

Illustrative Applications

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Gaussian Process Winter School
16 January 2014

About this project

- ▶ Joint collaboration



The
University
Of
Sheffield.

Neil Lawrence
Ricardo Andrade



John Quinn
Martin Mubangizi

- ▶ Coded on GPy

Data

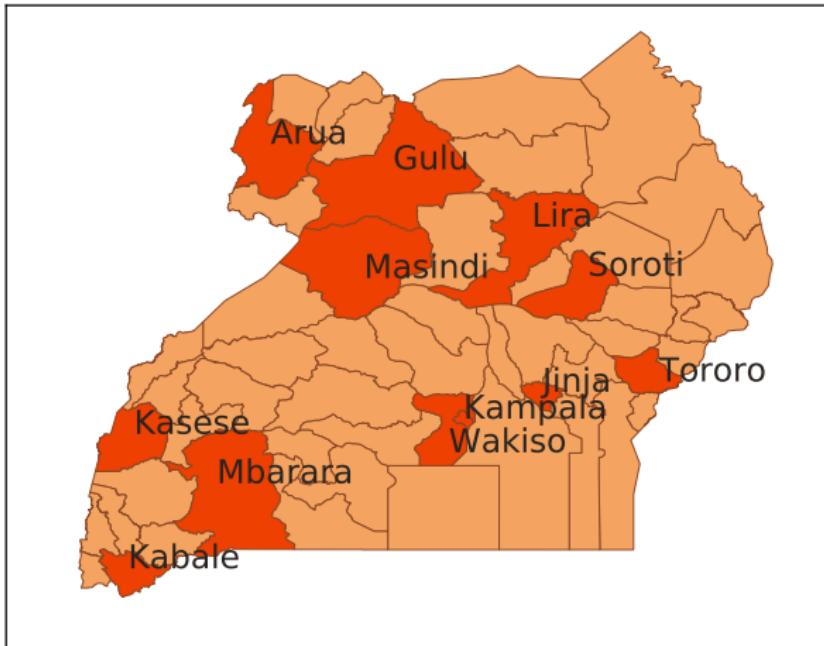
- ▶ Health Management Information System
- ▶ Weather stations (rain, temperature, humidity)
- ▶ Satellite information (vegetation index, rain)
- ▶ Geographic data (altitude)
- ▶ Sentinel data (incidence)

Data features

- ▶ Different spatial resolution
- ▶ Different temporal resolution
- ▶ Noisy records
- ▶ Changes in Districts limits along time

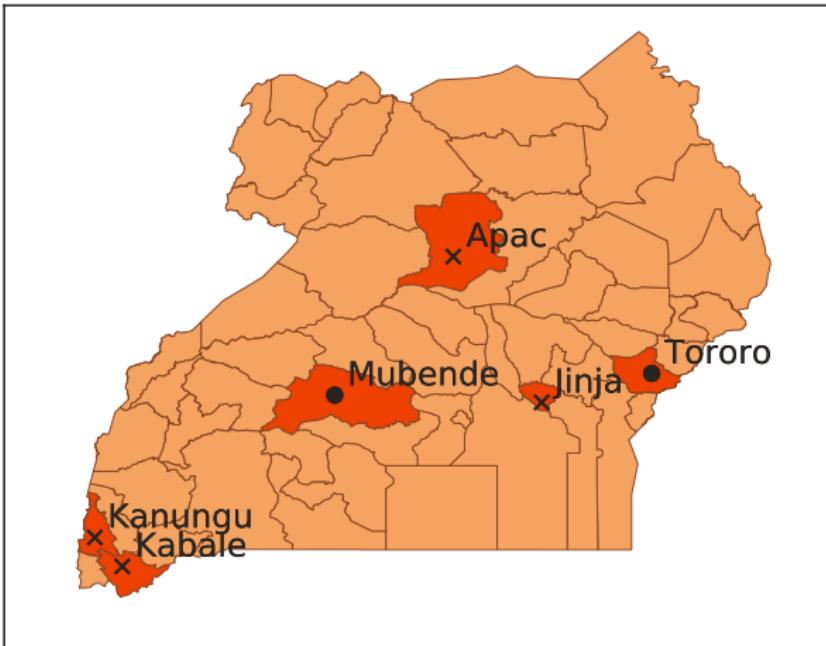
Data features

Weather stations



Data features

Sentinel sites



Multioutput Gaussian Processes (Review)

- ▶ D related tasks to be learnt.
- ▶ Each one with its corresponding output and inputs:
 $\{\mathbf{y}_1, \mathbf{X}_1\}, \dots, \{\mathbf{y}_D, \mathbf{X}_D\}$.
- ▶ Each task may have a different number of training examples N_d with $d = 1, \dots, D$.
- ▶ Stack inputs and outputs and treat it as a single output regression problem.

$$\mathbf{X} = \begin{pmatrix} \mathbf{X}_1 \\ \vdots \\ \mathbf{X}_D \end{pmatrix} \qquad \mathbf{y} = \begin{pmatrix} \mathbf{y}_1 \\ \vdots \\ \mathbf{y}_D \end{pmatrix}$$

Multioutput Gaussian Processes (Review)

- ▶ The kernel matrix is partitioned matrix as follows:

$$\mathbf{B} \otimes \mathbf{K} = \begin{pmatrix} B_{1,1} \times \mathbf{K}(\mathbf{X}_1, \mathbf{X}_1) & \dots & B_{1,D} \times \mathbf{K}(\mathbf{X}_1, \mathbf{X}_D) \\ \vdots & \ddots & \vdots \\ B_{D,1} \times \mathbf{K}(\mathbf{X}_D, \mathbf{X}_1) & \dots & B_{D,D} \times \mathbf{K}(\mathbf{X}_D, \mathbf{X}_D) \end{pmatrix}$$

$\mathbf{K}(\cdot, \cdot)$ is a kernel function,

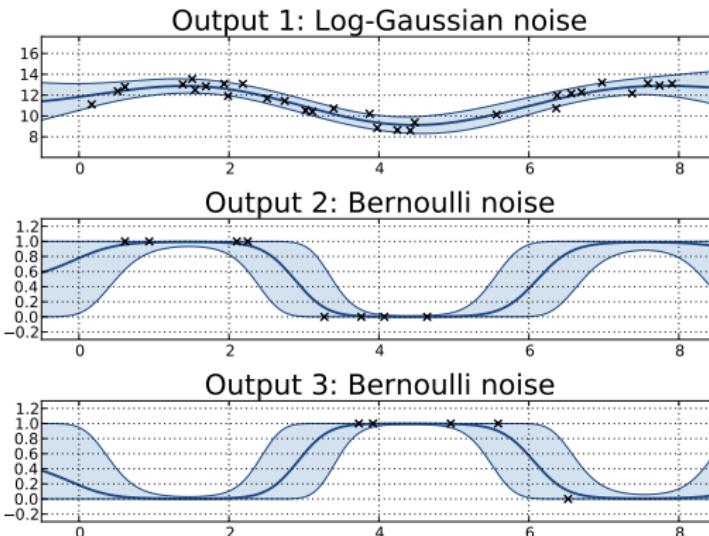
\mathbf{B} is known as the coregionalization matrix.

- ▶ A more general version:

$$K_{LCM} = \sum_{q=1}^Q \mathbf{B}_q \otimes \mathbf{K}_q(\mathbf{X}, \mathbf{X}).$$

Multioutput Gaussian Processes (Review)

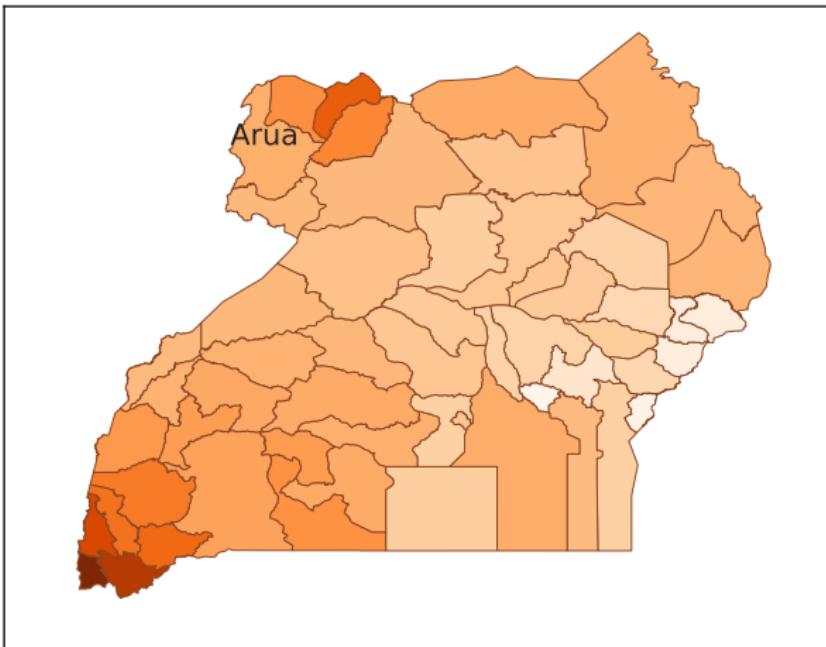
- ▶ A different noise term σ_d^2 for each output.
- ▶ Even a different noise model for each output.



