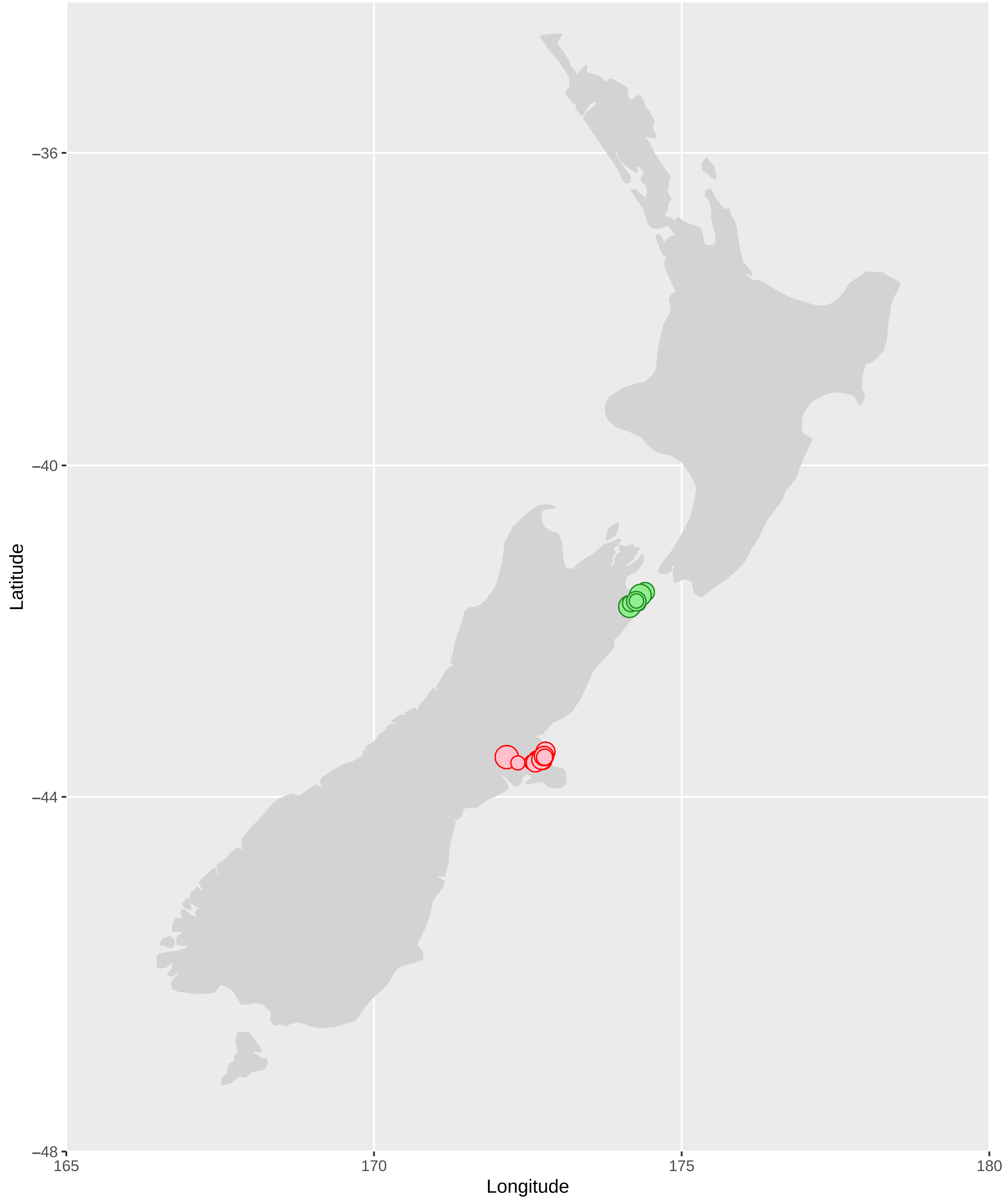
$$im(\boldsymbol{x}) = \mu(\boldsymbol{x}; rup) + \delta_L(\boldsymbol{x}_e) + \underbrace{\delta_C + \delta_{B,C}}_{\text{cluster-specific effect, and within-cluster source effect}} + \delta_{S2S}(\boldsymbol{x}_s) + \delta_{W_{es}}(\boldsymbol{x}_s)$$

$$\boldsymbol{\Sigma}(\boldsymbol{x}; rup) \equiv \tau_L^2(\boldsymbol{x}_e) + \underbrace{\tau_C^2 + \tau_{B,C}^2}_{\text{cluster-specific effect, and within-cluster source variability}} + \phi_{SS}^2(\boldsymbol{x}_s) + \phi_{S2S}^2(\boldsymbol{x}_s)$$



