# Parameter estimation using binary observations

O. Wani, F. Blumensaat, A. Scheidegger, T. Doppler, J. Rieckermann

**Presentation by:**

**Omar Wani**

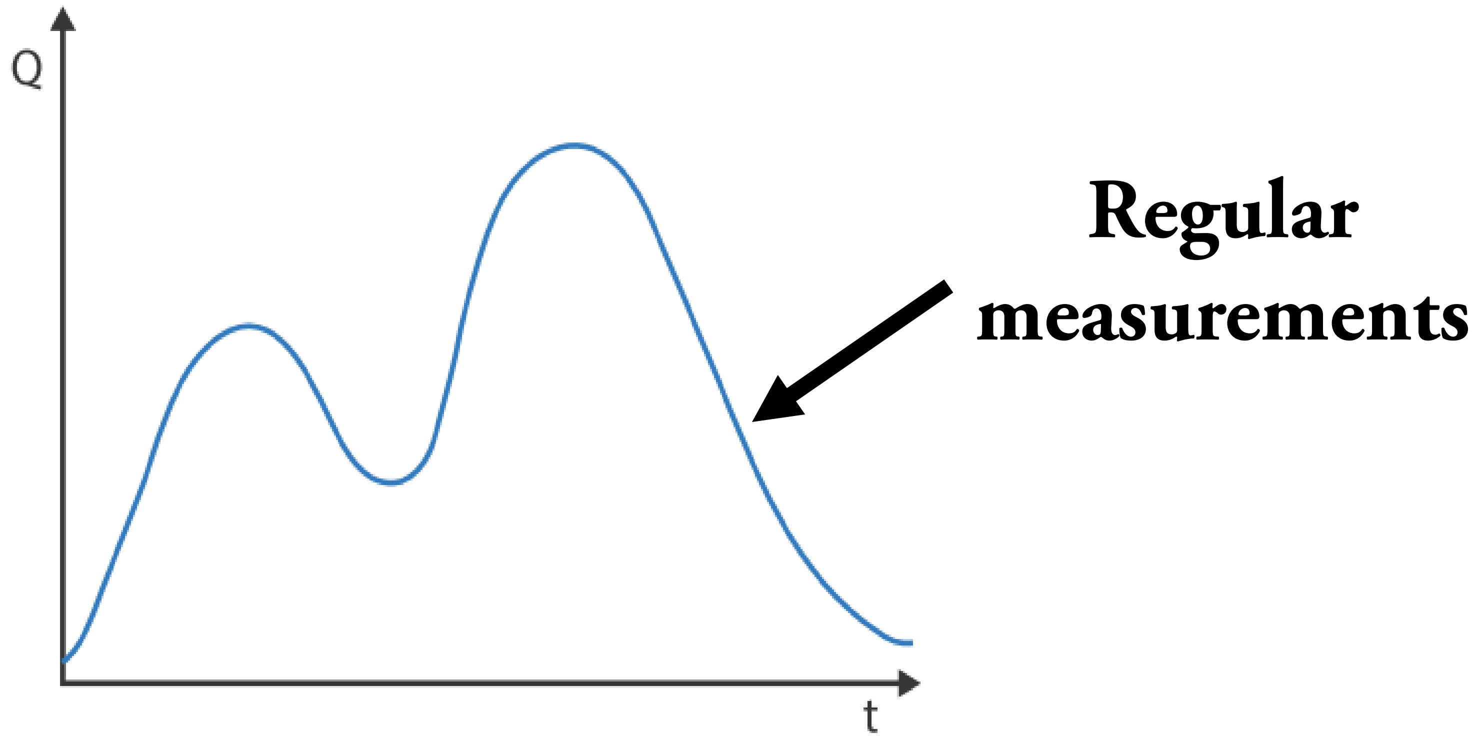
This project has received funding from the European Union's
Seventh Framework Programme for research,
technological development and demonstration
under grant agreement no 607000.

