

Bayesian analysis of plague in Kazakhstan

Geir Storvik

Dept. of Mathematics, University of Oslo
SFI², Statistics for innovation
Norwegian Computing Center
SFF-CEES, Ecology and Evolution synthesis

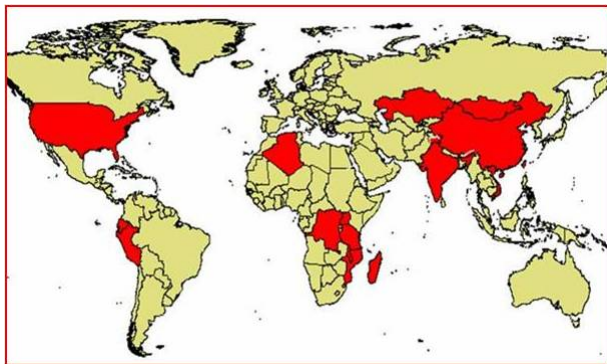
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Lise Heier, Hildegunn Viljugrein, Nils Chr Stenseth, Bård Ø. Kvaal

Outline

- 1 The plague disease
- 2 Data
- 3 Modelling
- 4 Inference
- 5 Preliminary results
- 6 Final remarks

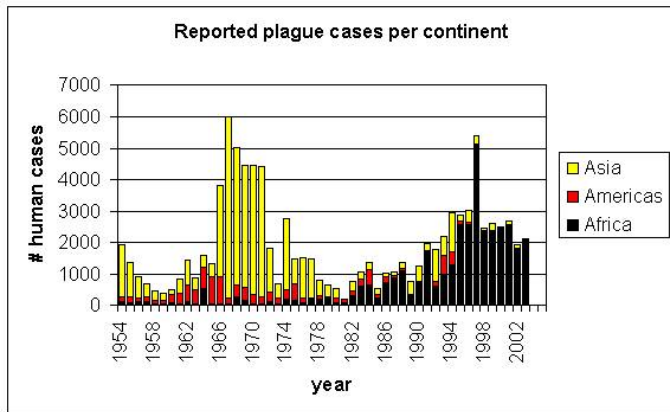
Human cases of Plague



Kausrud [2009]

Stenseth and

Cases per continent



Stenseth and Kausrud [2009]

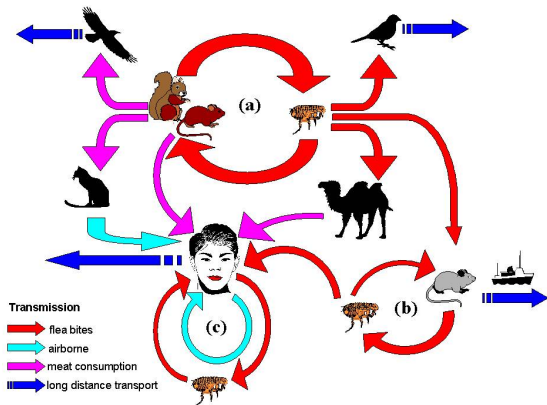
Plague is a highly variable disease

- Given rise to at least three pandemics, with smaller endemics in between.



- A variety of host species: Great Gerbils
- A variety of vector species (transmitting the bacteria (*Yersinia pestis*))
- Complex temporal patterns
- Complex spatial patterns

Plague system



Stenseth and Kausrud [2009]

Questions of interest

- Biology: Understand the dynamics of plague
 - Why do plague “disappear” in periods?
 - How do population sizes influence occurrence of plague
 - How do climatic variables influence plague and/or population sizes?
 - Are there spatial structure in where plague appear?
- Here: Mainly modelling absence/presence of plague

Kazakhstan data

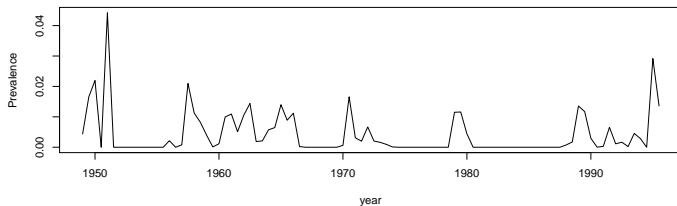
- Data collected within sectors (squares), spring and autumn



- Gerbils:
 - Observed ratio of occupied burrows, $R_{t,i}$ (“density”).
 - Number of tested $N_{t,i}$ and positive $Y_{t,i}$ animals
- Similar data for fleas.
- Much missing data