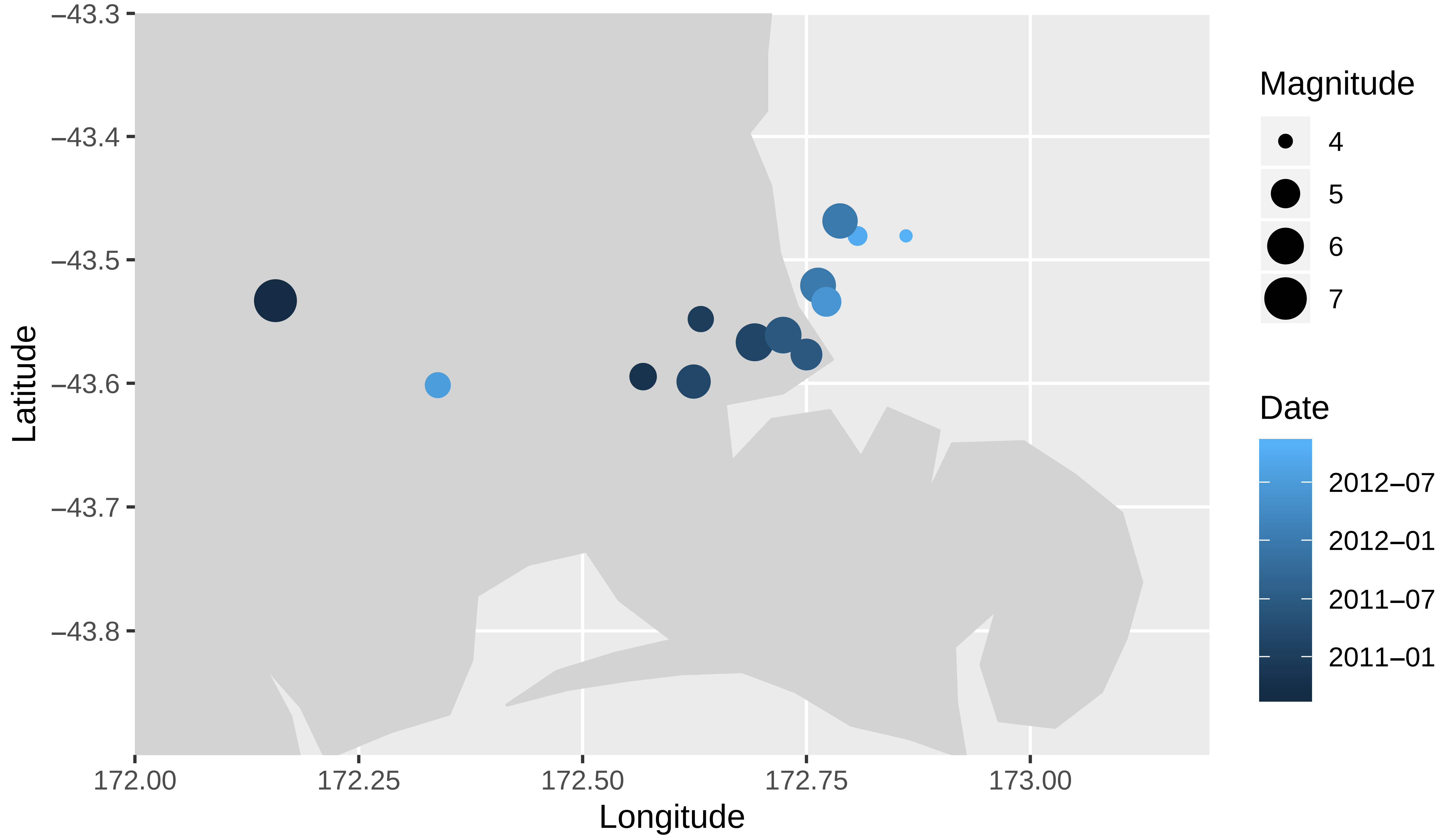
Earthquake sequences

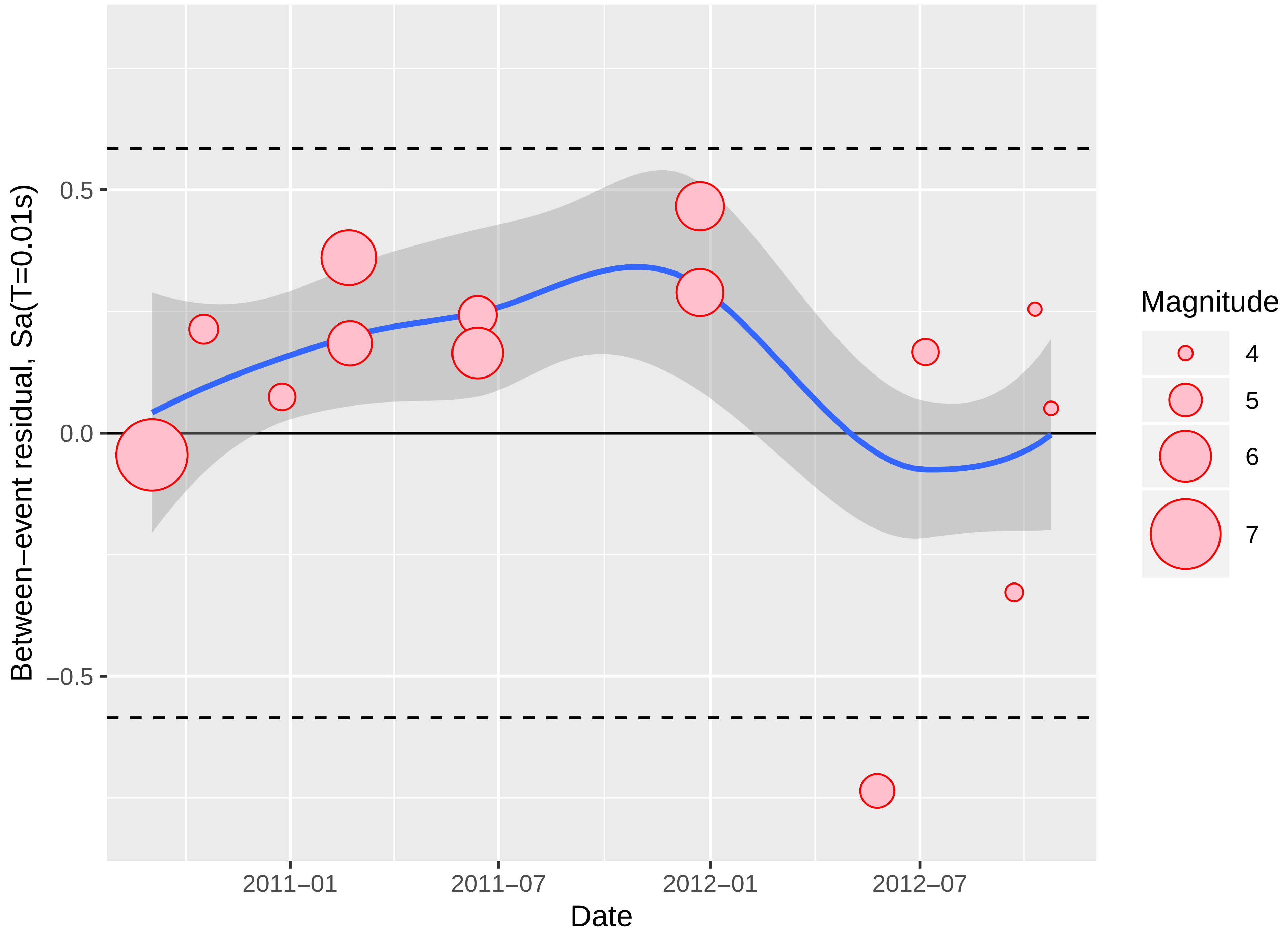
- Identify largest clusters according to the Gardner & Knopoff declustering algorithm
- Look at the between-event residuals (event random effects) for the events within these clusters
- Compare the variation of these random effects in time
- Compare the variability of random effects within cluster to that obtained for the entire NZ database