# Binary Sensor

Sensors that provide binary signals corresponding to a threshold

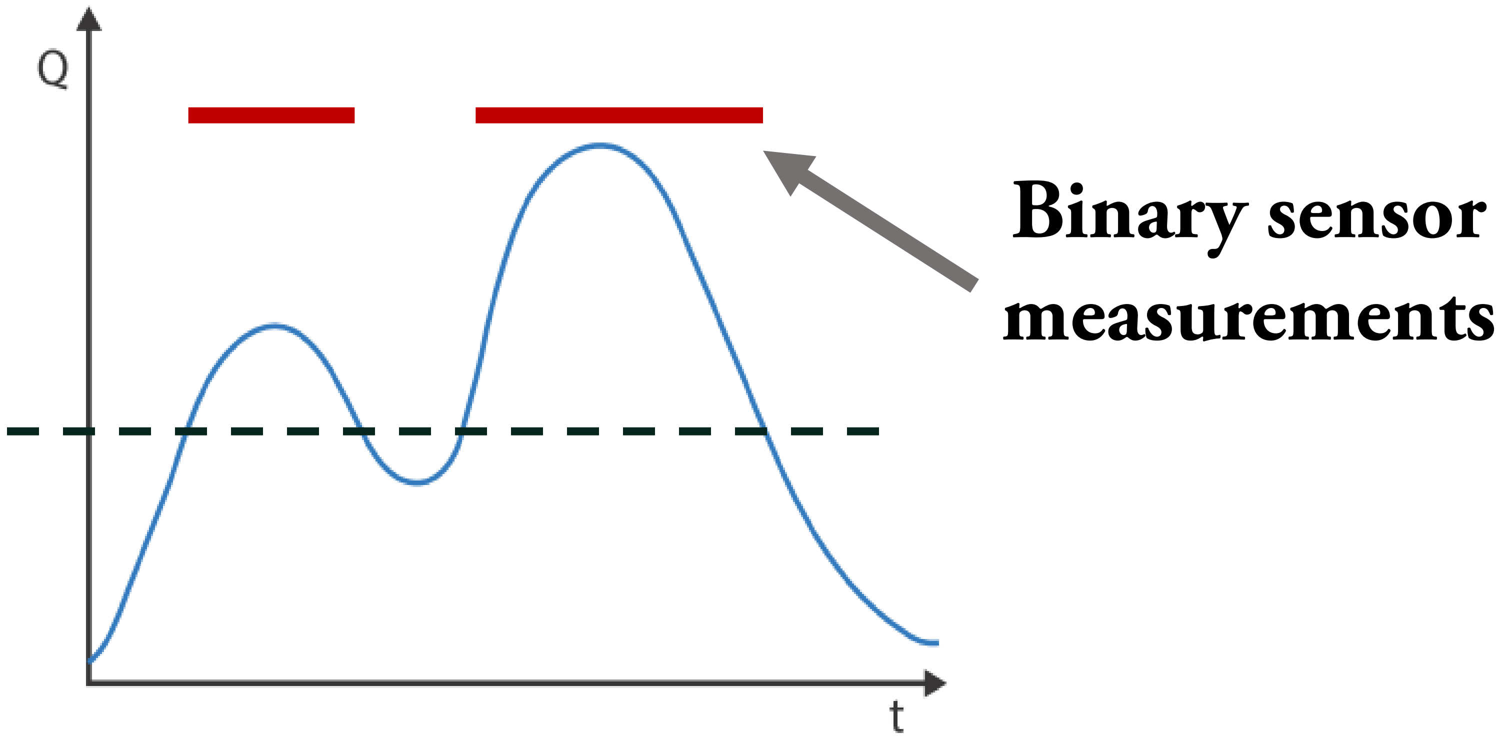
# Binary Sensor

Sensors that provide binary signals corresponding to a threshold



# Binary Sensor

Sensors that provide binary signals corresponding to a threshold



# Binary Sensor

Rassmussen et al, 2008

# Binary Sensor

Siemers et al, 2007

# Binary Sensor

Sensor detecting shakes


Threshold

# Binary Sensor

## Advantages of using binary sensors

# Binary Sensor

## Advantages of using binary sensors

- Robust

# Binary Sensor

## Advantages of using binary sensors

- Robust
- Cheap

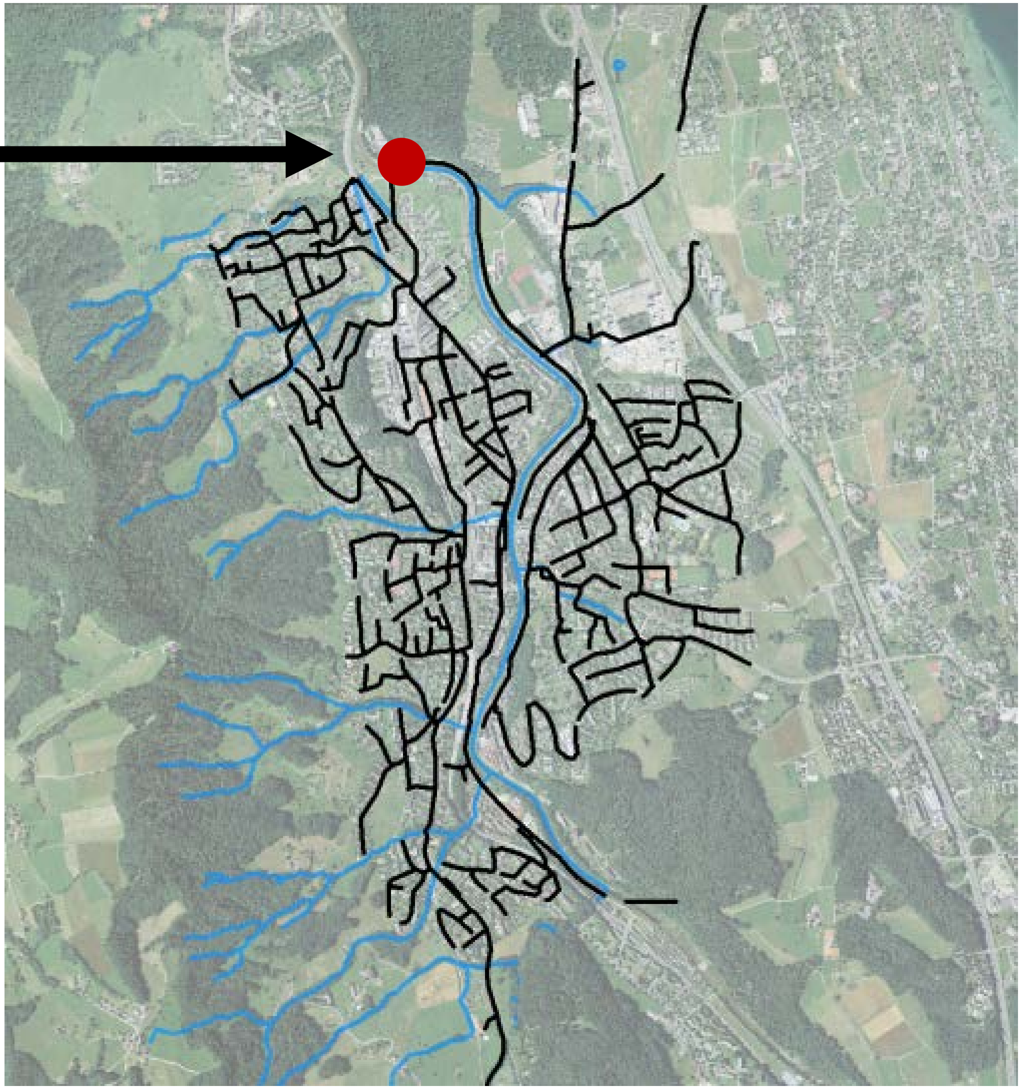
# Binary Sensor

Advantages of using binary sensors

- Robust
- Cheap
- Low maintainenece

# Problem

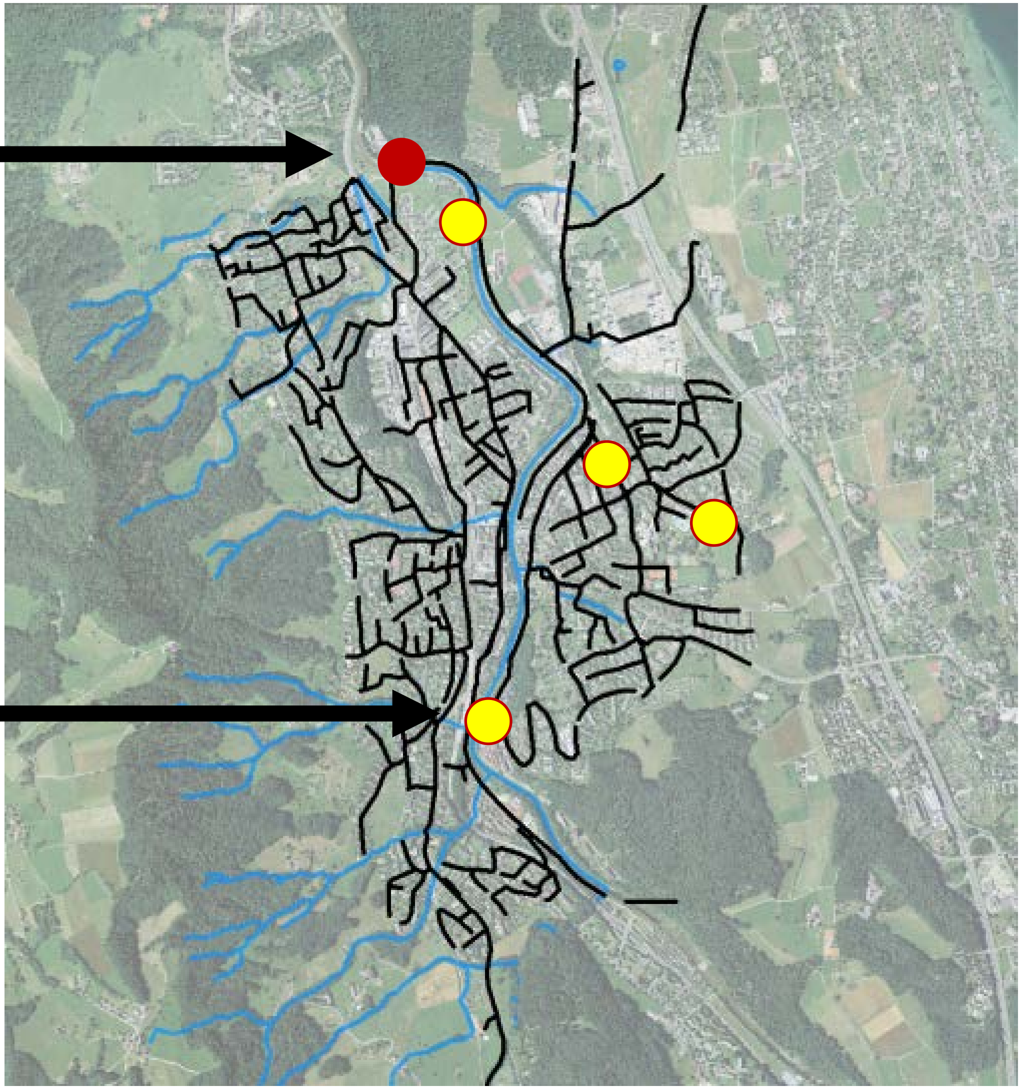
Limited number of flowmeters



# Idea

Limited number of flowmeters

More binary sensors feasible



# Idea

13th International Conference on Urban Drainage, Sarawak, Malaysia, 7–12 September 2014

## Using Temperature Sensors to Detect Occurrence and Duration of Combined Sewer Overflows

Thomas HOFER[1*], Günter GRUBER[1], Valentin GAMERITH[2], Albert MONTSERRAT[3], Lluís COROMINAS[3], Dirk MUSCHALLA[1]

**Low Cost Overflow Monitoring Techniques and Hydraulic Modeling of A Complex Sewer Network**

Laura Siemers, P.E., GHD Inc., and Joseph Dodd, GHD Inc.
Deborah Day, City of Utica Engineering Department; David Kerr, P.E., GHD Inc.; John LaGorga, P.E., GHD Inc.; Paul Romano, P.E., Shumaker Consulting Engineering & Land Surveying

GHD Inc.
16701 Melford Boulevard, Suite 330
Bowie, MD 20715

# Question?

How to use binary data
in model calibration?

