

# **A Bayesian hidden Markov model for notifiable disease surveillance**

Rochelle Watkins

**Australian Biosecurity CRC**

**Curtin University of Technology**

**Faculty of Health Sciences**

# Background

## Aim

- to develop an automated method to monitor routinely collected notifiable disease data
- efficient, comprehensive
- enable response, inform management

## Context

- data updated daily (0,0,0,0,0,0,0,0,...)
- postcode level
- detection goal: poorly defined, highly variable

- Data Layers
  - Ross River virus infection

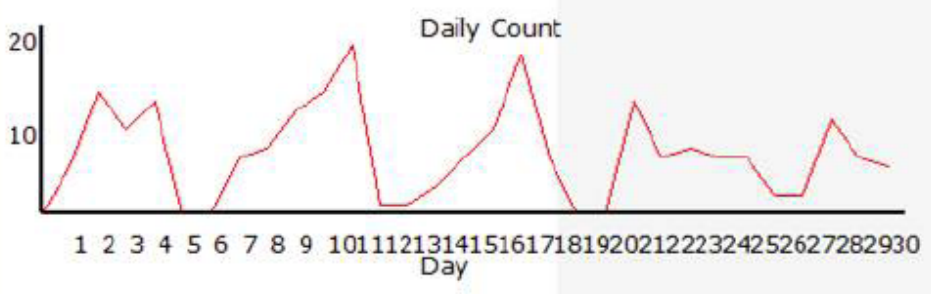
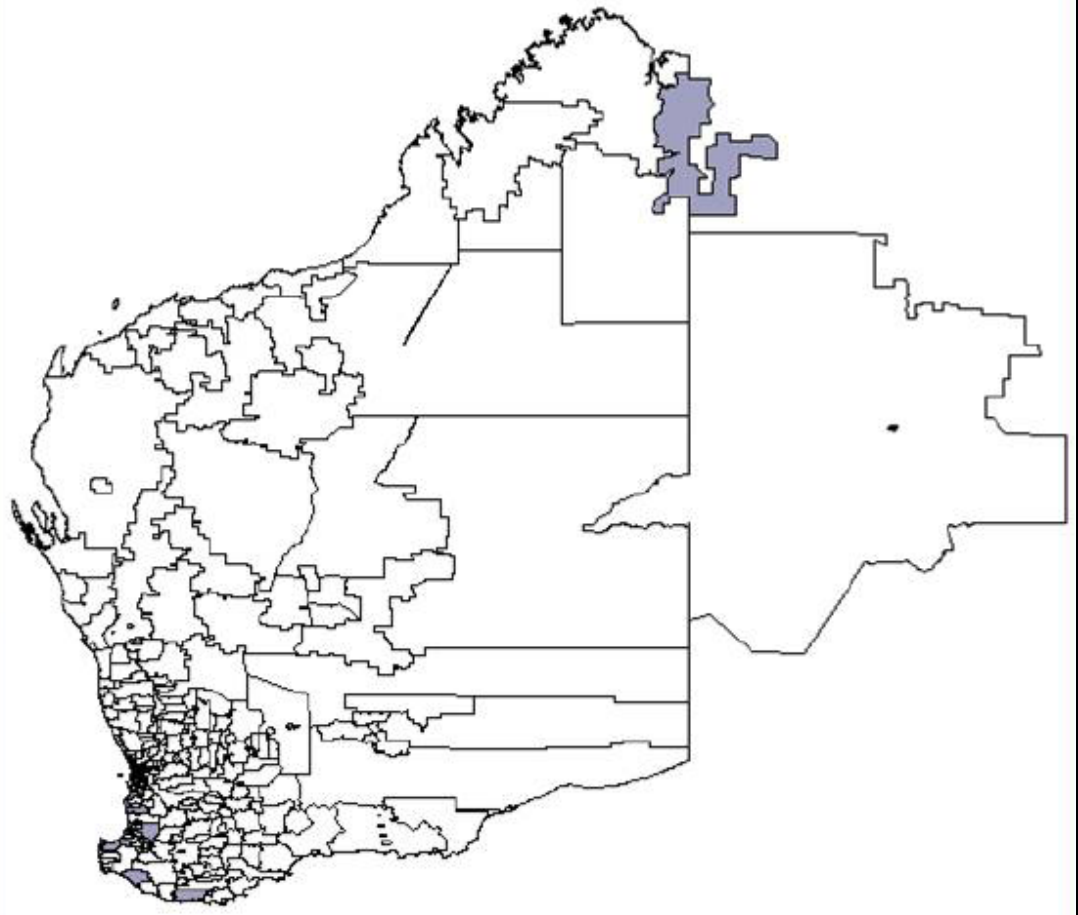
Filter