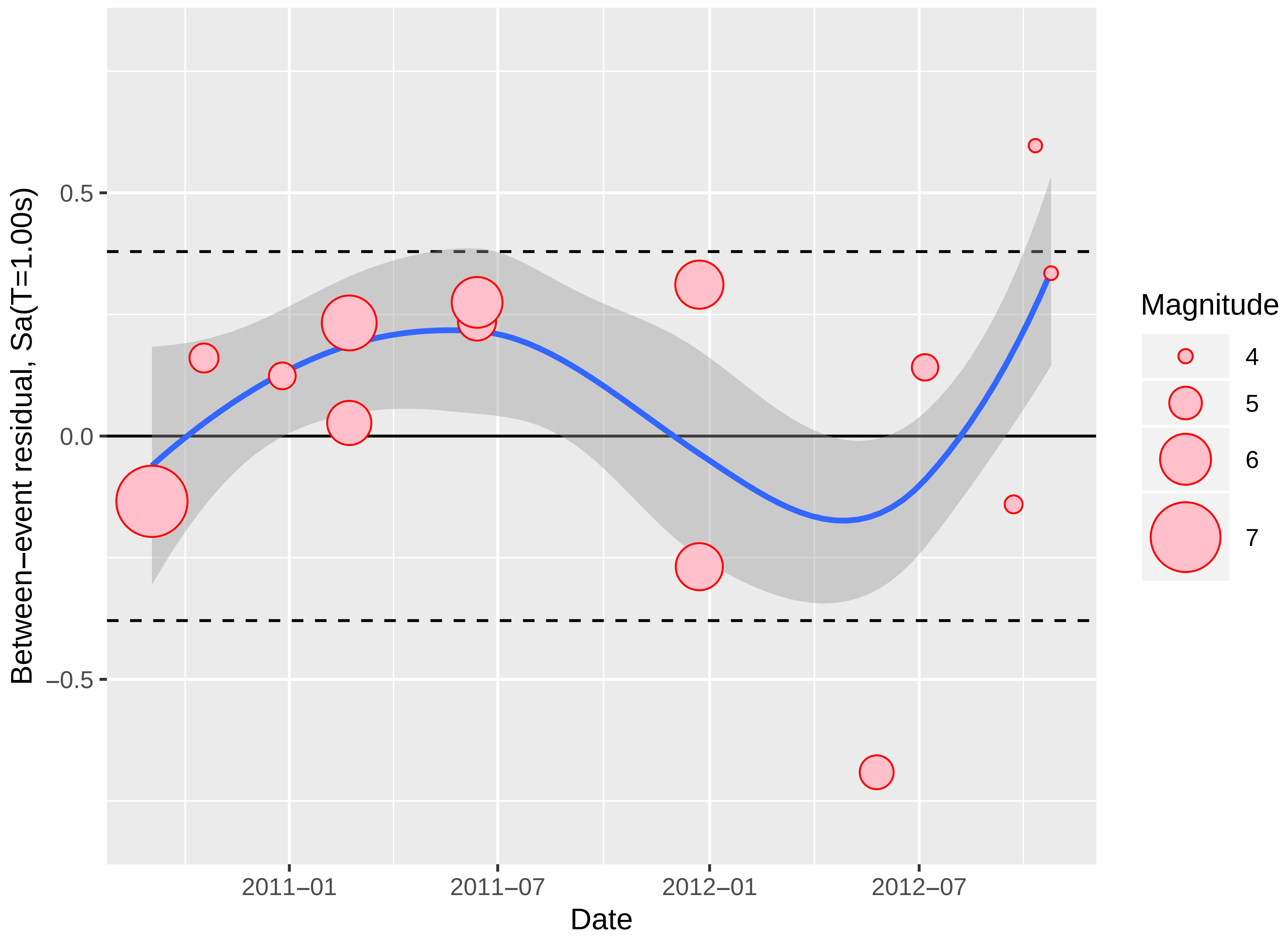


Canterbury sequence 2010-2011

- Particularly for the first year we have within-cluster variability that is significantly lower than ergodic variability
- We can progressively updated the estimate of δ_C as each new event arrives
- Higher-than average event terms (higher risk), but lower between-event variability (lower risk)