(in a statistically sound way)

Realistic error model:

* Model structure deficits
- Input errors
- * Incomplete knowledge on model parameters

# Idea

11th International Conference on Urban Drainage, Edinburgh, Scotland, UK, 2008

**A low cost calibration method for urban drainage models**

M. R. Rasmussen*, S. Thorndahl and K. Schaarup-Jensen

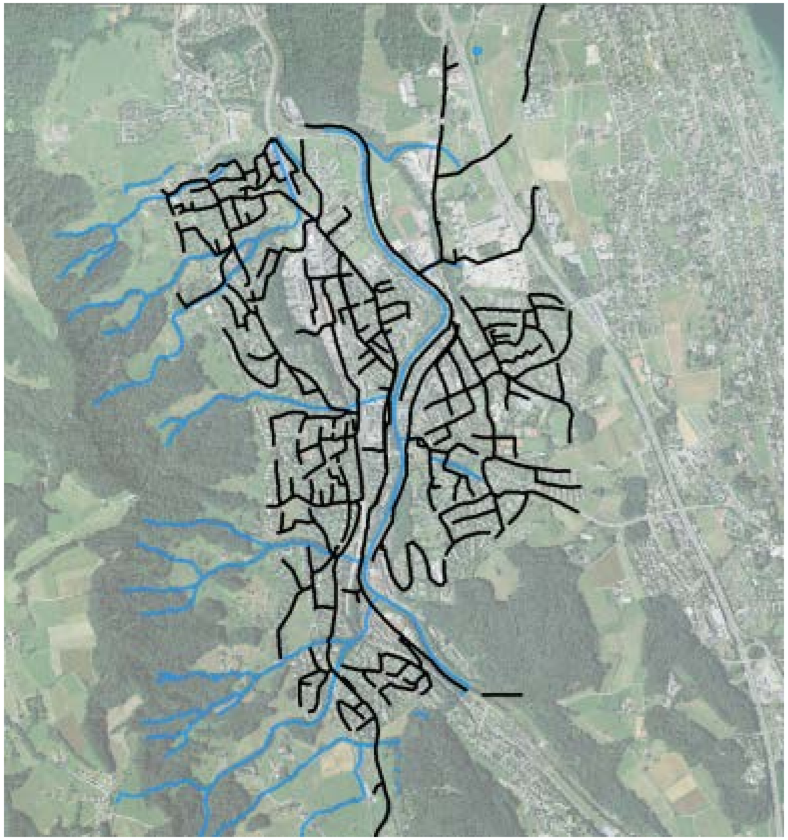
Stoch Environ Res Risk Assess (2015) 29:119–129
DOI 10.1007/s00477-014-0908-1

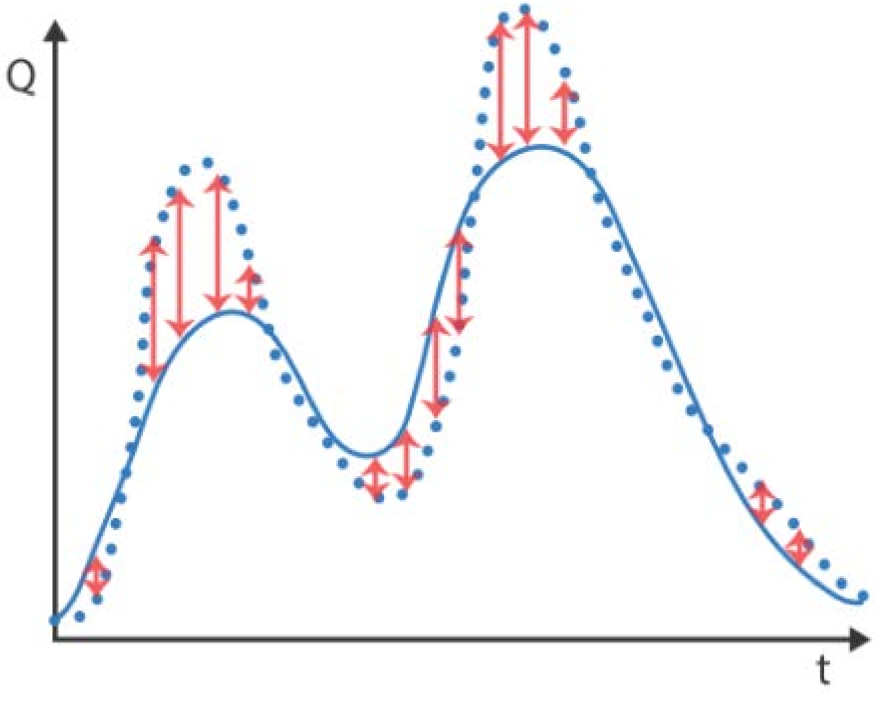
ORIGINAL PAPER

**A partial ensemble Kalman filtering approach to enable use of range limited observations**

**Morten Borup · Morten Grum · Henrik Madsen · Peter Steen Mikkelsen**

# Bias






Mismatch between reality and model predictions

# Solution: Realistic error model

Use a statistical description of bias in addition to the model

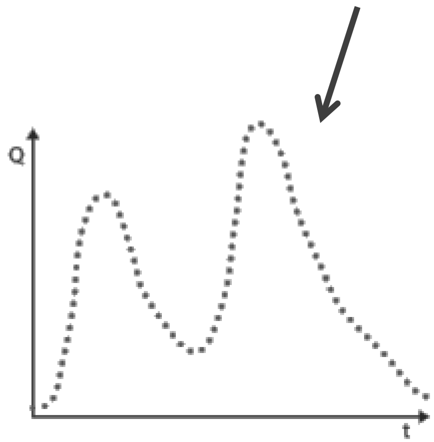
Formulate a formal likelihood function for binary observations

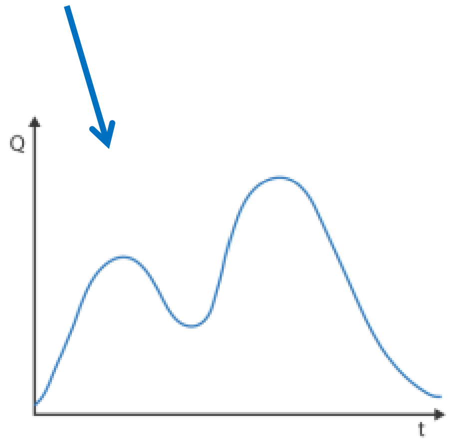
# How can we describe model bias?

$$Y_{obs} = y_M + B$$

# How can we describe model bias?

$$Y_{obs} = y_M + B$$



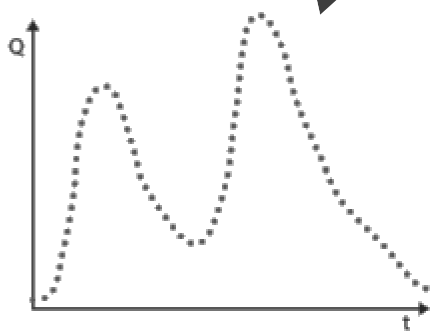



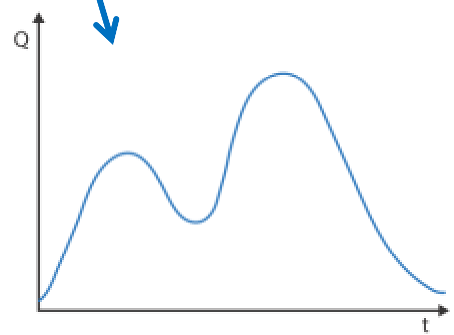
# How can we describe model bias?