Data aggregated over space

Observed prevalence of Plague, averaged over sites



Observed density of Great gerbils, averaged over sites



Previous analyses

- Time series approach, Spatially aggregated/single sites [Davis et al., 2004, Park et al., 2006a,b]
- Bayesian analysis, only Gerbils [Frigessi et al., 2005]
- GLMM approach with spatial random effects [Heier, L. and Storvik, G. and Davis, S. A. and Viljugrein, H. and Ageyev, V, A and Klassovskaya, E. and Stenseth NC, 2010]
 - Can use standard software
 - Many missing variables of plague or gerbil density (multiple imputation possible)
 - Difficult to take into account measurement errors (both in responses and covariates)
- Main interest been in presence/absence of plague

Overall model structure

- Process models
 - Model for plague given host density
 - So far only considering presence/absence of plague
 - Model for host “density”
 - Density actually fraction of occupied colonies
 - Model needed because of missing observations
- Measurement models
 - Plague data
 - Density data
- Bayesian approach
 - Prior models

Model for plague

- $z_{t,i} = 1$ if plague in site i at time t
- Logistic type models with random effects for all cases.

$$\text{logit}(\Pr(z_{t,i} = 1 | \text{past})) = \alpha_{t,i}(\text{past}) + \varepsilon_{t,i}$$

- $\{z_{t,i}, i = 1, \dots, N\}$ independent given $\{\alpha_{t,i}\}$ and $\{\varepsilon_{t,i}\}$.
- Spatial correlation through spatial correlation in $\{\varepsilon_{t,i}\}$.
- Temporal correlation through $\alpha_{t,i}(\text{past})$.
- $\varepsilon_t \sim \text{GCAR}(\rho_\varepsilon, \tau_\varepsilon)$, independent in time.

Model for α 's

- Three “cases” of plague, depending on past:

Persistence: $z_{t-1,i} = 1$

Spread: $z_{t-1,i} = 0, \sum_{j \sim i} z_{t-1,j} > 0$

Invasion: $z_{t-1,i} = 0, \sum_{j \sim i} z_{t-1,j} = 0$



Models for α 's (cont)

- $\phi_{t,i}$ is occupancy of gerbils at logit-scale.
- Persistence

$$\alpha_{t,i} = b_{p,P}\phi_{t,i} + c_{p,P} \sum_{j \in \delta_i} z_{t-1,j} + \mathbf{x}_{t,i}^T \alpha_P$$

- Spread

$$\alpha_{t,i} = b_{p,S}\phi_{t,i} + c_{p,S} \sum_{j \in \delta_i} z_{t-1,j} + \mathbf{x}_{t,i}^T \alpha_S$$

- Invasion

$$\alpha_{t,i} = b_{p,I}\phi_{t,i} + \mathbf{x}_{t,i}^T \alpha_I + s_{I,i}$$

- $\{s_{I,i}\}$ spatial process $\sim GCAR(\rho_S, \tau_S)$.

Measurement model

- Observed $(N_{t,i}, Y_{t,i})$.
- Assume no error in test
- Assume $Y_{i,t} \sim \text{Binom}(N_{t,i}, p_{t,i})$, $p_{t,i}$ prevalence of plague
- $Z_{t,i} = 1$ iff $p_{t,i} > 0$
- If $Y_{t,i} > 0$, then $Z_{t,i} = 1$
- If $Y_{t,i} = 0$, then $Z_{t,i} = ?$
- Assume $p_{t,i} \sim \text{Beta}(\alpha, \beta)$ if $Z_{t,i} = 1$.
- Gives

$$\Pr(Y_{t,i} = 0 | Z_{t,i} = 0) = 1$$

$$\Pr(Y_{t,i} = 0 | Z_{t,i} = 1) = \frac{\Gamma(\alpha + \beta)\Gamma(n + \beta)}{\Gamma(\beta)\Gamma(n + \alpha + \beta)}$$

Model for occupancy

$$\phi_{t,i} = \mathbf{x}_{t,i}^T \boldsymbol{\beta} + \rho_t(\phi_{t-1,i} - \mathbf{x}_{t-1,i}^T \boldsymbol{\beta}) + u_{t,i}$$

- $\mathbf{u}_t \sim GCAR(\rho_\phi, \tau_\phi)$, independent in time.