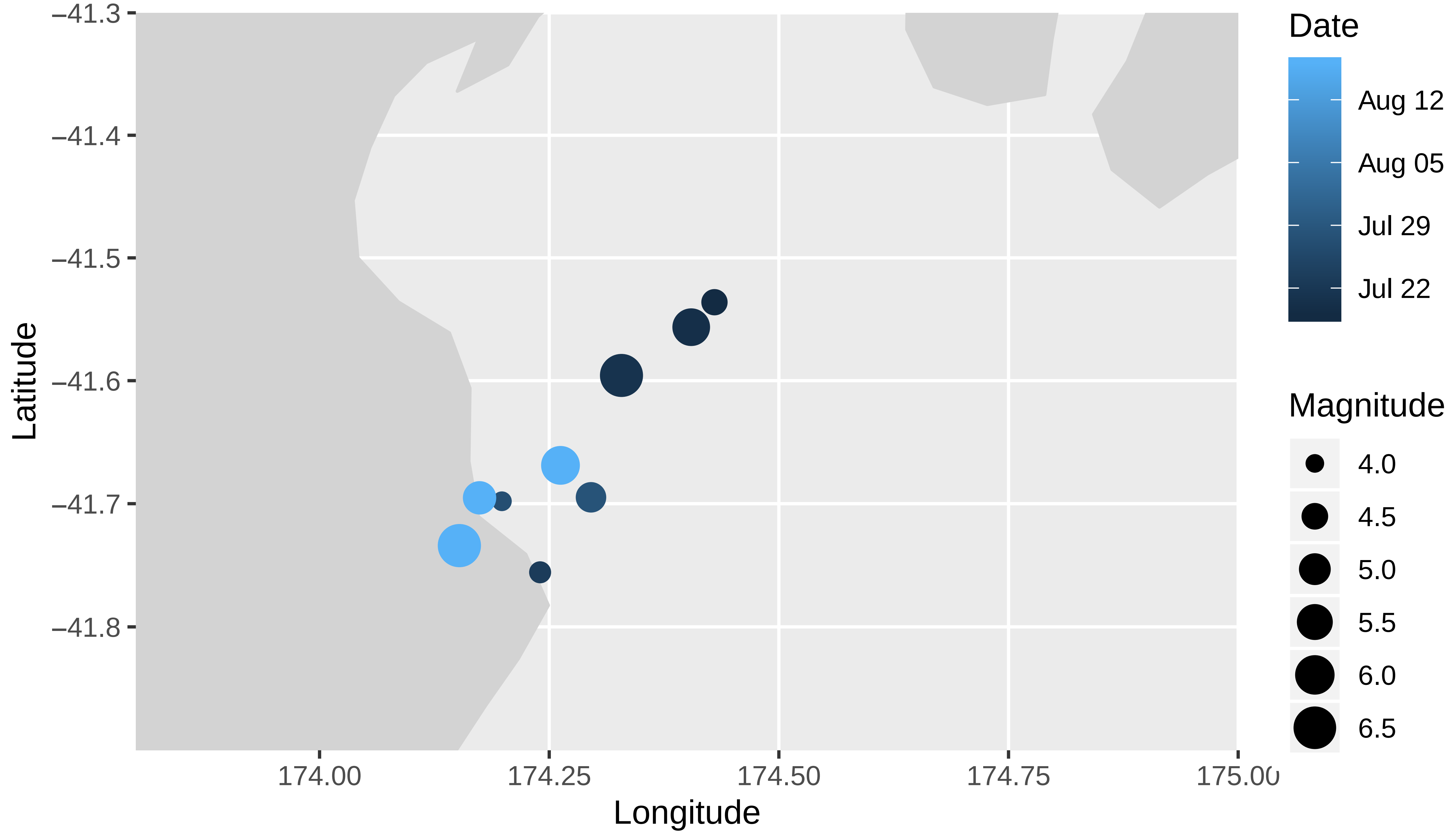


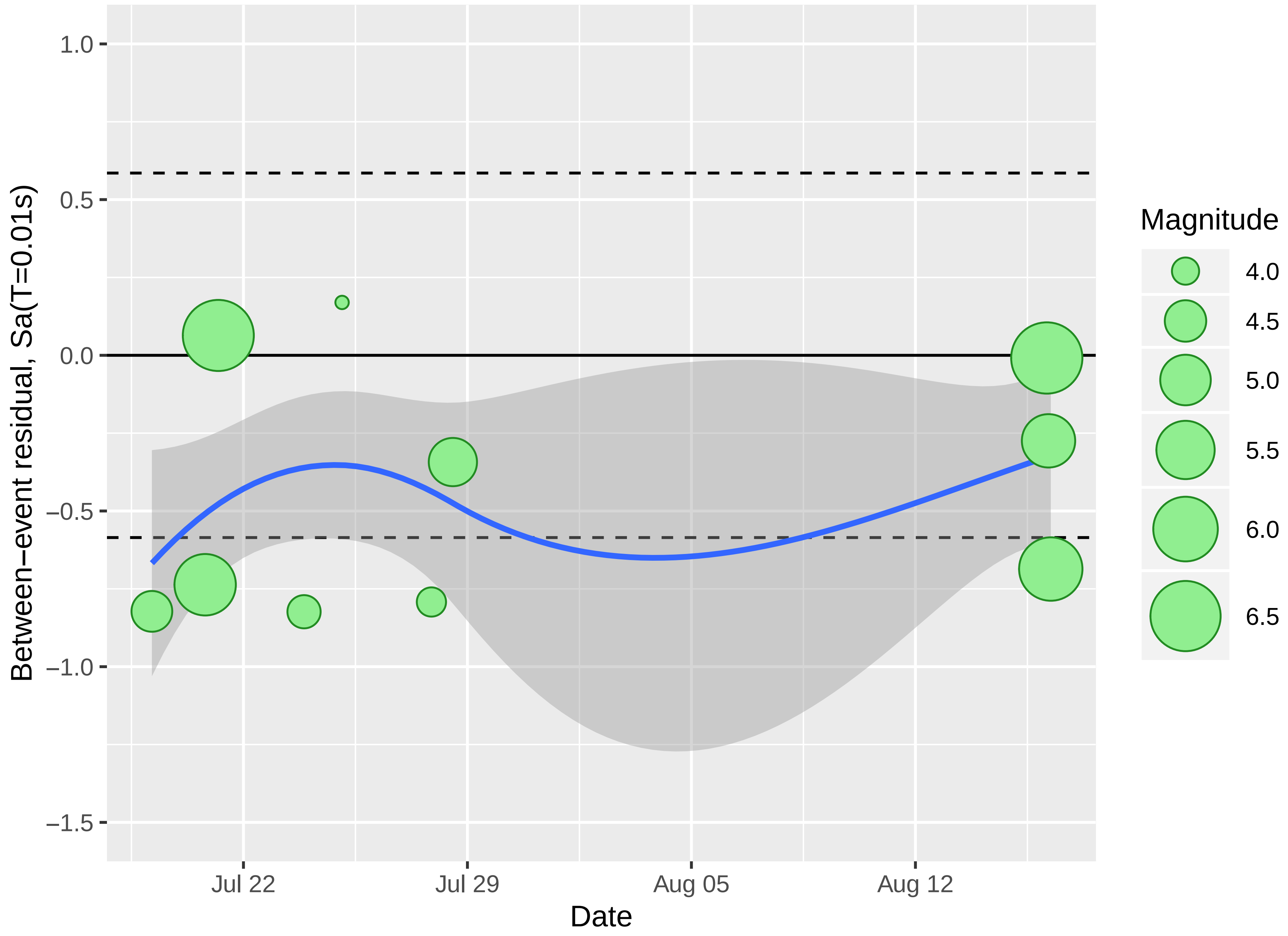


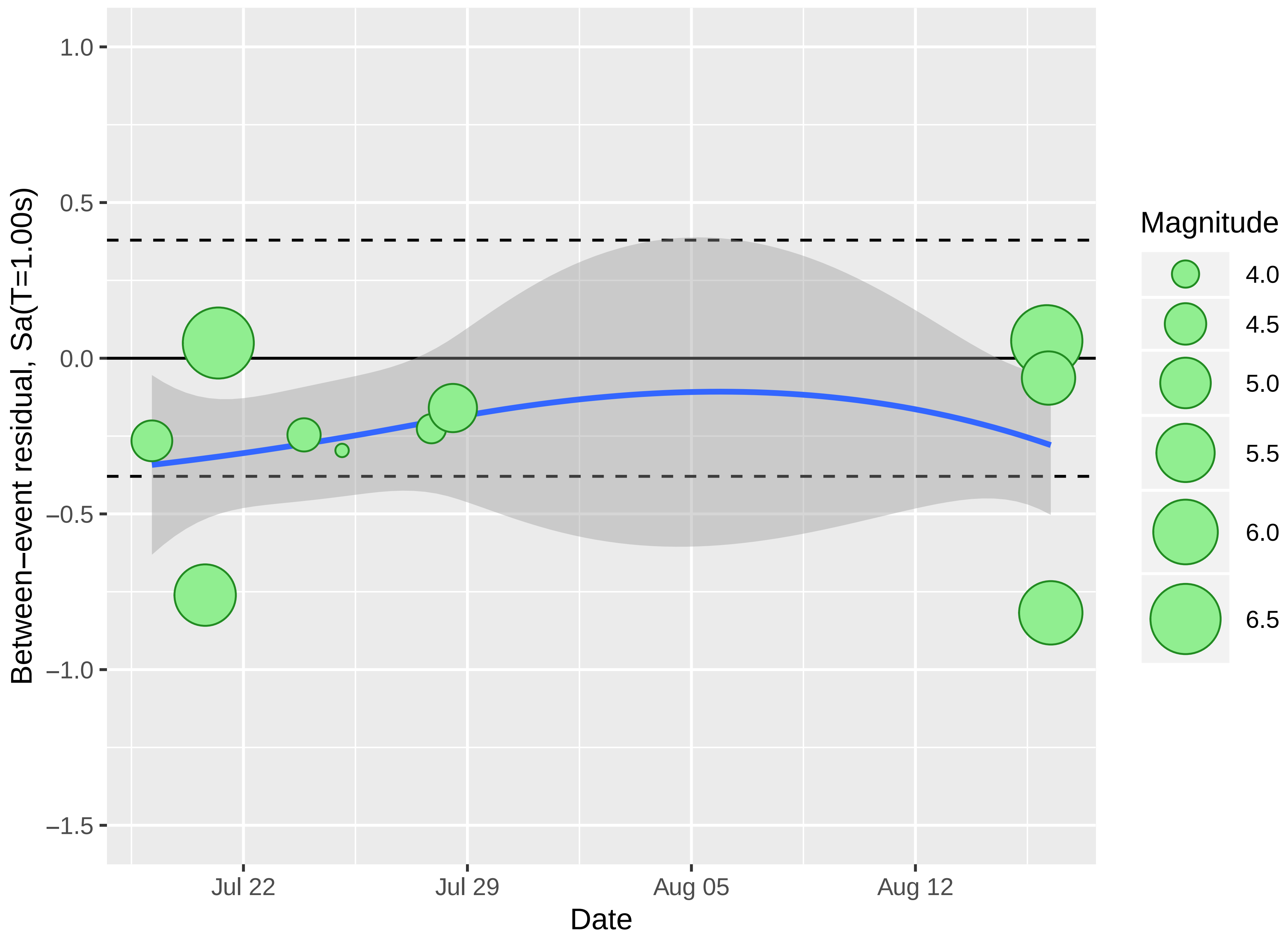
Marlborough sequence 2013

- More of a swarm than a typical aftershock sequence, but still a clear cluster offset, and reduced variability compared to the ergodic model

- Lower than average event terms (lower risk), lower between event variability (lower risk)