$$Y_{obs} = y_M + B$$

Gaussian, autocorrelated

Mimics the effects of Inp./Str. errors

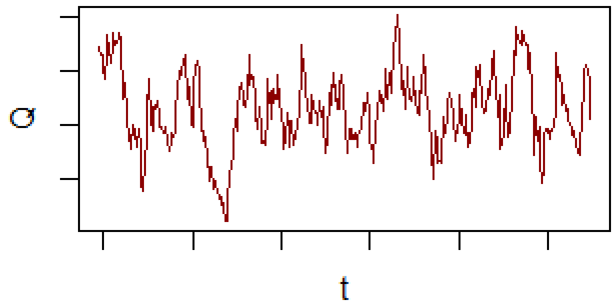


# How can we describe model bias?

$$Y_{obs} = y_M + B$$

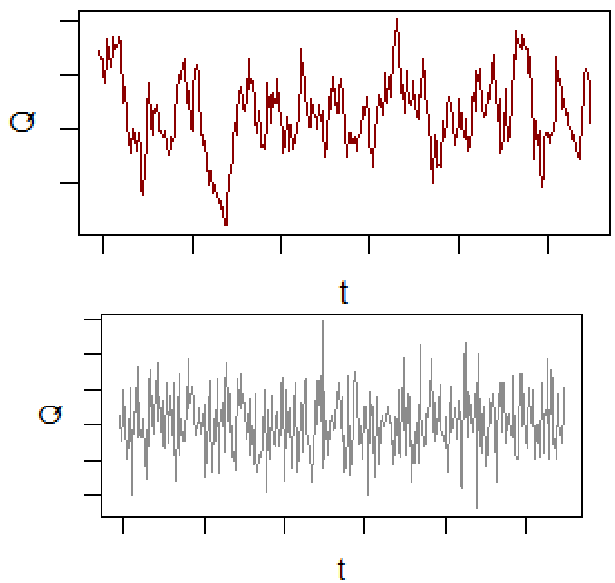
Ornstein–Uhlenbeck process with $\mu$=0



# How can we describe model bias?

$$Y_{obs} = y_M + B$$

Ornstein–Uhlenbeck process with $\mu$=0

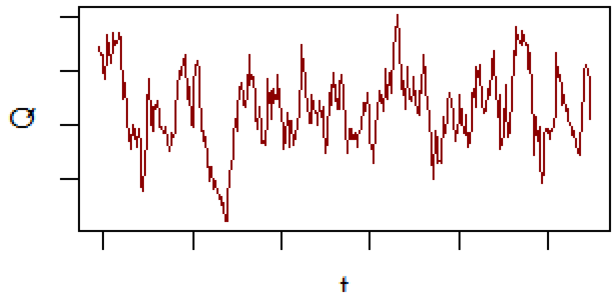


# How can we describe model bias?

$$\frac{(2\pi)^{-\frac{n}{2}}}{\sqrt{\det(\boldsymbol{\Sigma}(\psi,\mathbf{x}))}}\exp\left(-\frac{1}{2}[\mathbf{y}_o-\mathbf{y}_M(\theta,\mathbf{x})]^{\mathrm{T}}\boldsymbol{\Sigma}(\psi,\mathbf{x})^{-1}[\mathbf{y}_o-\mathbf{y}_M(\theta,\mathbf{x})]\right)$$

$$Y_{obs} = y_M + B$$

Ornstein–Uhlenbeck process with $\mu$=0




Bayesian inference

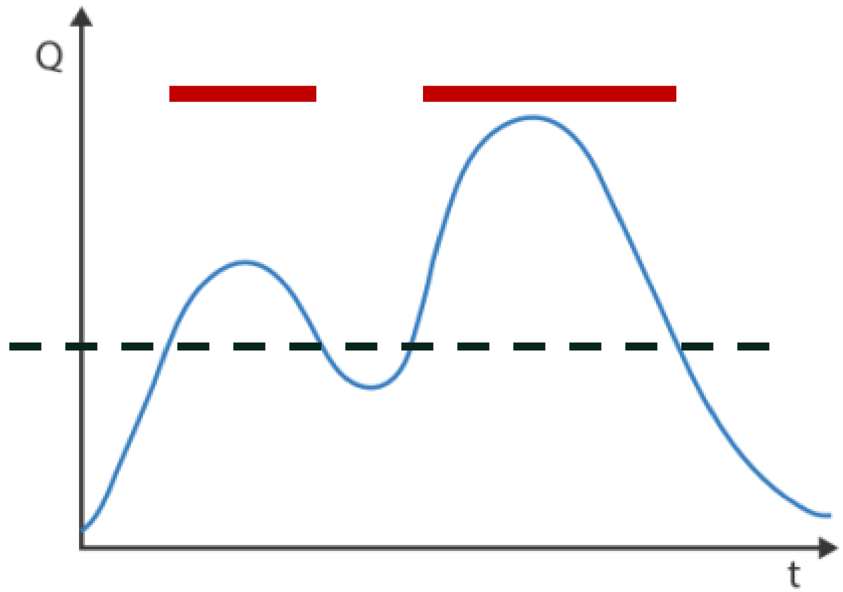
$$p_\theta(\theta \mid \mathbf{Z}) = \frac{p_\mathbf{Z}(\mathbf{Z} \mid \theta) \times p_\theta(\theta)}{p_\mathbf{Z}(\mathbf{Z})}$$

# Likelihood for binary observations

$$Z_t = \begin{cases} 1 & \mathrm{Y_t} > y_{threshold} \\ 0 & \mathrm{Y_t} \leq y_{threshold} \end{cases}$$

Likelihood function

$$p_{\mathbf{Z}}(\mathbf{Z} \mid \theta) = \int_{l_1}^{u_1} \dots . \int_{l_n}^{u_n} p_Y\left(\mathrm{Y_{t1}}, \dots, \mathrm{Y_{t_n}} \mid \theta\right) \mathrm{dY_{t1}} \dots \mathrm{dY_{t_n}}$$

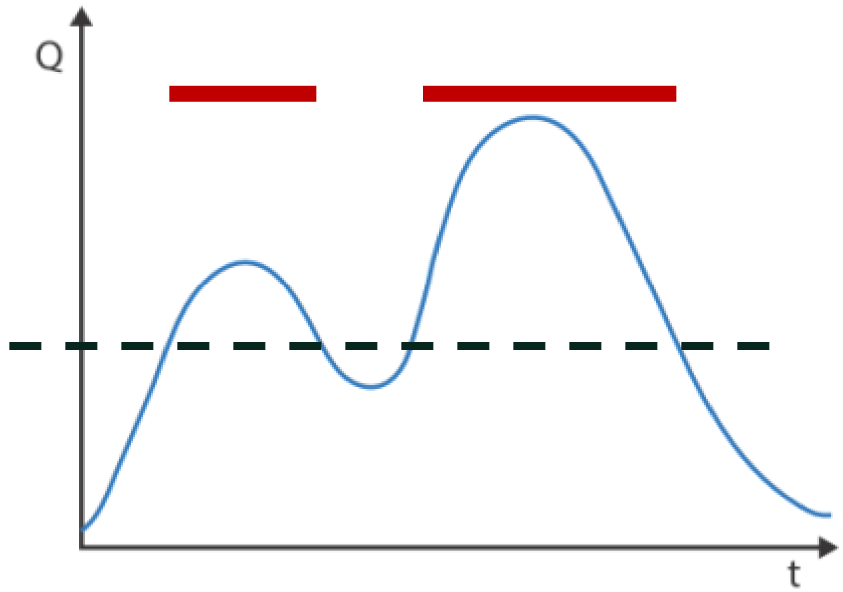


# Likelihood for binary observations

$$Z_t = \begin{cases} 1 & \mathrm{Y_t} > y_{threshold} \\ 0 & \mathrm{Y_t} \leq y_{threshold} \end{cases}$$

Likelihood function

$$p_{\mathbf{Z}}(\mathbf{Z} \mid \theta) = \int_{l_1}^{u_1} \ldots . \int_{l_n}^{u_n} p_Y\left(\mathrm{Y_{t1}}, \ldots, \mathrm{Y_{t_n}} \mid \theta\right) \mathrm{dY_{t1}} \ldots \mathrm{dY_{t_n}}$$