Disease Name:

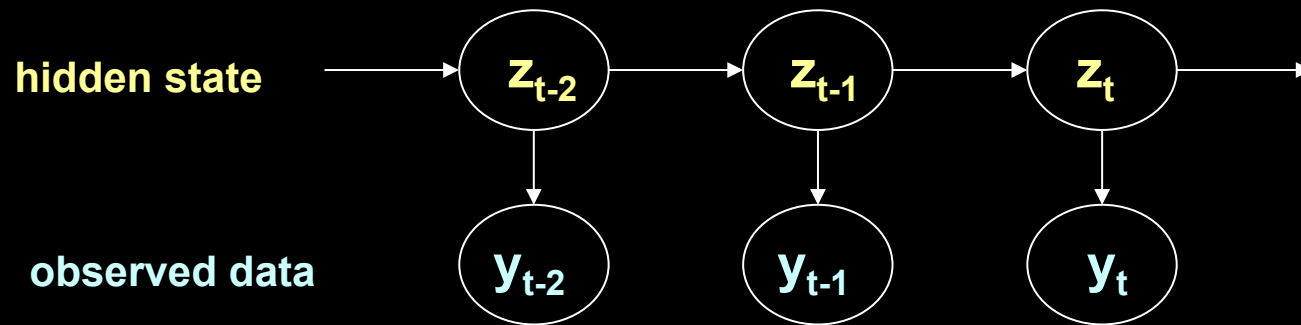
State:

Start Date:

End Date:



# Bayesian Hidden Markov Model



**2 hidden states used to classify observed data based on pre-specified distributions**

## Intuitive

- model what we are interested in
- serial dependency a key component of the model

## Interpretation

- what is the probability of an outbreak today, given our data?

# Bayesian Approach

**Provides a formal method to incorporate expert knowledge**

- **account for uncertainty in these unknowns**

**May be more robust to system changes over time**

- **simplify maintenance**

**Computationally intensive for large scale spatio-temporal data**

# Model

**t: time (day)**

**i: area (postcode)**

**z: state (endemic, outbreak)**

**$x[t,i] \leftarrow \text{count}[t,i] + \text{count\_neigh}[t,i]$**

**$x[t,i] \sim \text{dpois}(\mu[z[t,i]])$**

**$z[t,i] \sim \text{dcat}(p[z[t-1,i], 1:K])$**

**7 day model structure**

- **analyse 7, 14, 28 days of data**

# Priors

Relatively uninformative constrained priors for means:

$\mu[1] \sim \text{dgamma}(10,10)$

$\mu[2] \sim \text{dgamma}(40,20)|(\mu[1],)$

Gamma equivalent to Dirichlet prior on transition matrix:

for(k in 1:K)

for (l in 1:K)