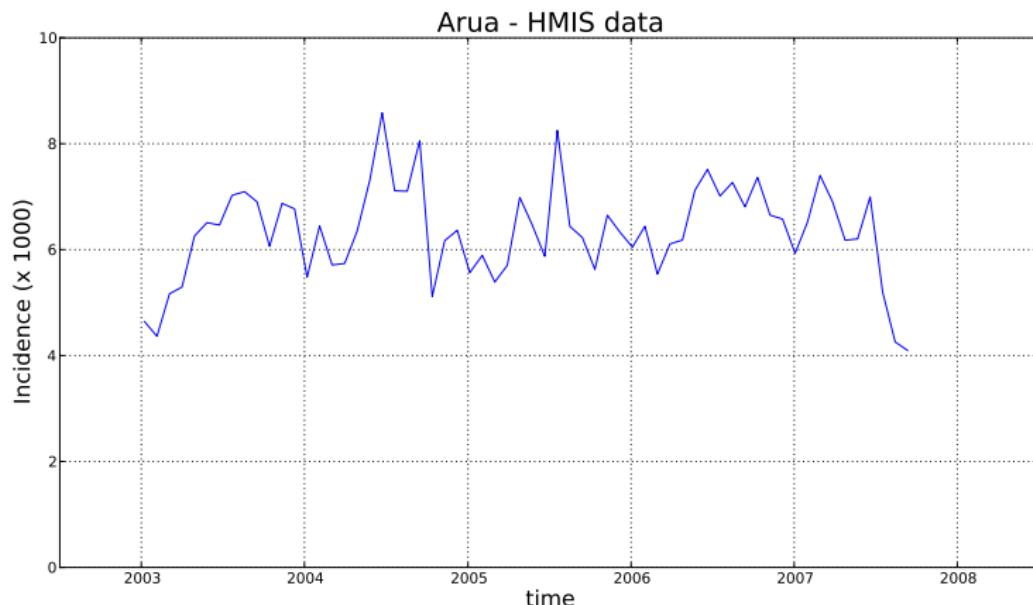
Where to start?



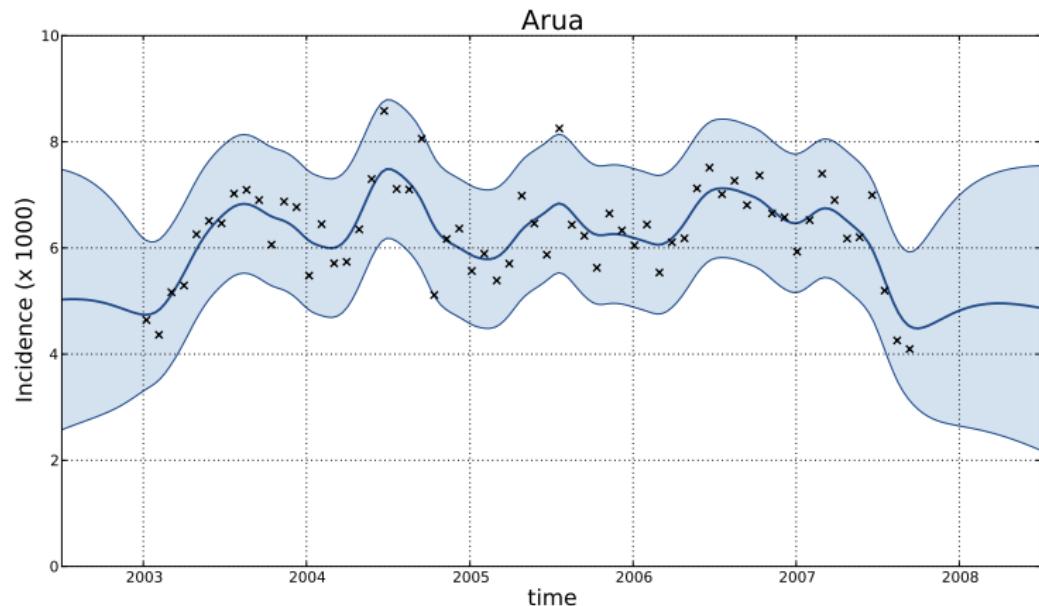
Single output model



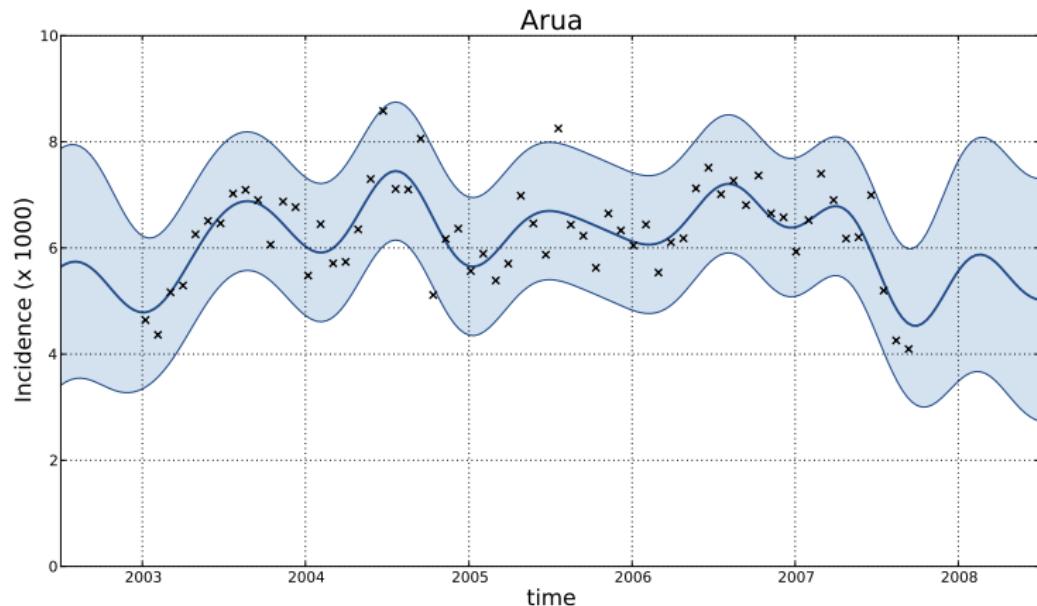
Single output model



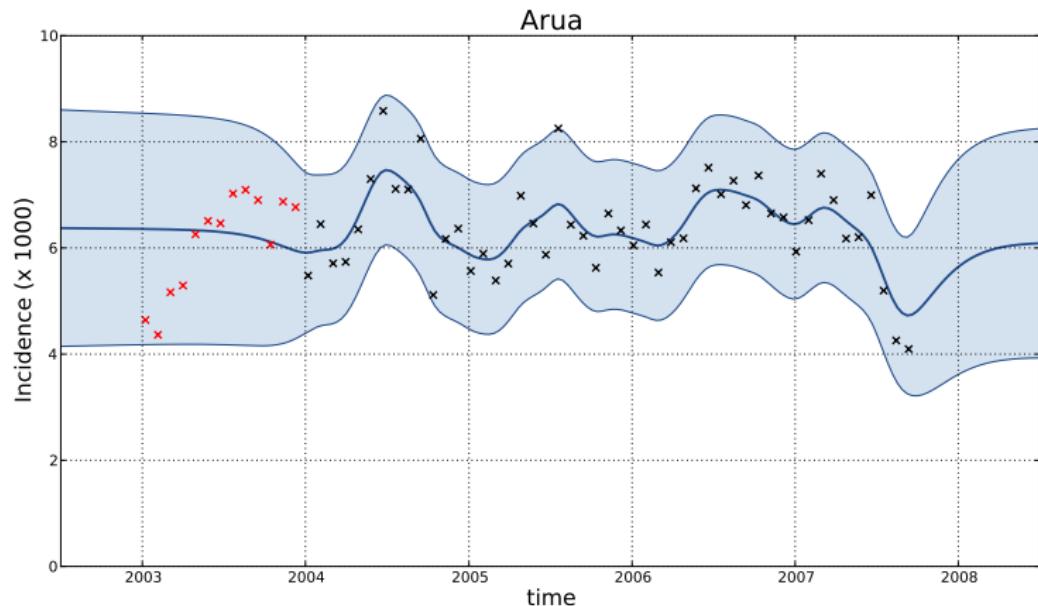
Single output model



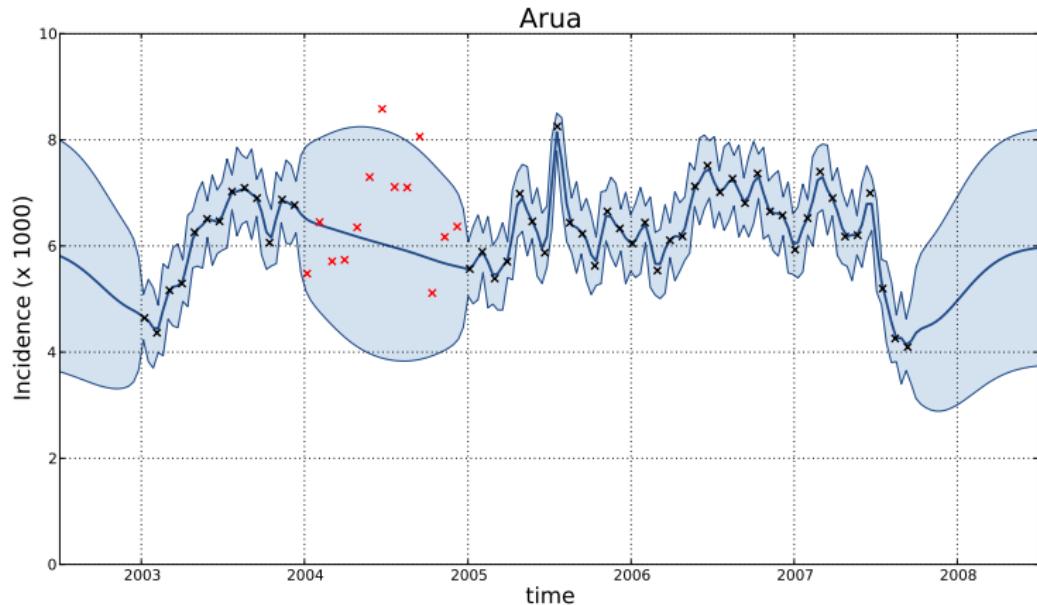
Single output model with a periodic kernel