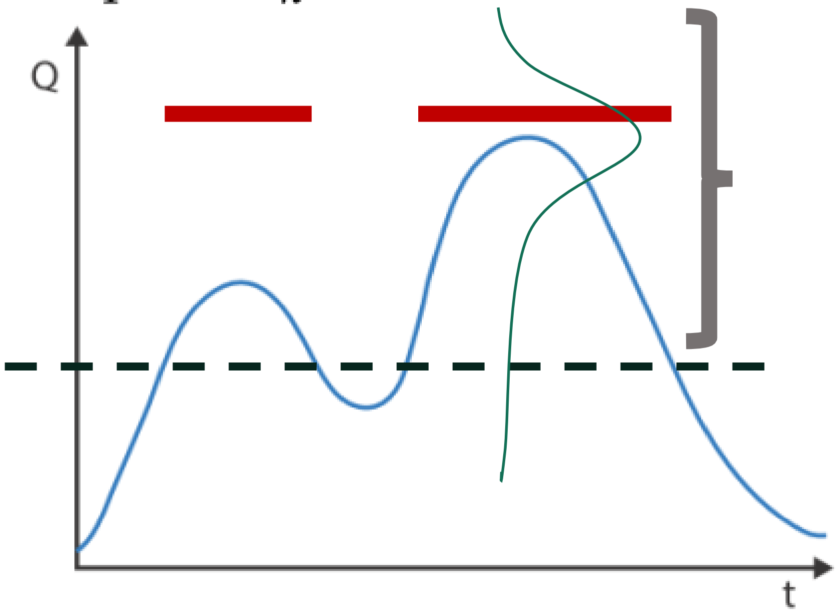


# Likelihood for binary observations

$$Z_t = \begin{cases} 1 & Y_t > y_{threshold} \\ 0 & Y_t \leq y_{threshold} \end{cases}$$

Likelihood function

$$p_{\mathbf{Z}}(\mathbf{Z} \mid \theta) = \int_{l_1}^{u_1} \dots . \int_{l_n}^{u_n} p_Y\left(Y_{t1}, \dots, Y_{t_n} \mid \theta\right) dY_{t1} \dots dY_{t_n}$$



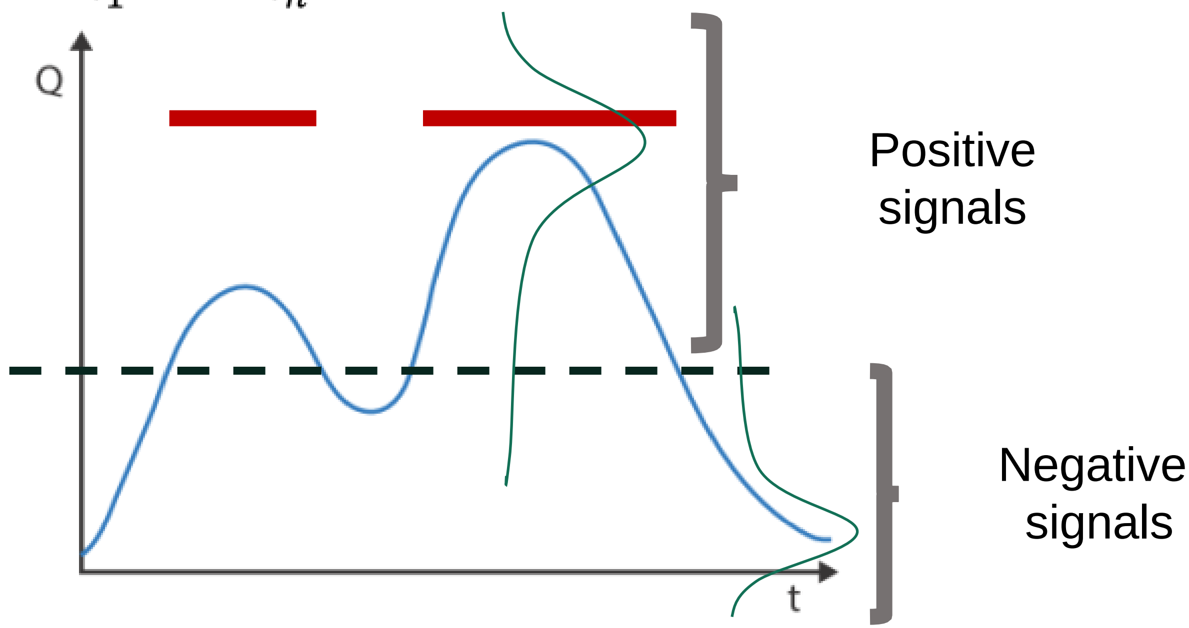

Positive signals

# Likelihood for binary observations

$$Z_t = \begin{cases} 1 & Y_t > y_{threshold} \\ 0 & Y_t \leq y_{threshold} \end{cases}$$

Likelihood function

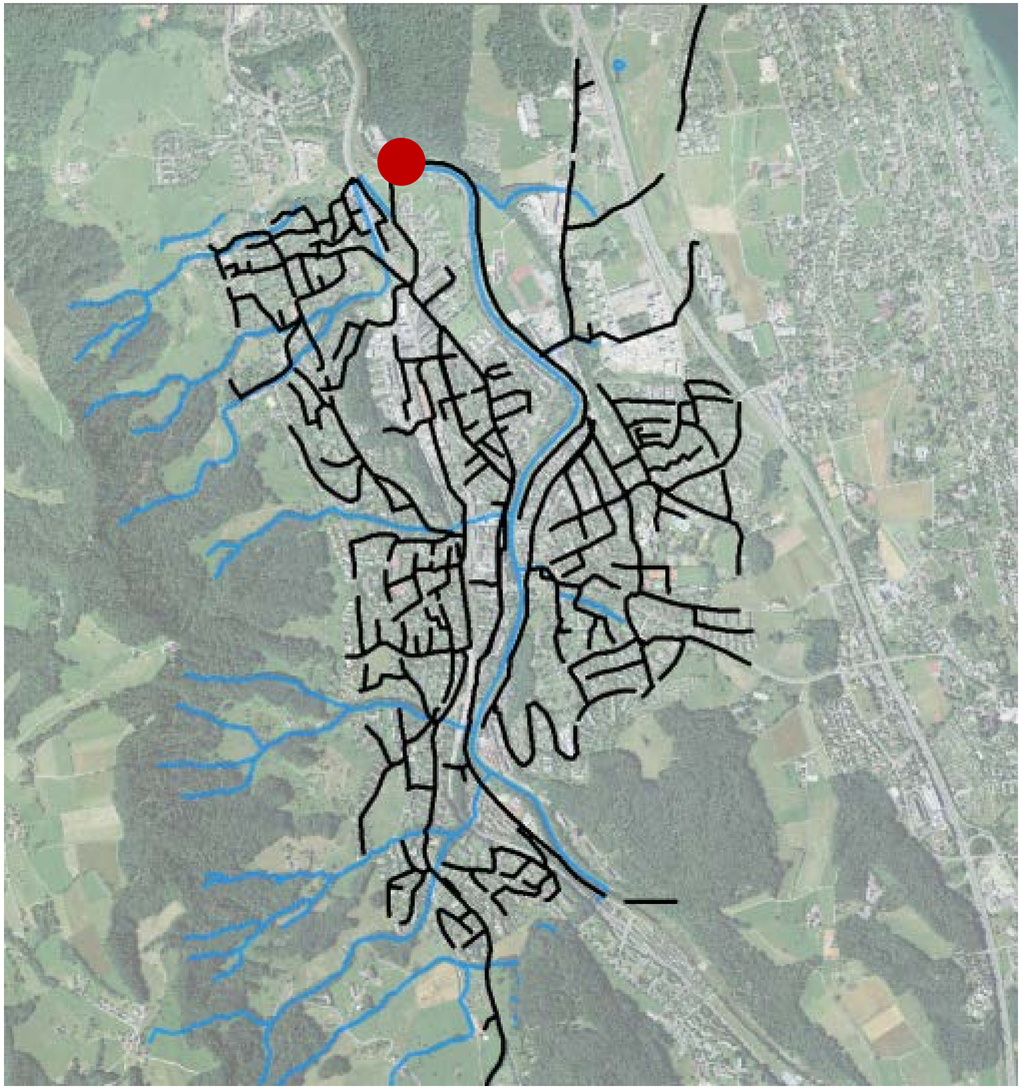
$$p_{\mathbf{Z}}(\mathbf{Z} \mid \theta) = \int_{l_1}^{u_1} \dots \int_{l_n}^{u_n} p_Y\left(\mathrm{Y}_{t1}, \dots, \mathrm{Y}_{t_n} \mid \theta\right) \mathrm{dY}_{t1} \dots \mathrm{dY}_{t_n}$$