$p[k,l] \leftarrow \text{px}[k,l]/\text{sum}(\text{px}[k,])$

$\text{px}[k,l] \sim \text{dgamma}(\text{alpha}[l],1)$

# Evaluation Scenario

## Hepatitis A in Western Australia

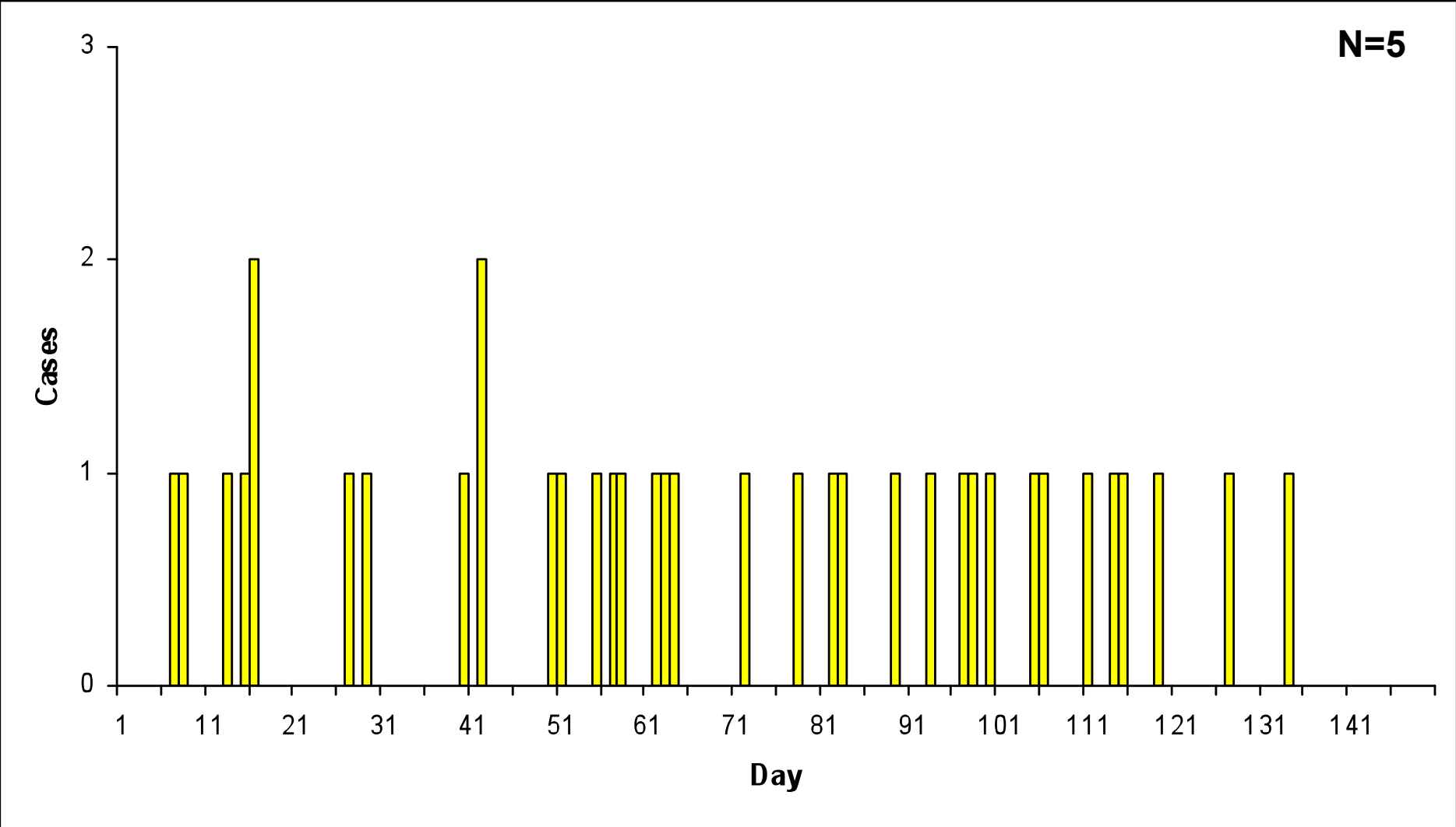
- simulated outbreaks
- authentic baseline