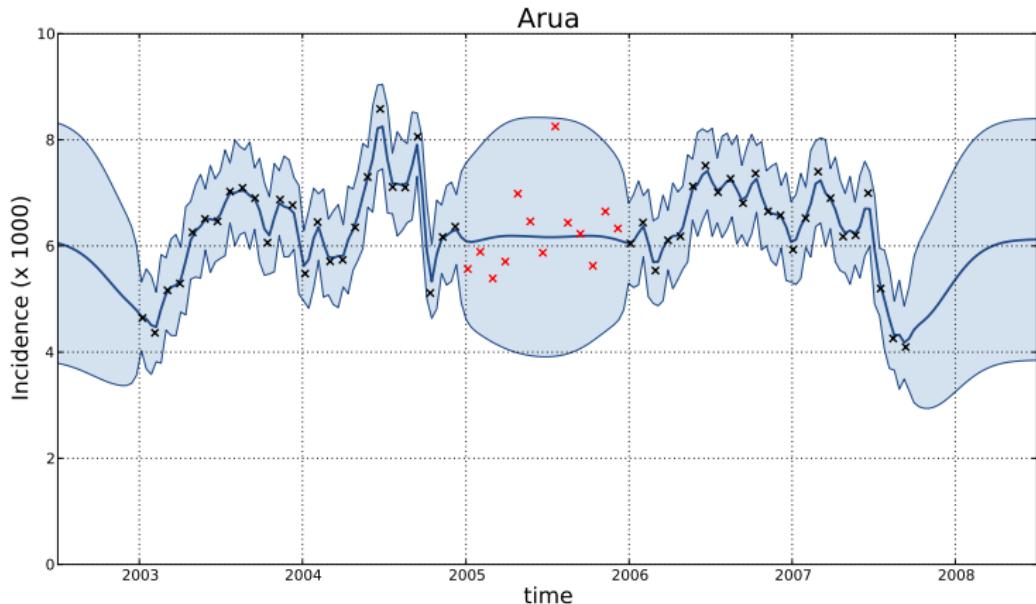
Model without periodic kernel



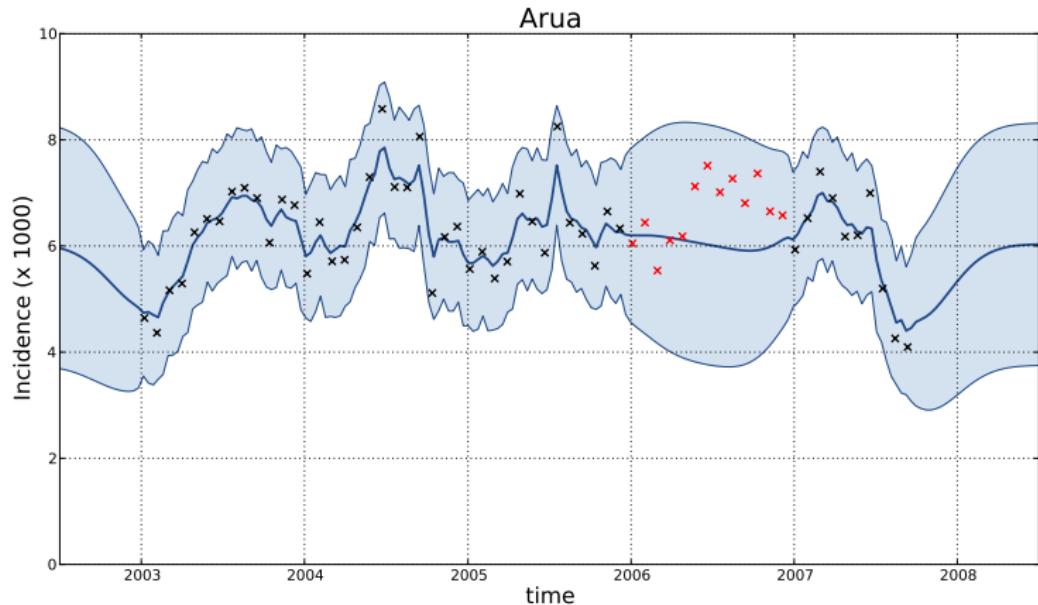
Model without periodic kernel



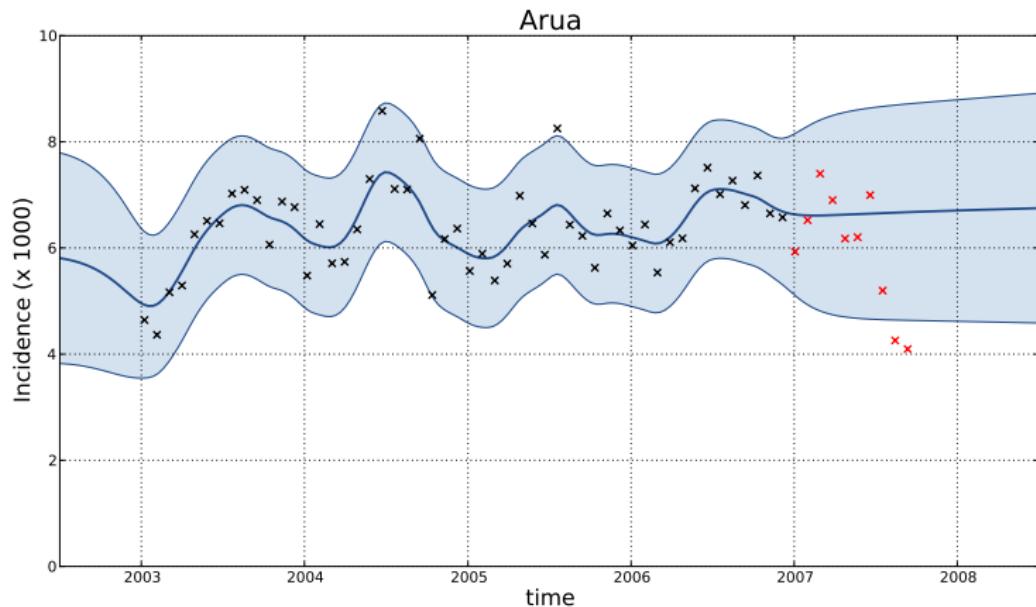
Model without periodic kernel



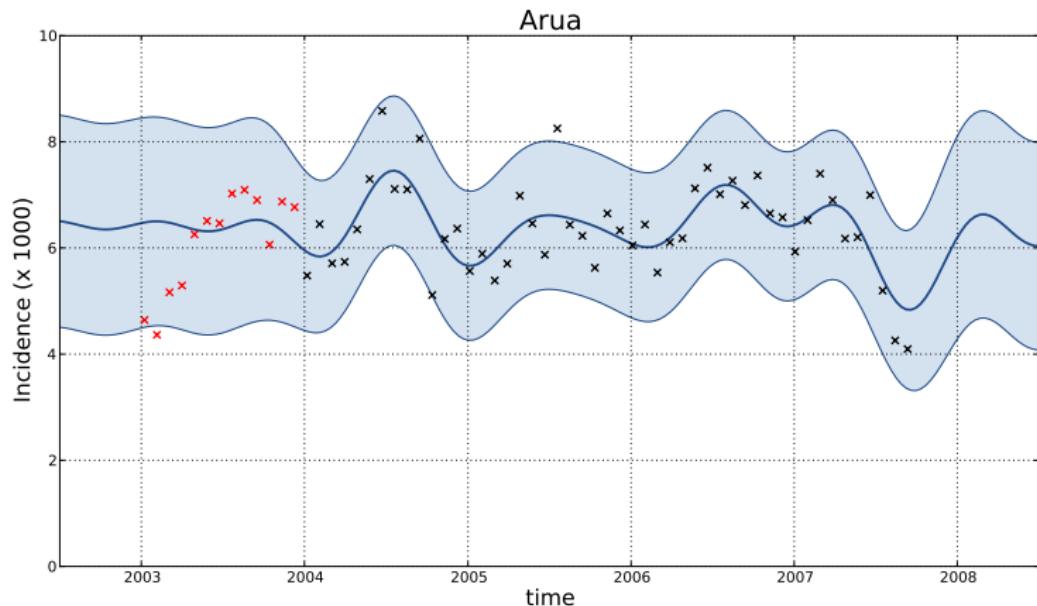
Model without periodic kernel