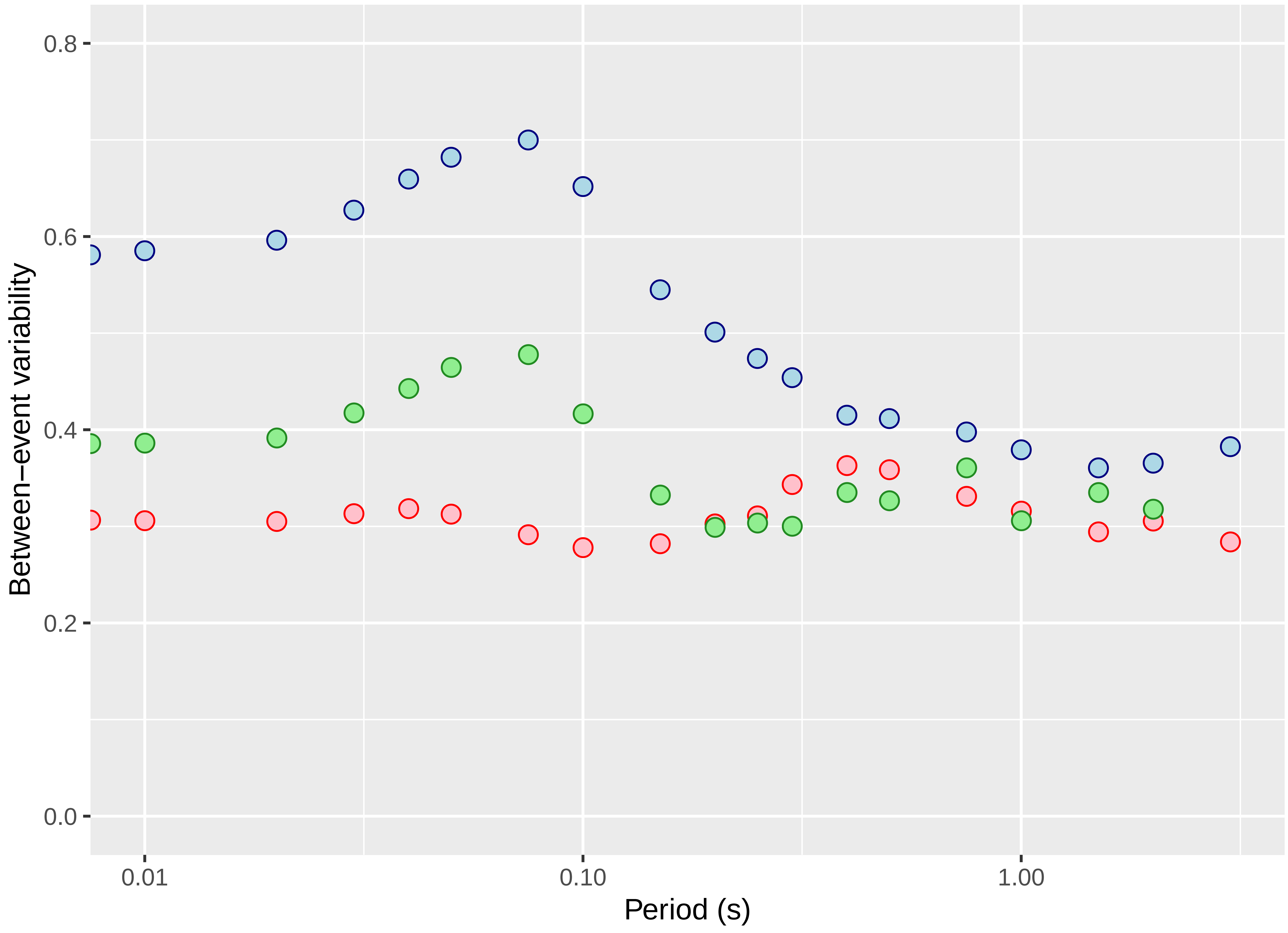




Source variability within sequences

- When evaluated across all response periods, the within-cluster variability is clearly lower than the general between-event variability from the entire NZ database

- Two factors at play here, the location specific effect, and the cluster-specific effect



Conclusions

- Ground-motion models and correlation models used in risk analyses almost always make use of the ergodic assumption

- This leads to inflated estimates of the variance (higher risk) and potentially inflated estimates of correlations among intensity measures

- In locations like Istanbul it should be possible to reduce the degree of aleatory variability to reflect the quite specific dominant source (lower between-event variability), and to capitalise upon the relatively good characterisation of the local soil deposits (lower within-event variability, and more accurate spatial correlation models)

- For post-mainshock risk analyses, information from the sequence as it develops can be used to refine risk estimates