**4 replications of 150 days \* 60+ trials**

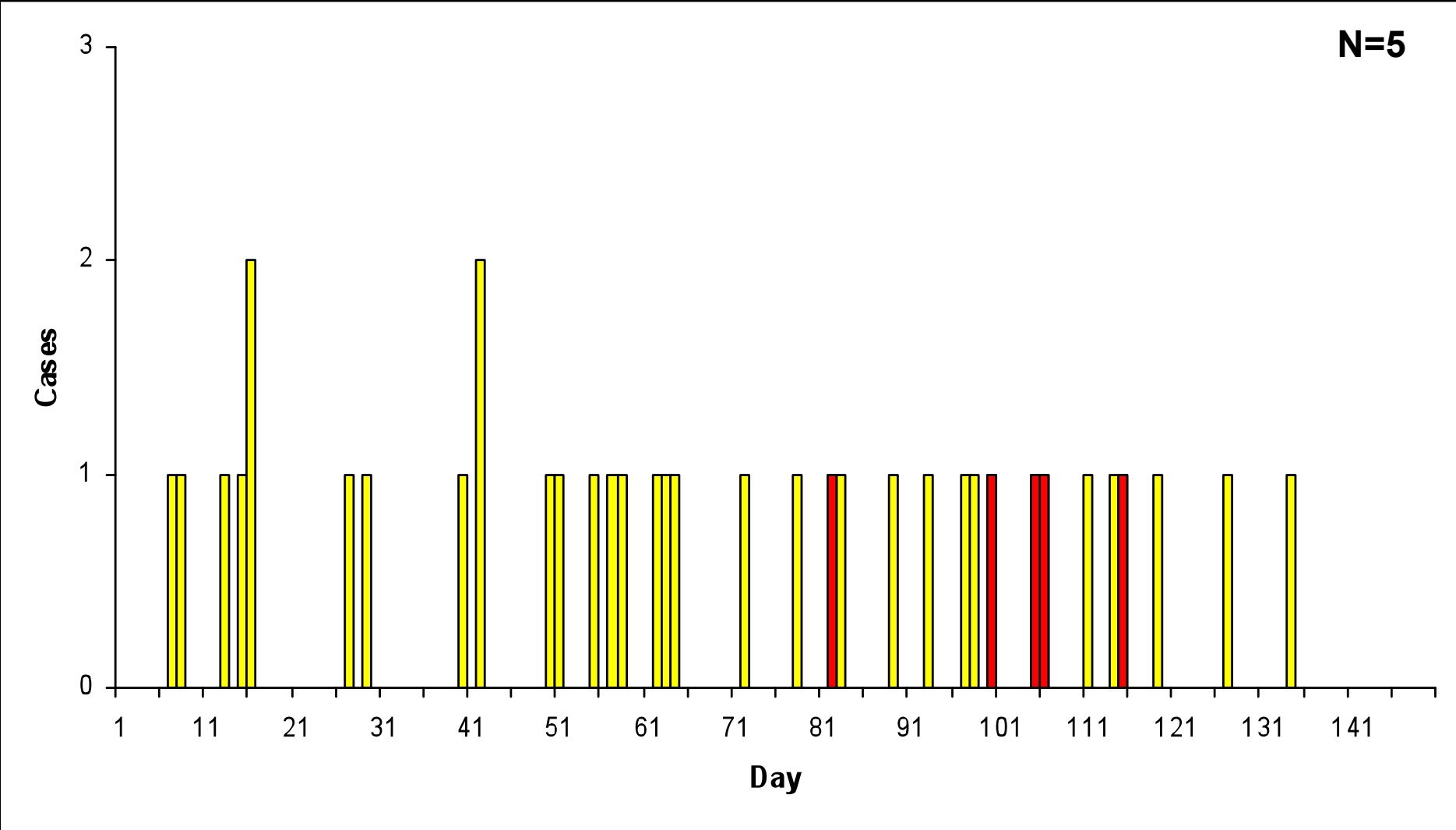
- size of outbreak
- clustering of cases