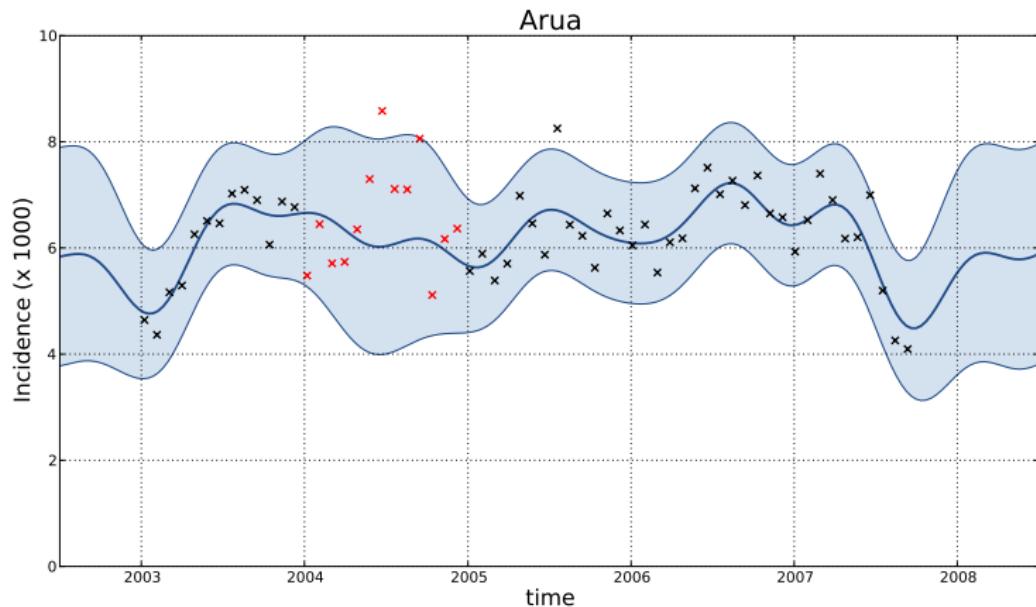
Model without periodic kernel



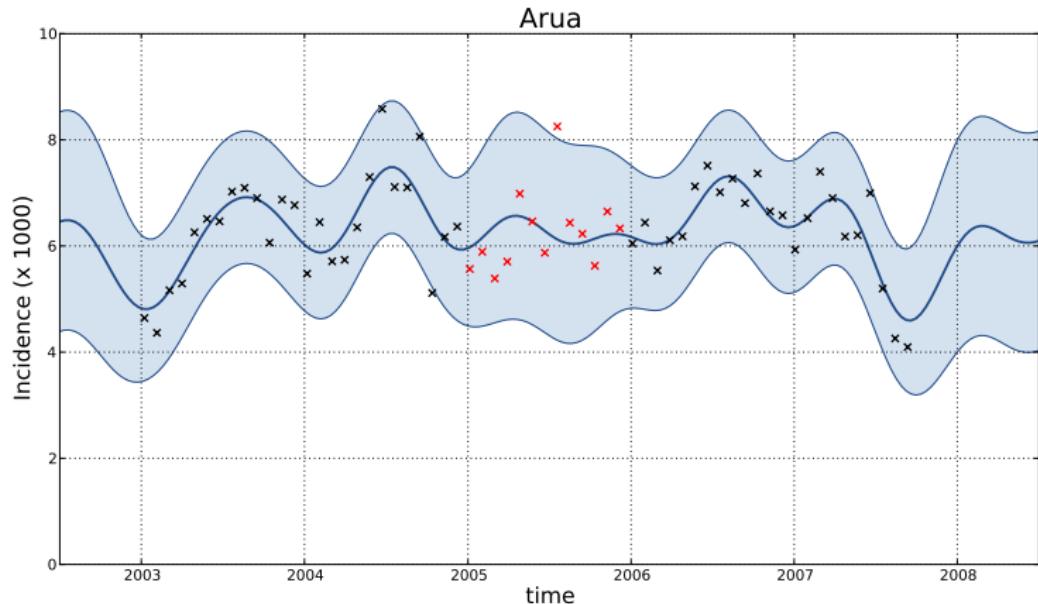
Model with a periodic kernel



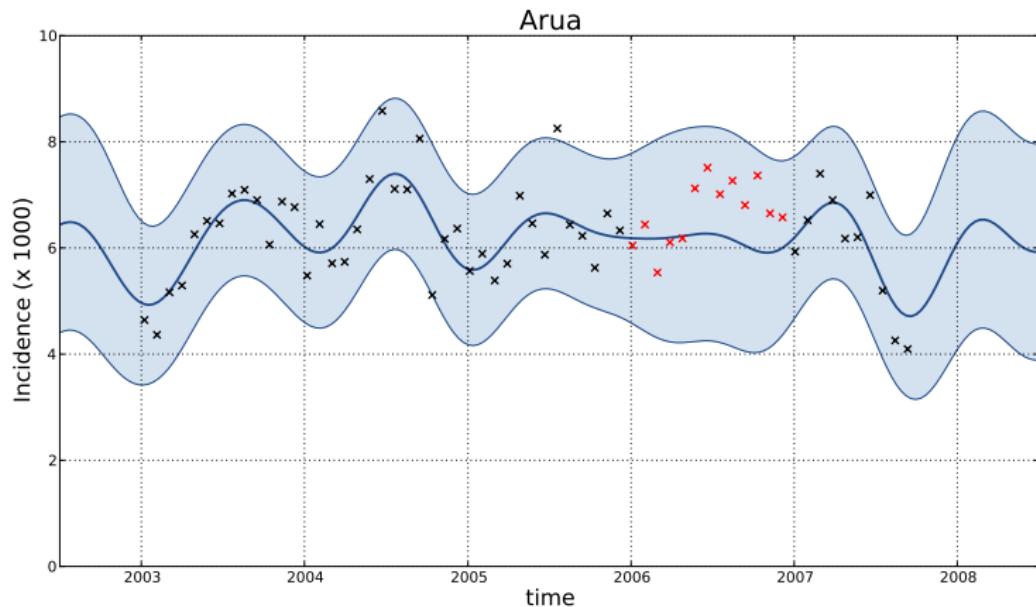
Model with a periodic kernel



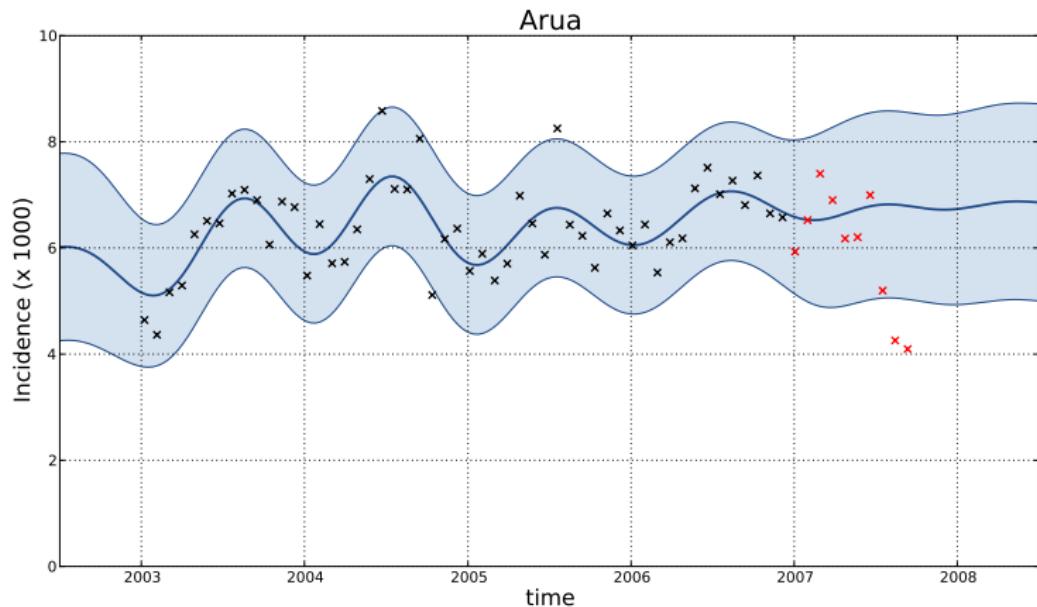
Model with a periodic kernel



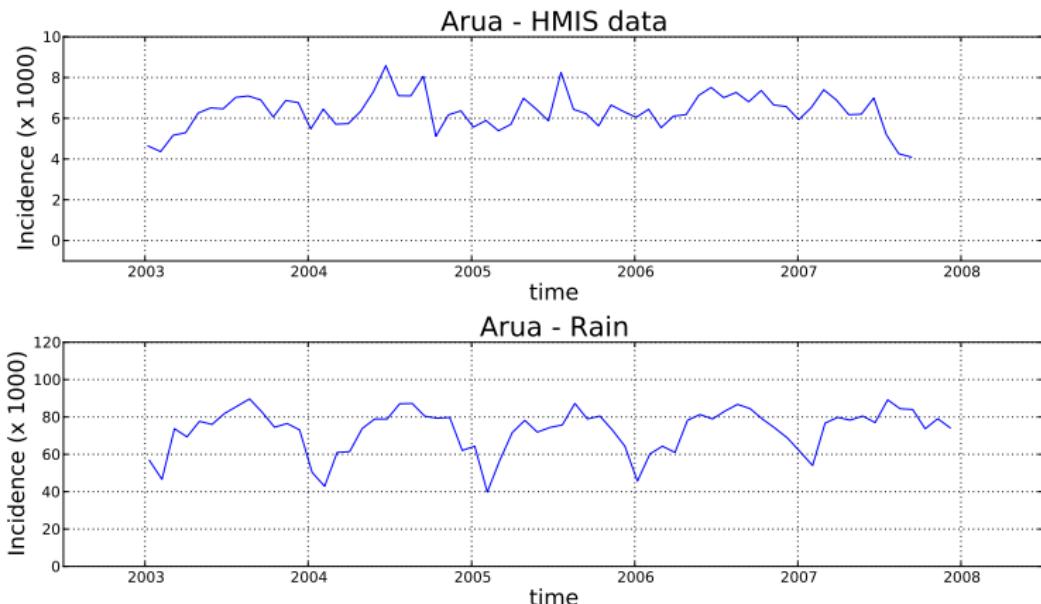