Spatial models

GCAR(ρ, τ) Gaussian conditional autoregressive model

$$\mathbf{U} \sim \text{MVN}(\mathbf{0}, (\tau \mathbf{Q}(\rho))^{-1})$$

$$\mathbf{Q}(\rho) = \rho \mathbf{P} + (1 - \rho) \mathbf{I}$$

$$P_{ij} = \begin{cases} m_i & j = i \\ -1 & j \in \delta_i \\ 0 & \text{otherwise} \end{cases}$$

MacNab [2003]: avoiding potential identifiability problems.

$\rho = 1$ corresponds to the intrinsic autoregression model

$\rho = 0$ corresponds to an independence model.

Note: \mathbf{Q} is sparse!

“Direct” approach

- θ_a parameters for abundance model
- θ_p parameters for plague model

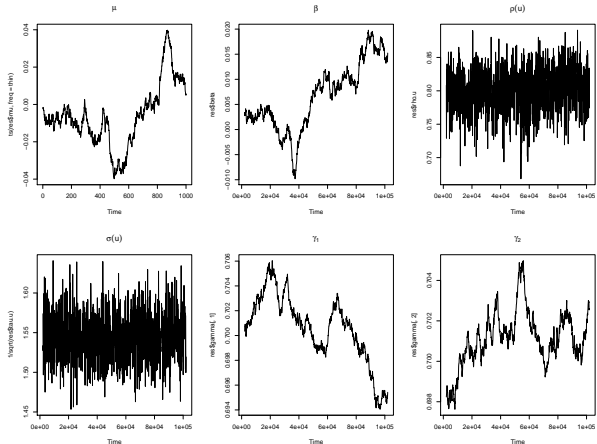
$$\begin{aligned} f(\phi, \mathbf{Z} | \theta_a, \theta_p) &= \prod_t f(\phi_t | \phi_{t-1}; \theta_a) f(\mathbf{Z}_t | \mathbf{Z}_{t-1}, \phi_t; \theta_p) \\ &= \prod_t f(\phi_t | \phi_{t-1}; \theta_a) \\ &\quad \prod_t f(\mathbf{Z}_t | \mathbf{Z}_{t-1}, \phi_t; \theta_p) \end{aligned}$$

- Each part GLMM type
- Missing/incomplete data: Multiple imputation
- Works, but complicated, not utilizing data fully

Bayesian analysis

- Denote θ hyperparameters involved
 - Regression parameters
 - Precisions
 - Correlation parameters
- Prior $\pi(\theta)$ mainly noninformative
- Bayesian inference: $\pi(\theta, \phi, \mathbf{z}|\mathbf{y})$
- Computation through Markov Chain Monte Carlo
- Possible to use Winbugs/Jags?

Using existing software - JAGS



Markov chain Monte Carlo

- Many variables to be updated
- Plague: $\{z_{t,i}\}$, $N \times T$, binary
- Random effects plague: $\{\varepsilon_{t,i}\}$, $N \times T$, Gaussian prior
- Invasion process: $\{s_{l,i}\}$, N , Gaussian prior
- Occupancy: $\{\phi_{t,i}\}$, $N \times T$, Gaussian prior
- Regression parameters, $b_{p,P/S/I}$, $c_{p,P/S}$, α_P , α_S , α_I , β
- Precision parameters, τ_ε , τ_S , τ_ϕ
- Correlation parameters: ρ_ε , ρ_S , ρ_ϕ , ρ_t
- Fast convergence: Update (large) blocks simultaneously (GMRFLib)

Block-updating continuous processes

- Knorr-Held and Rue [2002], Rue and Held [2005]
- Continuous processes of the form

$$\pi(\mathbf{x}|\boldsymbol{\theta}, \mathbf{y}) \propto \exp\left\{-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu}(\boldsymbol{\theta}))^T \mathbf{Q}(\boldsymbol{\theta})(\mathbf{x} - \boldsymbol{\mu}(\boldsymbol{\theta})) + \sum_i d_i \log g(x_i; y_i, \boldsymbol{\theta})\right\}$$

- Regression parameters included in \mathbf{x} .
- Metropolis Hastings: $\boldsymbol{\theta}^* \sim q_1(\cdot|\boldsymbol{\theta})$, $\mathbf{x}^* \sim q_2(\cdot|\boldsymbol{\theta}^*, \mathbf{x})$
- q_2 Gaussian approx. to $\pi(\mathbf{x}|\boldsymbol{\theta}^*)$, independent of \mathbf{x} !
- Acceptance ratio

$$R = \frac{\pi(\boldsymbol{\theta}^*)\pi(\mathbf{x}^*|\boldsymbol{\theta}^*)f(\mathbf{y}|\mathbf{x}^*, \boldsymbol{\theta}^*)}{\pi(\boldsymbol{\theta})\pi(\mathbf{x}|\boldsymbol{\theta}^*)f(\mathbf{y}|\mathbf{x}, \boldsymbol{\theta})} \times \frac{q_1(\boldsymbol{\theta}|\boldsymbol{\theta}^*)q_2(\mathbf{x}|\boldsymbol{\theta}, \mathbf{x}^*)}{q_1(\boldsymbol{\theta}^*|\boldsymbol{\theta})q_2(\mathbf{x}^*|\boldsymbol{\theta}^*, \mathbf{x})}$$