# Case study: Adliswil

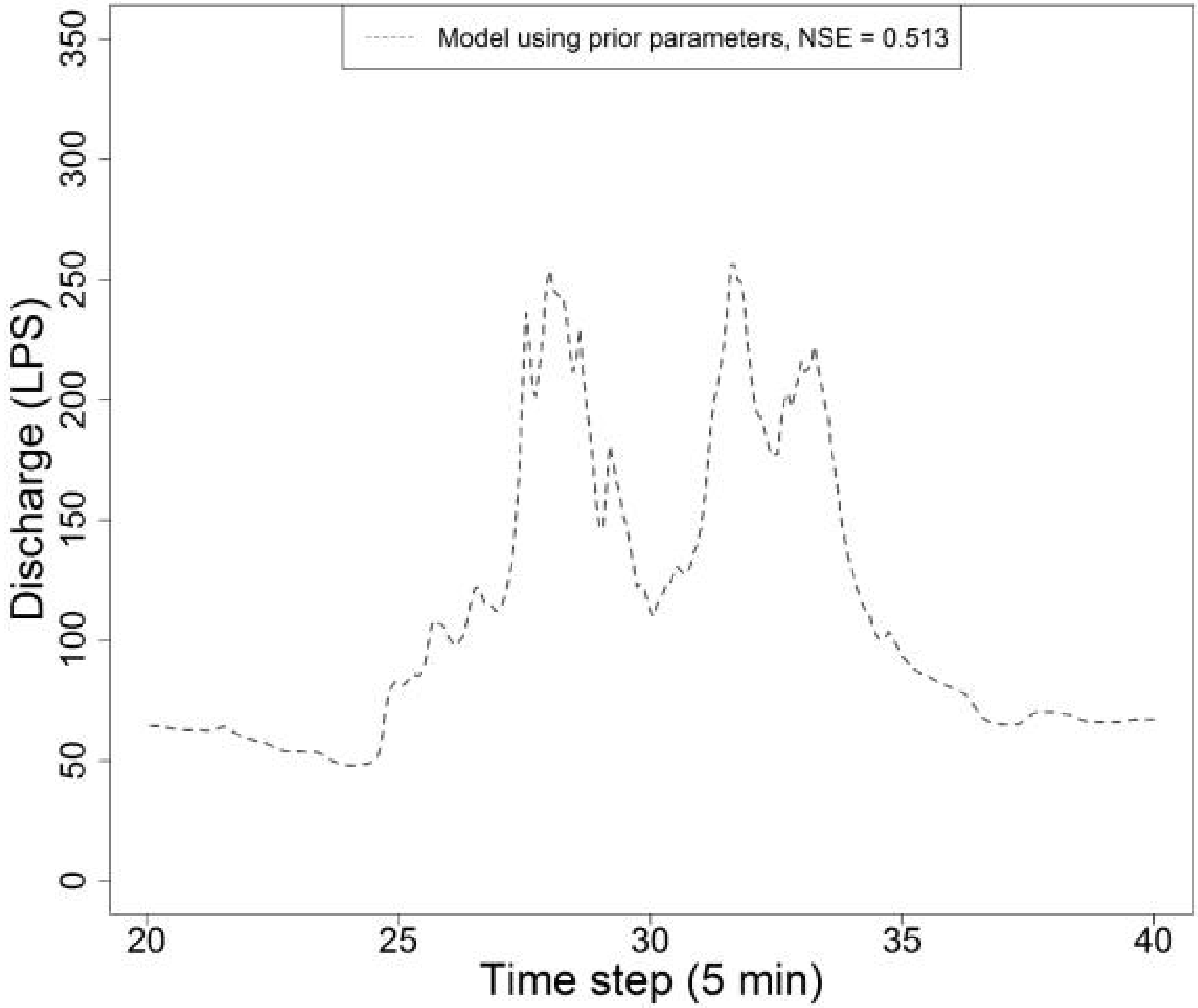
Adliswil

- South of Zürich
- Area: 7.8 $km^2$
- Population: 18000



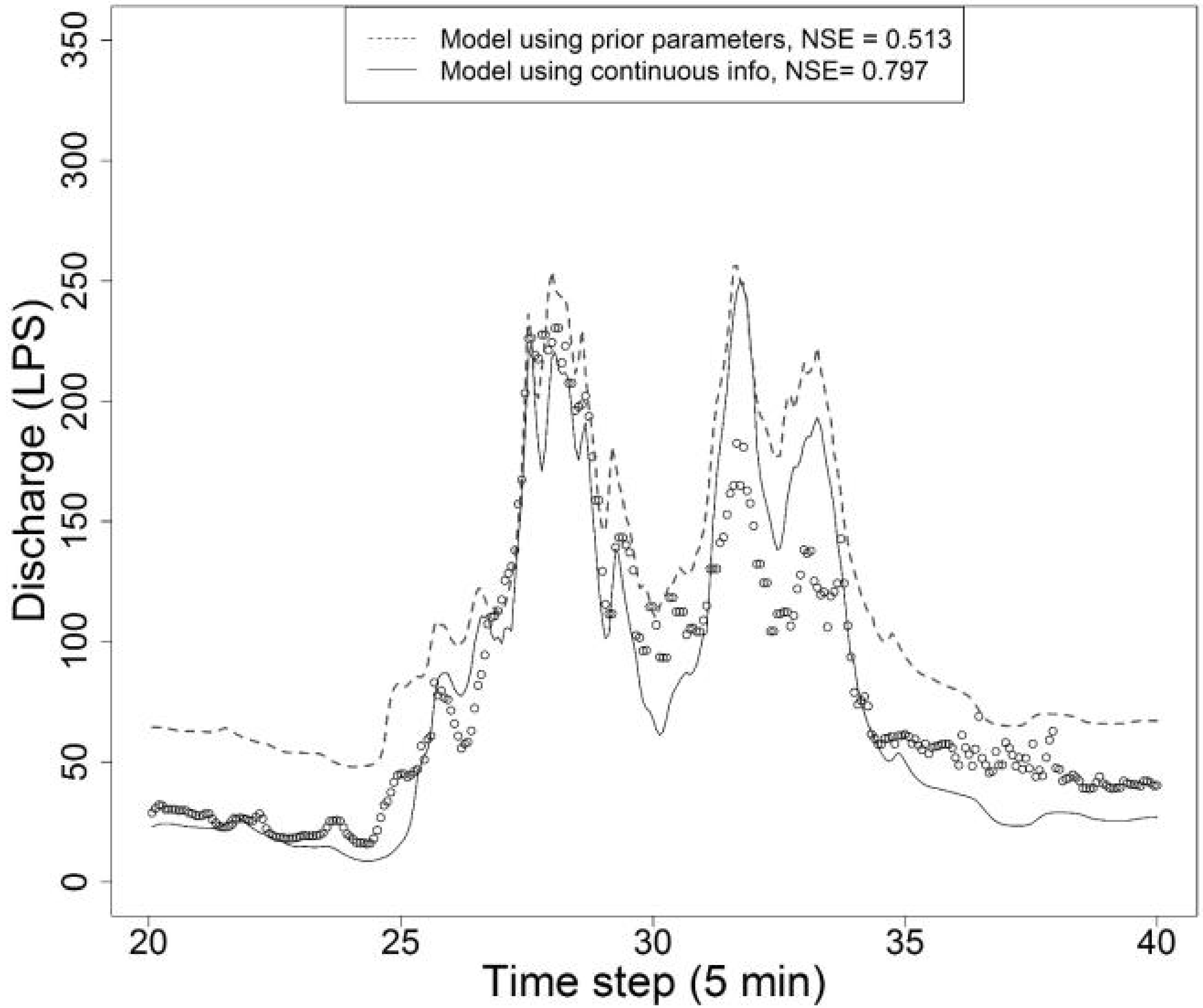
# Results

**Prior -NSE = 0.51**



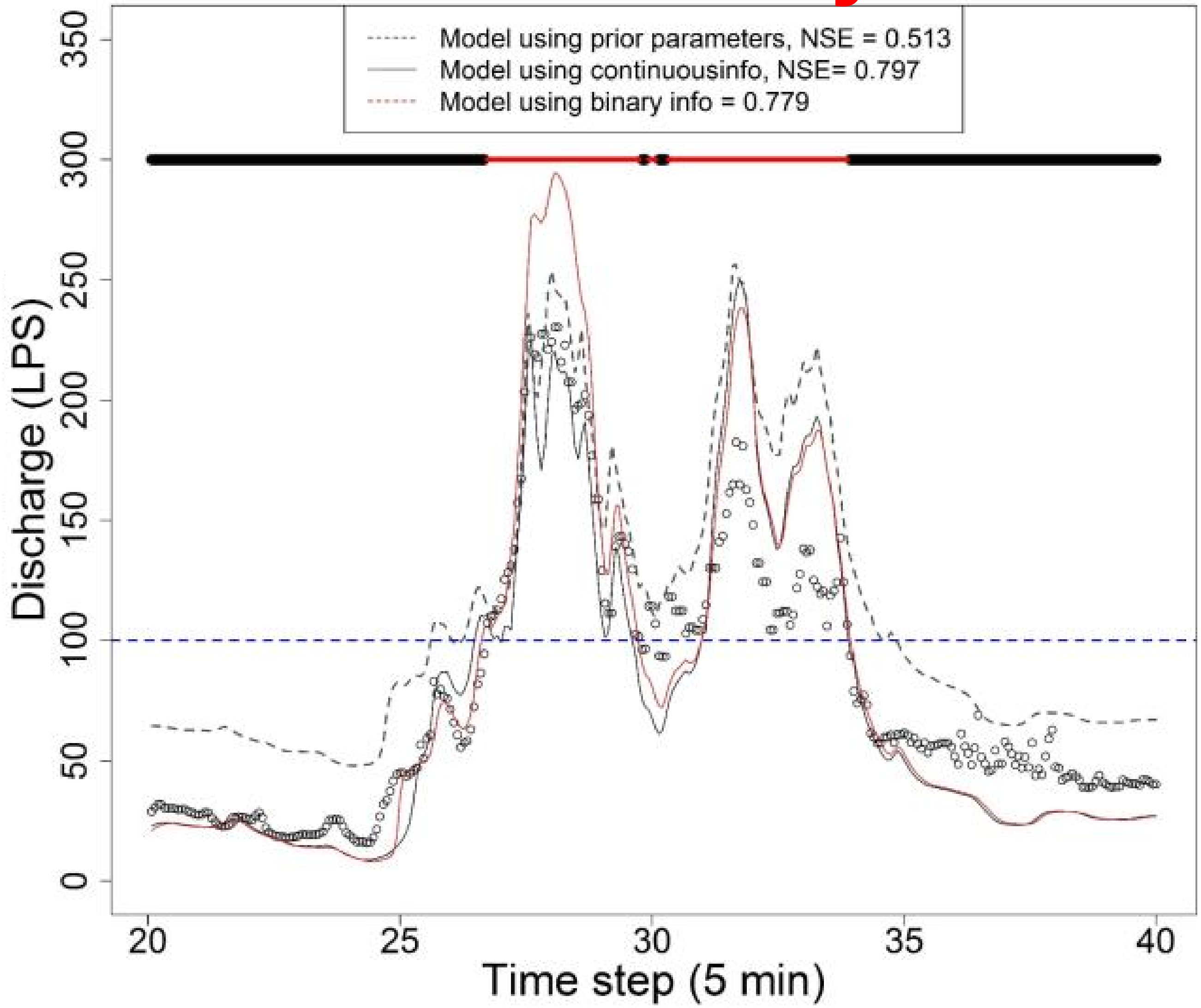
## Results

# Continuous - NSE = 0.8



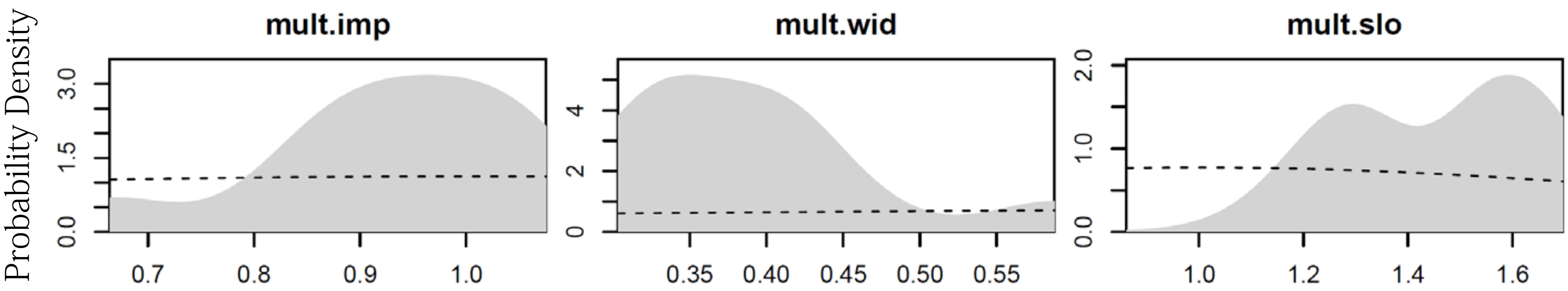
# Results

## Binary - NSE = 0.77

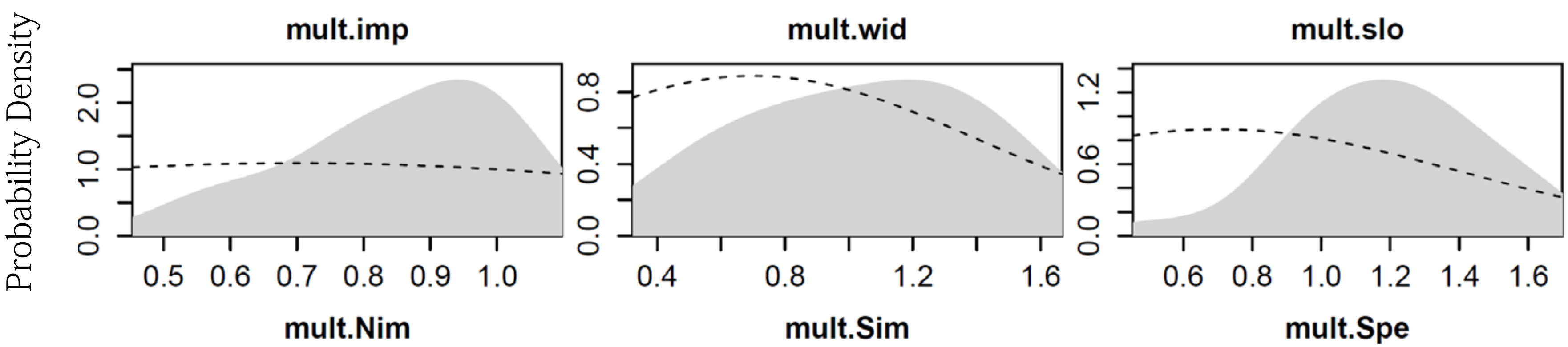