Model with a periodic kernel



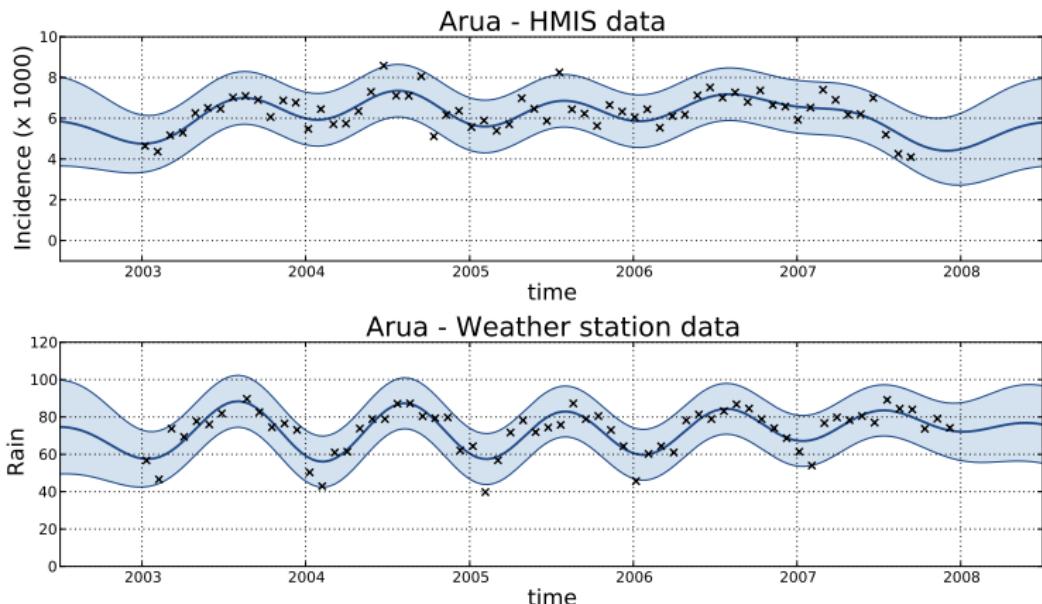
Model with a periodic kernel



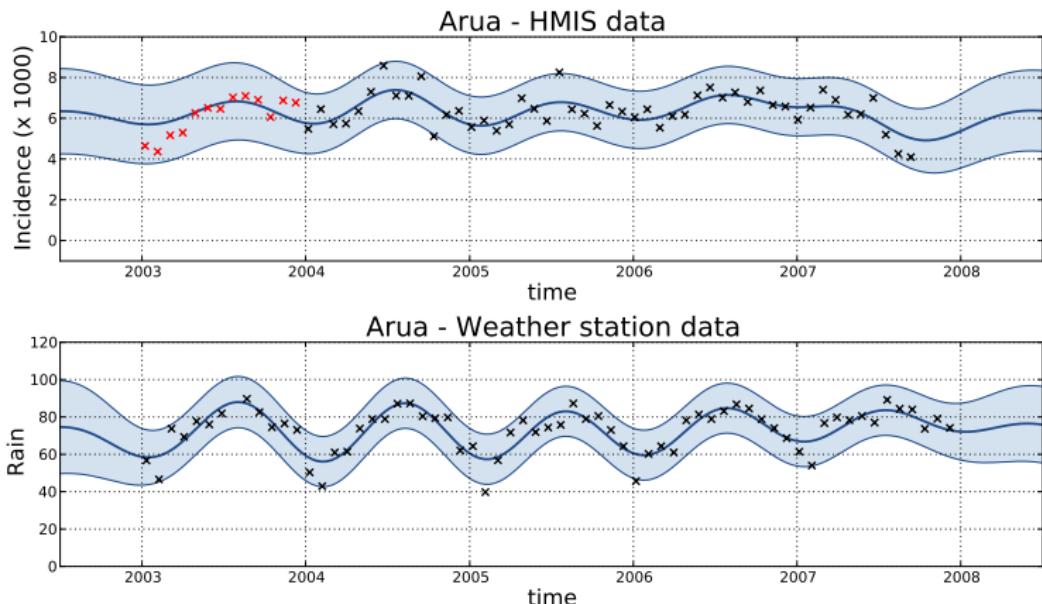
Two outputs



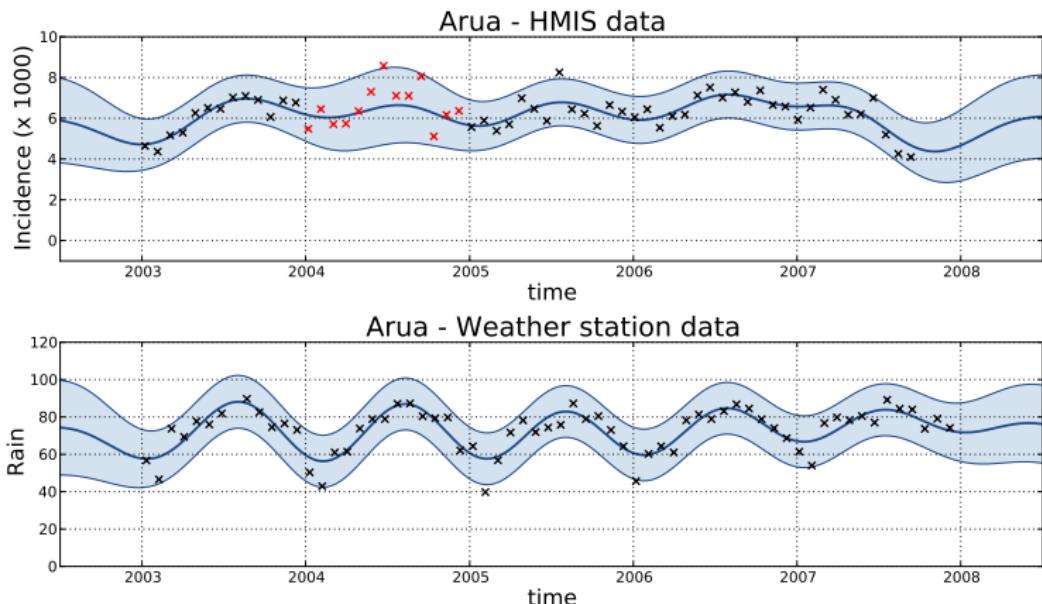
Two outputs



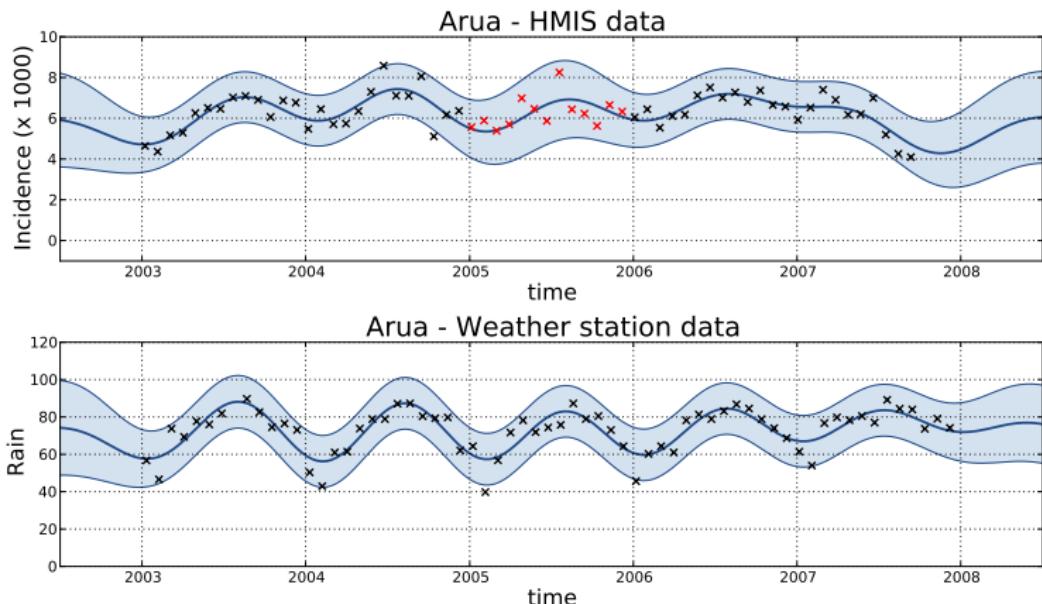
Two outputs



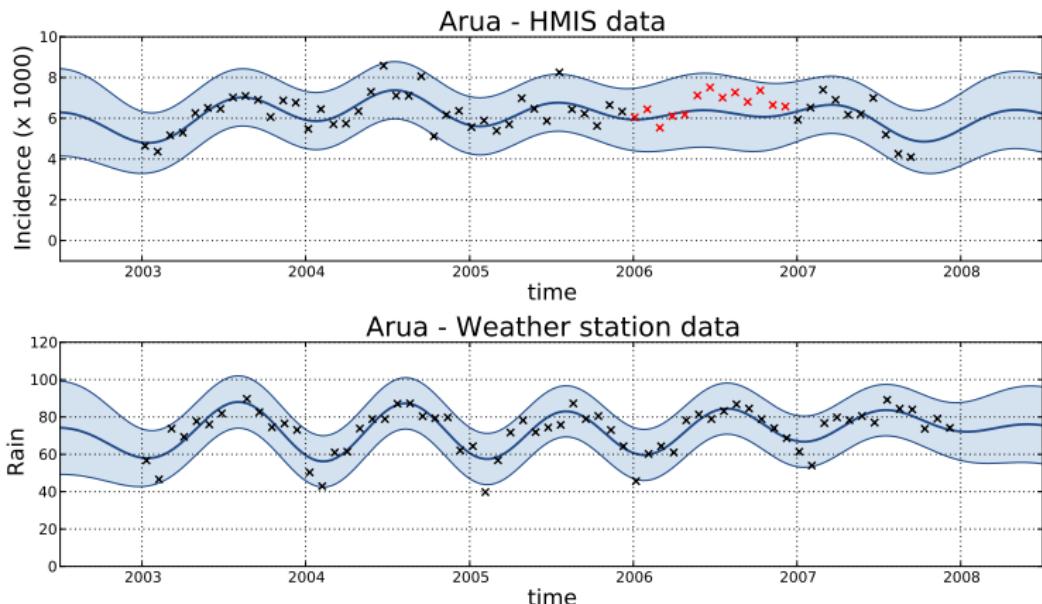