Sparse matrix operations

- \mathbf{Q} sparse, both in time and space.
- GMRFLib [Rue and Held, 2005], a C-library for automatic simulation from

$$\pi(\boldsymbol{\theta}, \mathbf{x} | \mathbf{y}) \propto \pi(\boldsymbol{\theta}) \exp\left\{-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu}(\boldsymbol{\theta}))^T \mathbf{Q}(\boldsymbol{\theta})(\mathbf{x} - \boldsymbol{\mu}(\boldsymbol{\theta})) + \sum_i d_i \log g(x_i; y_i, \boldsymbol{\theta})\right\}$$

- Sparseness in time could have been handled through Kalman filter approximation.
- GMRFLib automatically handles sparseness both in space and time.
- Example: \mathbf{Q} 3480×3480 , : Acceptance rate 0.29!

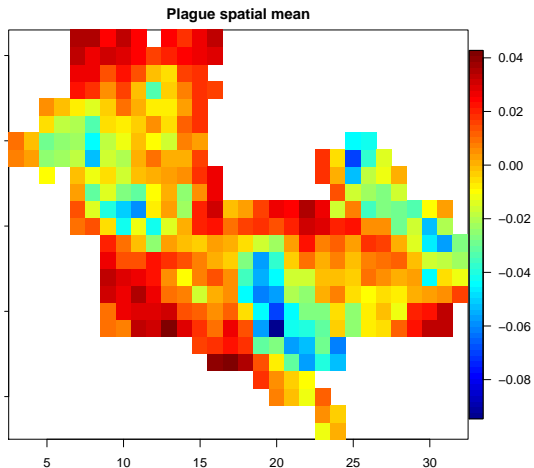
Preliminary results

- Years 1986-1995
- Only gerbils data
- Only data from fall
- Covariate: Absolute minimum of air temperature in one month.
- MCMC: 1000 burnin, 50000 additional iterations

Results

- Density highly significant for plague
- Past presence of plague slightly significant
- Clear spatial structure both in density and in plague
- Absolute minimum of air temperature in one month slightly significant on density but not on plague
- Spatial structure in invasion but significant?

Plague spatial mean (logit-scale)



Residuals

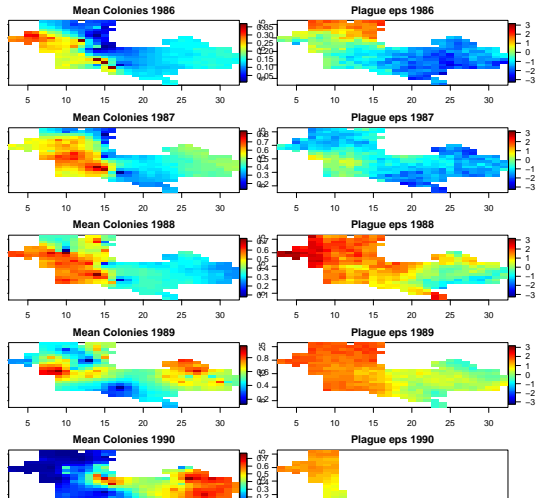
Model

$$\phi_{t,i} = \rho_t \phi_{t-1,i} + \mathbf{x}_{t,i}^T \boldsymbol{\beta} + u_{t,i}$$

$$\text{logit}(\Pr(z_{t,i} = 1 | \text{past})) = \alpha_{t,i}(\text{past}) + \varepsilon_{t,i}$$

Structure in $\{\varepsilon_{t,i}\}$, $\{u_{t,i}\}$?

Residuals



Extensions

- Better observation models
- Including fleas data
- Nonlinear relation to gerbil density
- Better proposals in MCMC
- Model criticism/evaluation!

Summary/Discussion

- Preliminary version of full Gerbil-plague analysis
- Seems to confirm previous analyses
- Efficient MCMC implementation
- Further improvements/extensions needed

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