# Parameter Posteriors

## Continuous data

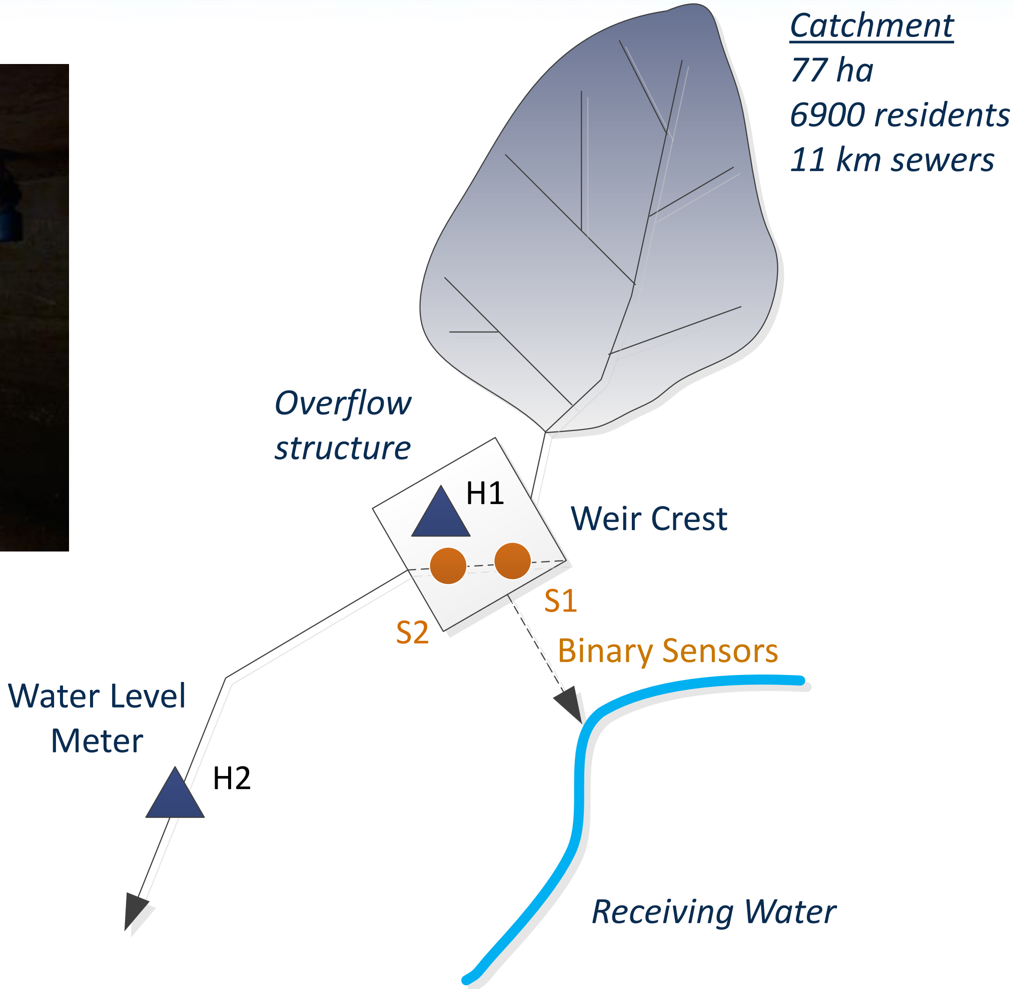



## Binary data



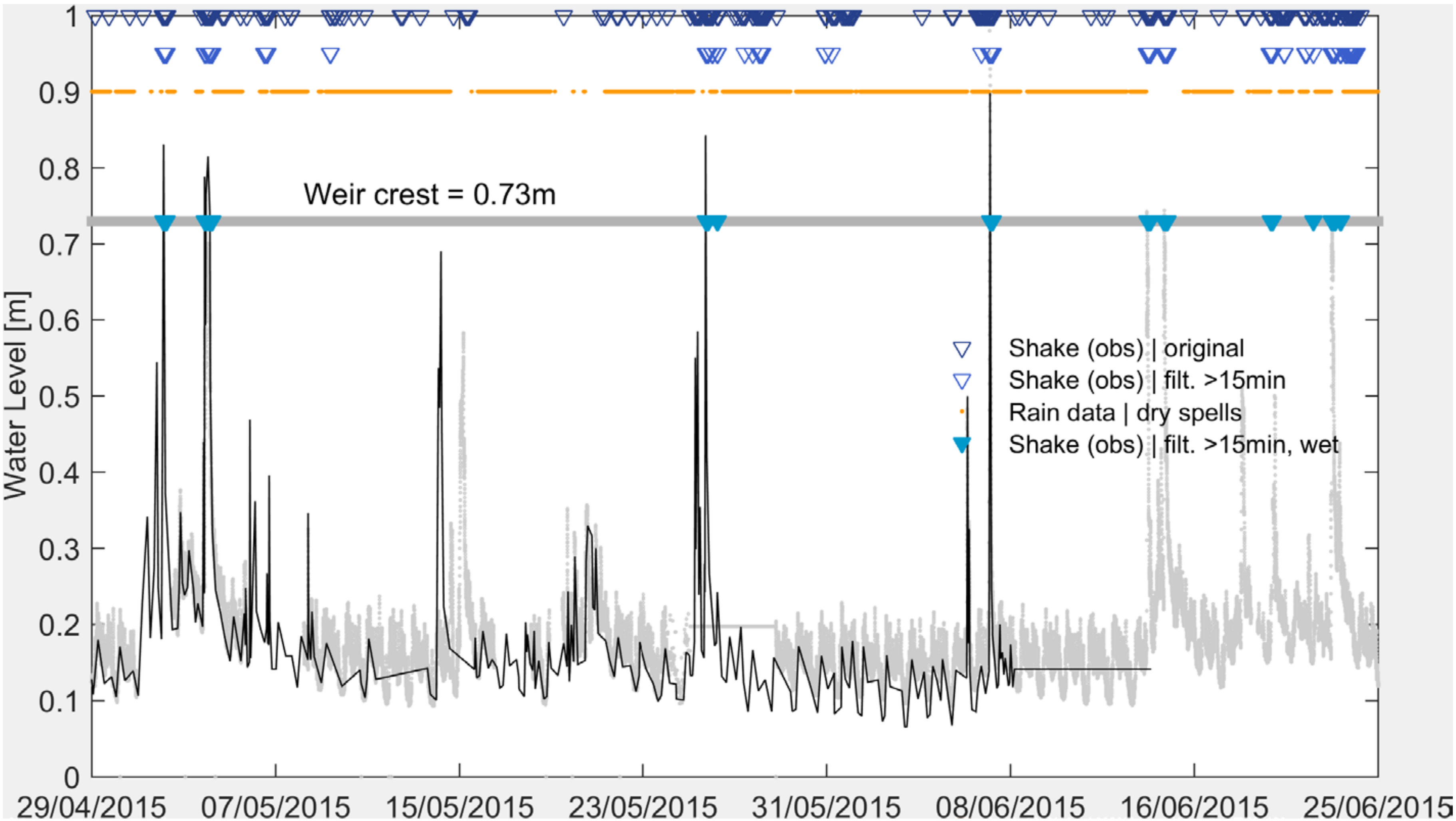
# Real Data

S2
S1

Catchment
77 ha
6900 residents
11 km sewers
Overflow structure
H1
Weir Crest
S1
S2
Binary Sensors
Water Level Meter
H2
Receiving Water

# Real Data



Weir crest = 0.73m
Shake (obs) | original
Shake (obs) | filt. >15min
Rain data | dry spells
Shake (obs) | filt. >15min, wet
Water Level [m]
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
29/04/2015
07/05/2015
15/05/2015
23/05/2015
31/05/2015
08/06/2015
16/06/2015
25/06/2015

# Conclusions

Binary data from sensors can be used for model calibration

# Conclusions

Binary data from sensors can be used for model calibration

A formal likelihood function allows for:

The incorporation of structural deficits and input errors

The evaluation of posterior of parameters

Thank You!