Two outputs



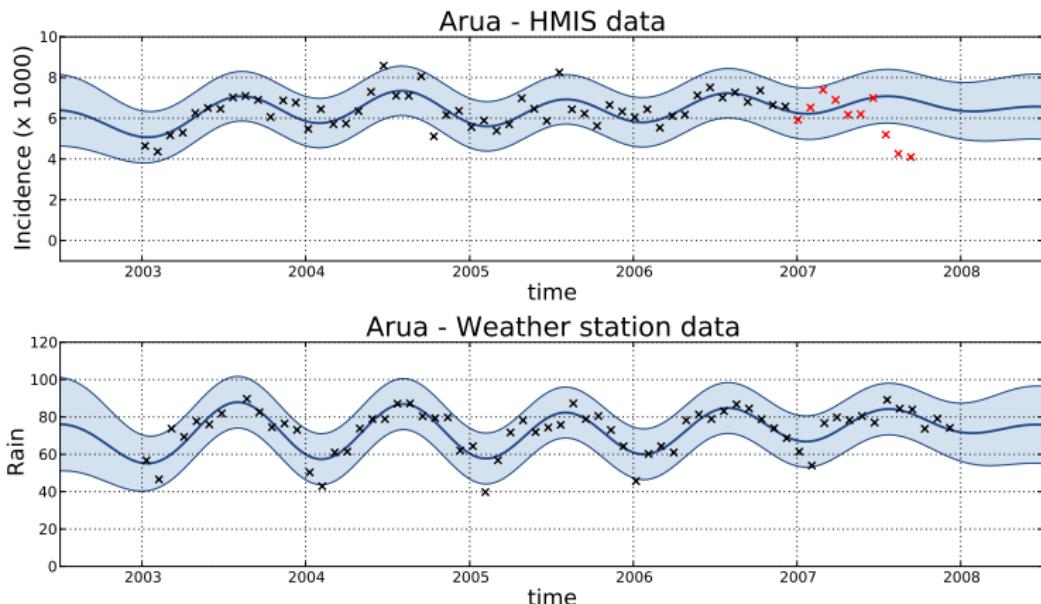
Two outputs



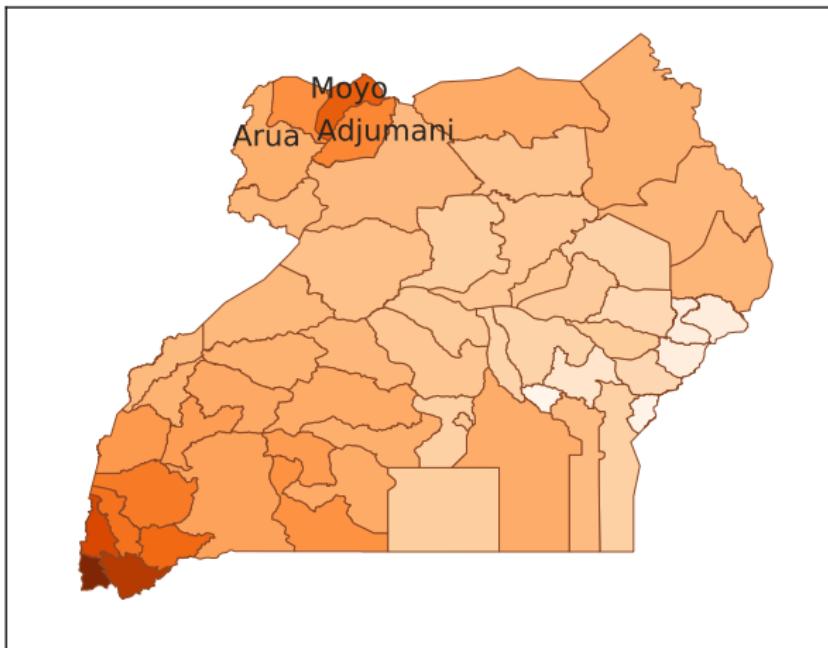
Two outputs



Two outputs



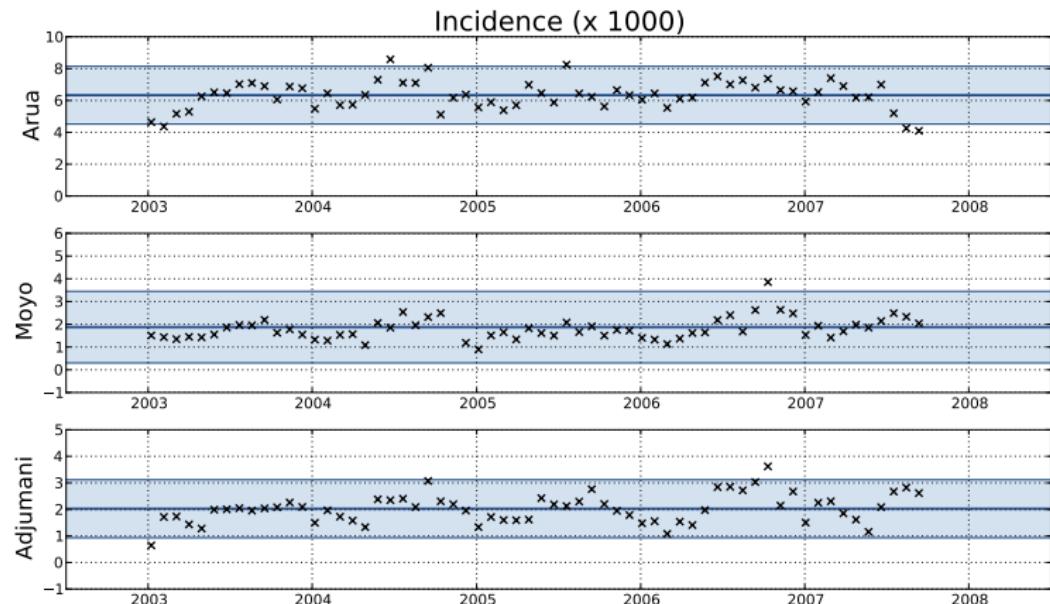
3 districts



Kernel design: bias

- ▶ Useful for outputs with different magnitudes
- ▶ Otherwise prior standardization is needed

