

Estimation of the effect of climate on infectious diseases

Table of contents

1	Motivating Question	1
2	Data & model	1
2.1	State Process (Evolution) Equation	2
2.2	Latent Driver Process	2
2.3	Observation Equation	2
2.4	Priors	3

1 Motivating Question

If climate change (through some sort of variable such as temperature or precipitation) is affecting the number of cases of infectious disease, it is an outstanding question how strong this effect must be to identify it from some background autocorrelated value.

How strong does the signal of climate change need to be to detect it?

2 Data & model

Assuming we have some data on observed cases of a given infectious disease. The relationship between those observed cases and actual cases is a state process with some observation error, ϵ_o . Cases themselves are now given as a state space model where the number of cases at time $t + 1$ are driven by the effect of both temperature variance (consistent through time) and mean temperature (increasing through time), as well as an unobserved driver that is correlated through time with the mean temperature.

Let: - Y_t represent the true number of cases at time t . - Y_t^{obs} represent the observed number of cases at time t , which includes observational error ϵ_o . - X_μ represent the mean temperature at time t , and let X_σ represent the temperature variance, assumed constant over time. - U_t represent the unobserved driver correlated with mean temperature X_μ .

2.1 State Process (Evolution) Equation

For the true cases Y_t , we specify that the cases at time $t + 1$ are driven by the temperature effects and an unobserved driver U_t as follows:

$$Y_{t+1} \mid Y_t, X_\mu, U_t \sim \text{Poisson} \left(Y_t \exp \left(\alpha + \beta_\mu X_\mu + \beta_\sigma X_\sigma + \gamma U_t \right) \right) \quad (1)$$

where: - α is an intercept term. - β_μ is the effect of mean temperature X_μ on the cases. - β_σ is the effect of temperature variance X_σ . - γ captures the effect of the unobserved driver U_t on the cases.

2.2 Latent Driver Process

We assume that the unobserved driver U_t has temporal correlation and is influenced by the mean temperature:

$$U_{t+1} \mid U_t, X_\mu \sim \mathcal{N}(\phi U_t + \eta X_\mu, \sigma_U^2) \quad (2)$$

where: - ϕ is an autoregressive parameter governing the temporal correlation of U_t . - η is the strength of the correlation between U_t and X_μ . - σ_U^2 is the variance of U_t .

2.3 Observation Equation

The observed cases Y_t^{obs} are related to the true cases Y_t with observation error ϵ_o :

$$Y_t^{\text{obs}} \mid Y_t \sim \text{Poisson}(Y_t e^{\epsilon_o}) \quad (3)$$

with $\epsilon_o \sim \mathcal{N}(0, \sigma_o^2)$, where σ_o^2 is the variance of the observation error.

2.4 Priors

The priors for the parameters could be specified as follows:

$$\alpha \sim \mathcal{N}(0, 10) \tag{4a}$$

$$\beta_\mu \sim \mathcal{N}(0, 1) \tag{4b}$$

$$\beta_\sigma \sim \mathcal{N}(0, 1) \tag{4c}$$

$$\gamma \sim \mathcal{N}(0, 1) \tag{4d}$$

$$\phi \sim \text{Uniform}(-1, 1) \tag{5a}$$

$$\eta \sim \mathcal{N}(0, 1) \tag{5b}$$

$$\sigma_U^2 \sim \text{Inverse-Gamma}(2, 1) \tag{5c}$$

$$\sigma_o^2 \sim \text{Inverse-Gamma}(2, 1) \tag{5d}$$