Kernel design: bias



Kernel design: ICM vs LCM

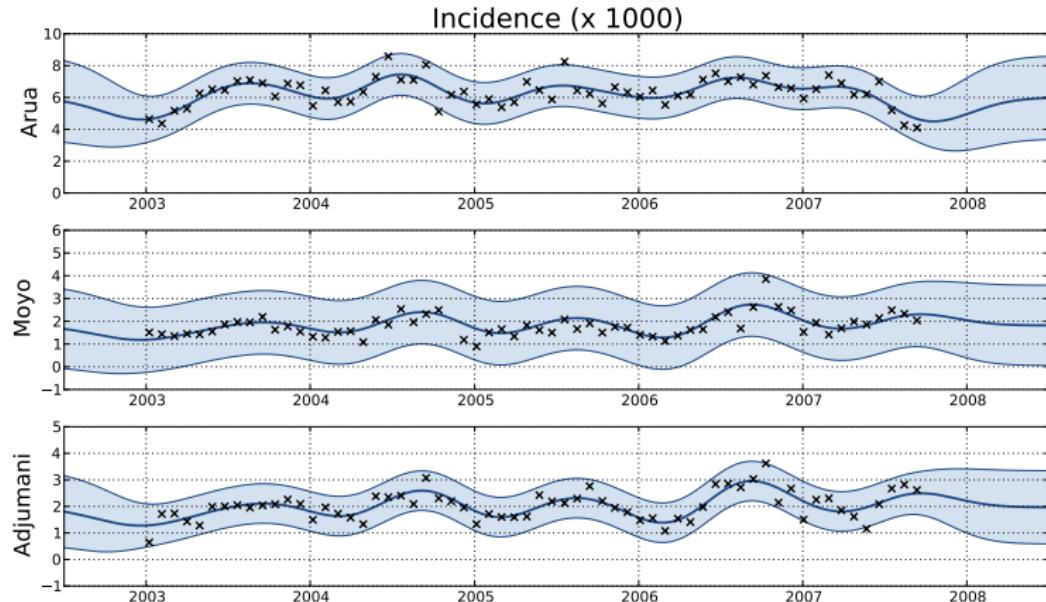
IMC

$$\text{Kernel} = \mathbf{B} \otimes (\mathbf{K}_1 + \mathbf{K}_2)$$

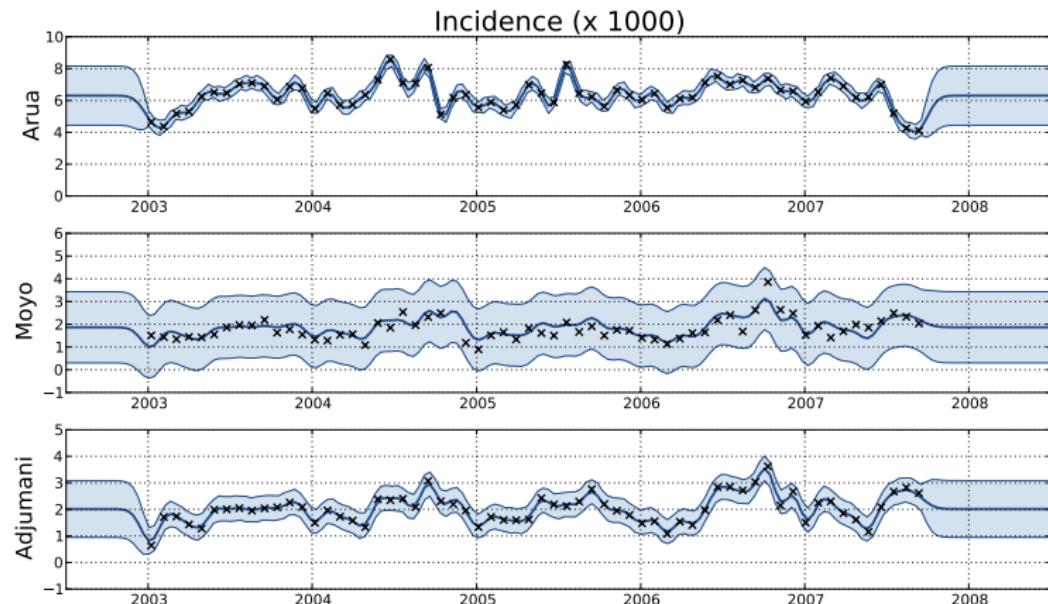
LMC

$$\text{Kernel} = \mathbf{B}_1 \otimes \mathbf{K}_1 + \mathbf{B}_2 \otimes \mathbf{K}_2$$

Kernel design: ICM



Kernel design: LCM



Kernel design: correlated vs uncorrelated components

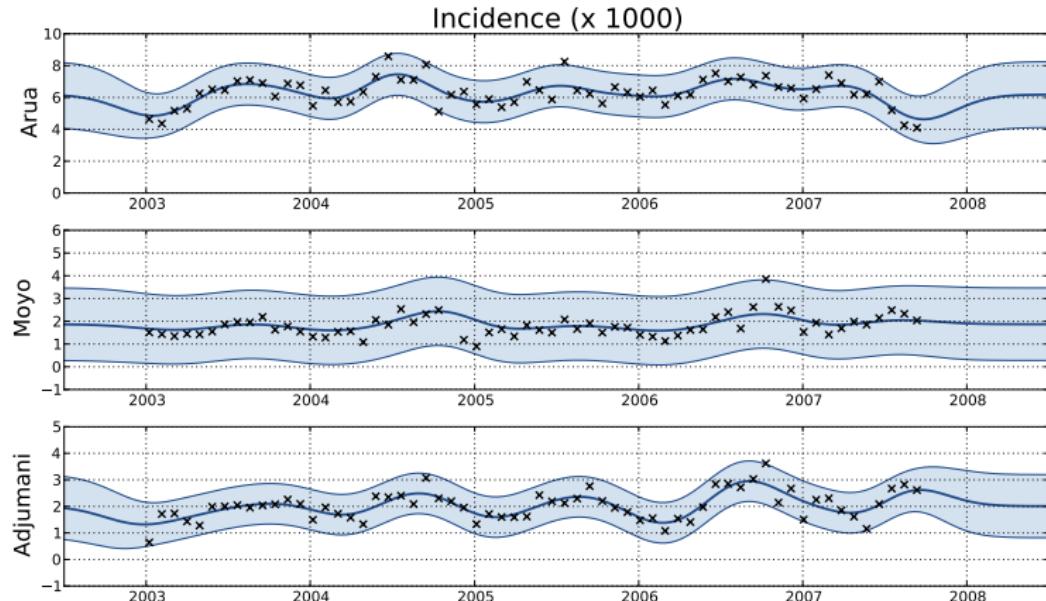
Correlated components

$$\mathbf{B} \otimes \mathbf{K} = \begin{pmatrix} B_{1,1} \times \mathbf{K}(\mathbf{X}_1, \mathbf{X}_1) & B_{1,2} \times \mathbf{K}(\mathbf{X}_1, \mathbf{X}_2) & B_{1,3} \times \mathbf{K}(\mathbf{X}_1, \mathbf{X}_3) \\ B_{2,1} \times \mathbf{K}(\mathbf{X}_2, \mathbf{X}_1) & B_{2,2} \times \mathbf{K}(\mathbf{X}_2, \mathbf{X}_2) & B_{2,3} \times \mathbf{K}(\mathbf{X}_2, \mathbf{X}_3) \\ B_{3,1} \times \mathbf{K}(\mathbf{X}_3, \mathbf{X}_1) & B_{3,2} \times \mathbf{K}(\mathbf{X}_3, \mathbf{X}_2) & B_{3,3} \times \mathbf{K}(\mathbf{X}_3, \mathbf{X}_3) \end{pmatrix}$$

Uncorrelated components

$$\mathbf{B} \otimes \mathbf{K} = \begin{pmatrix} B_{1,1} \times \mathbf{K}(\mathbf{X}_1, \mathbf{X}_1) & 0 & 0 \\ 0 & B_{2,2} \times \mathbf{K}(\mathbf{X}_2, \mathbf{X}_2) & 0 \\ 0 & 0 & B_{3,3} \times \mathbf{K}(\mathbf{X}_3, \mathbf{X}_3) \end{pmatrix}$$

Kernel design: uncorrelated components

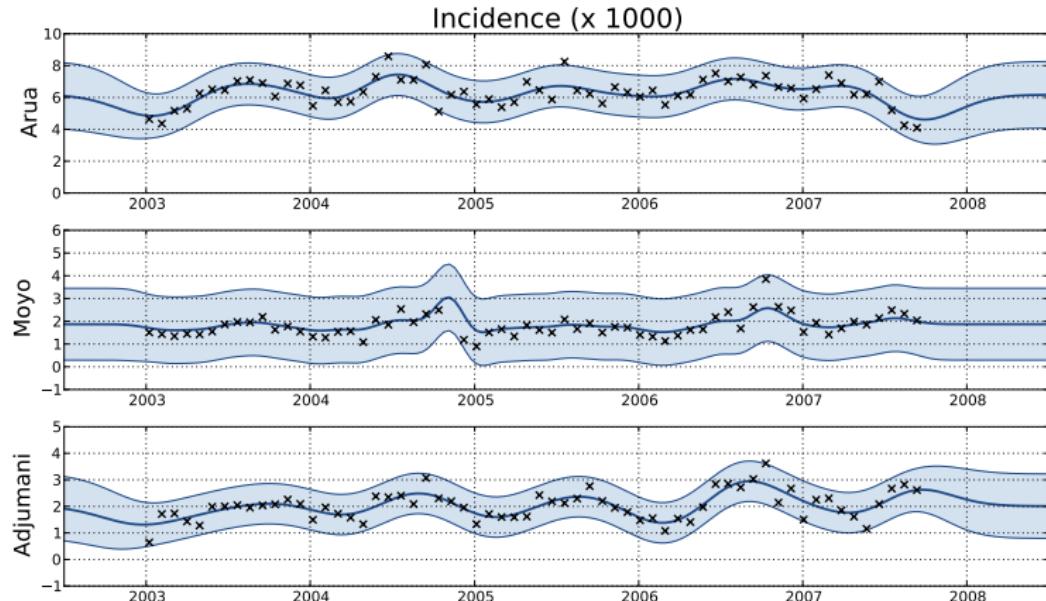


Kernel design: private kernel parameters

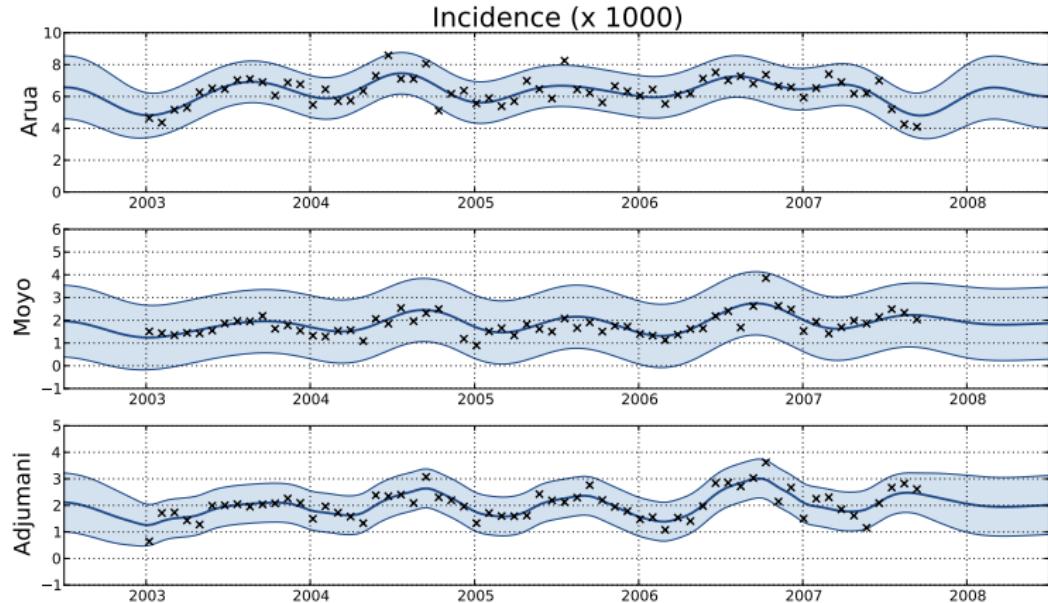
Private kernel parameters

$$\mathbf{B} \otimes \mathbf{K} = \begin{pmatrix} B_{1,1} \times \mathbf{K}_1(\mathbf{X}_1, \mathbf{X}_1) & 0 & 0 \\ 0 & B_{2,2} \times \mathbf{K}_2(\mathbf{X}_2, \mathbf{X}_2) & 0 \\ 0 & 0 & B_{3,3} \times \mathbf{K}_3(\mathbf{X}_3, \mathbf{X}_3) \end{pmatrix}$$

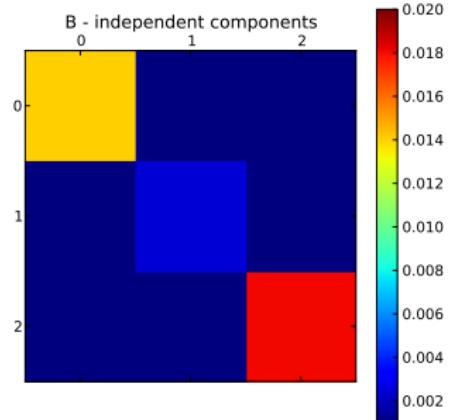
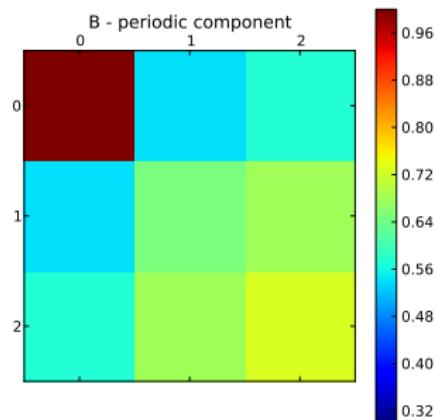
Kernel design: private components



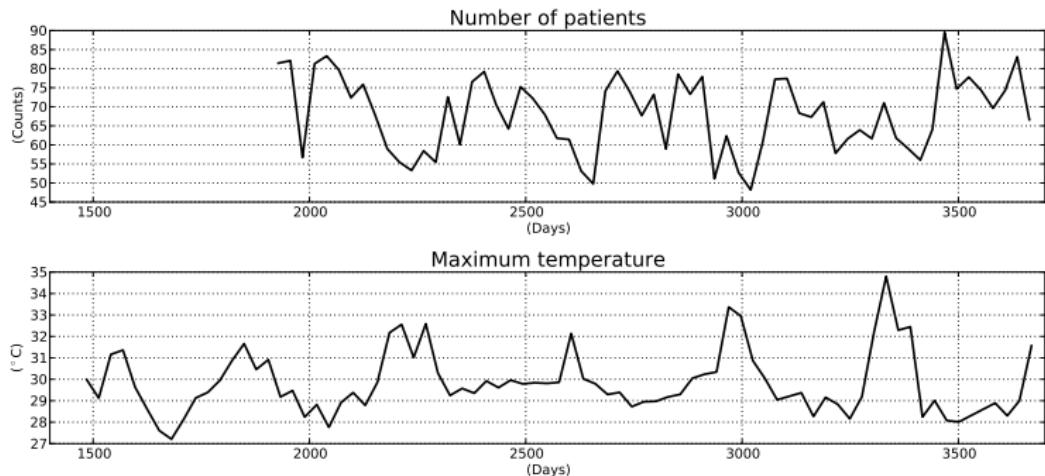
Kernel design: periodic kernel added



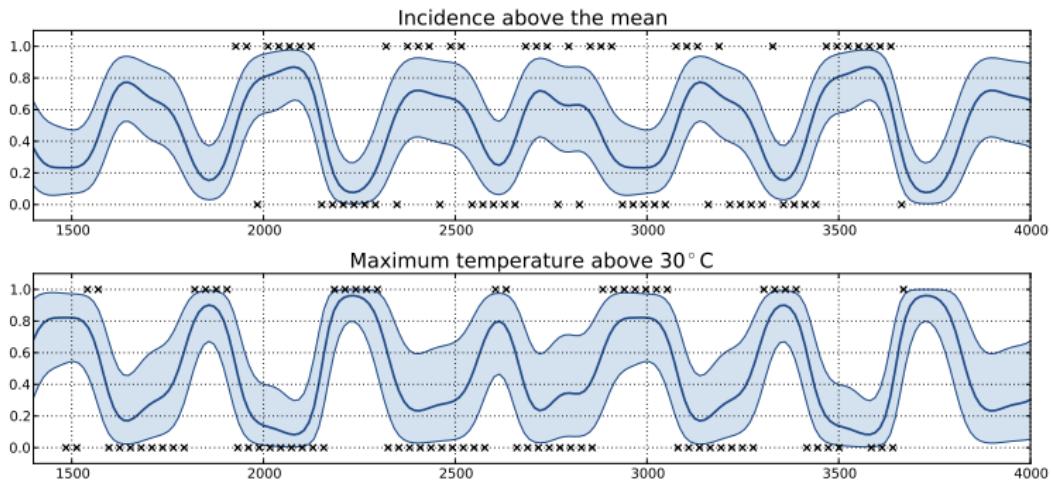
Dominant components



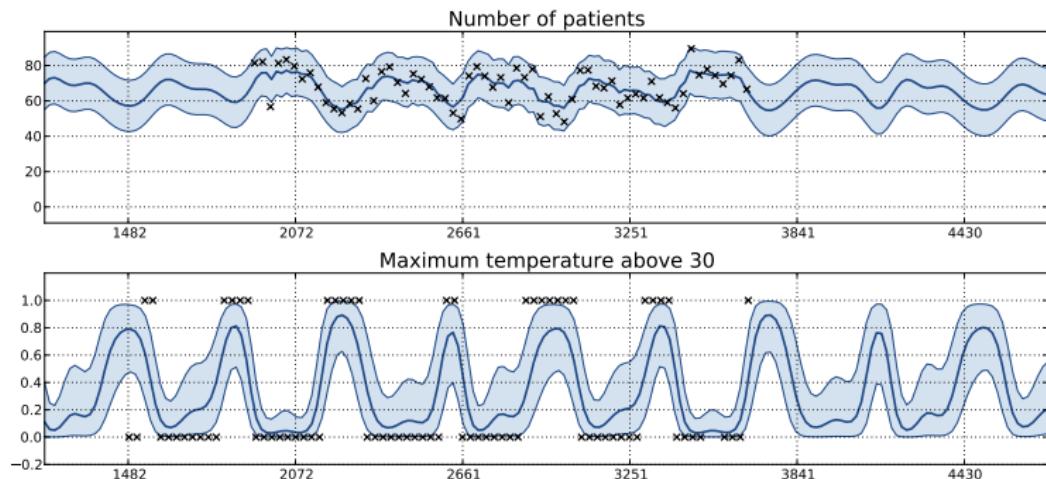
Period extraction: some ideas



Period extraction: some ideas



Period extraction: some ideas



Next

- ▶ Components dominance and parameters redundancy
- ▶ Spatial dimension
- ▶ Extend the model to the whole country