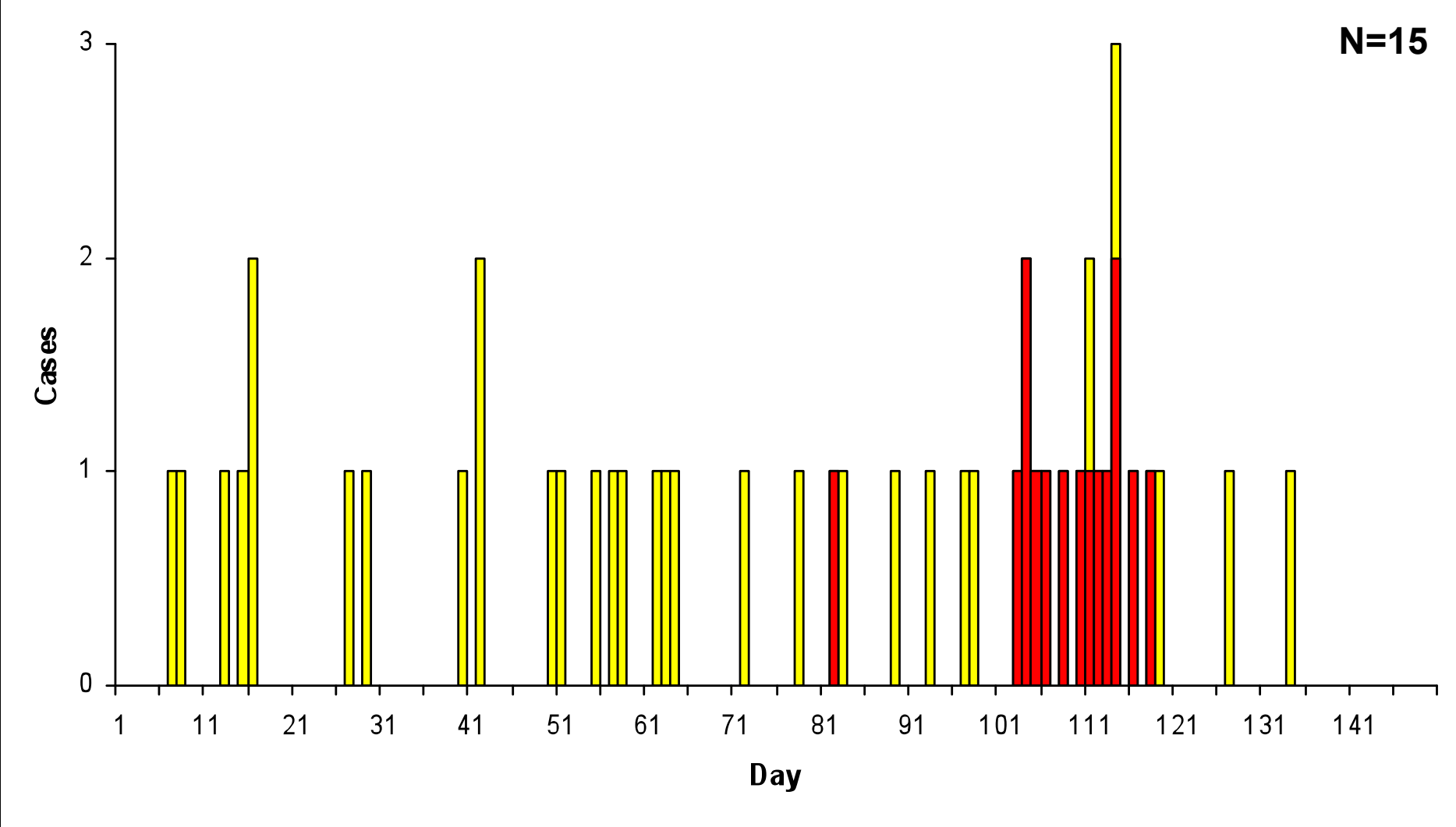
# Small outbreak



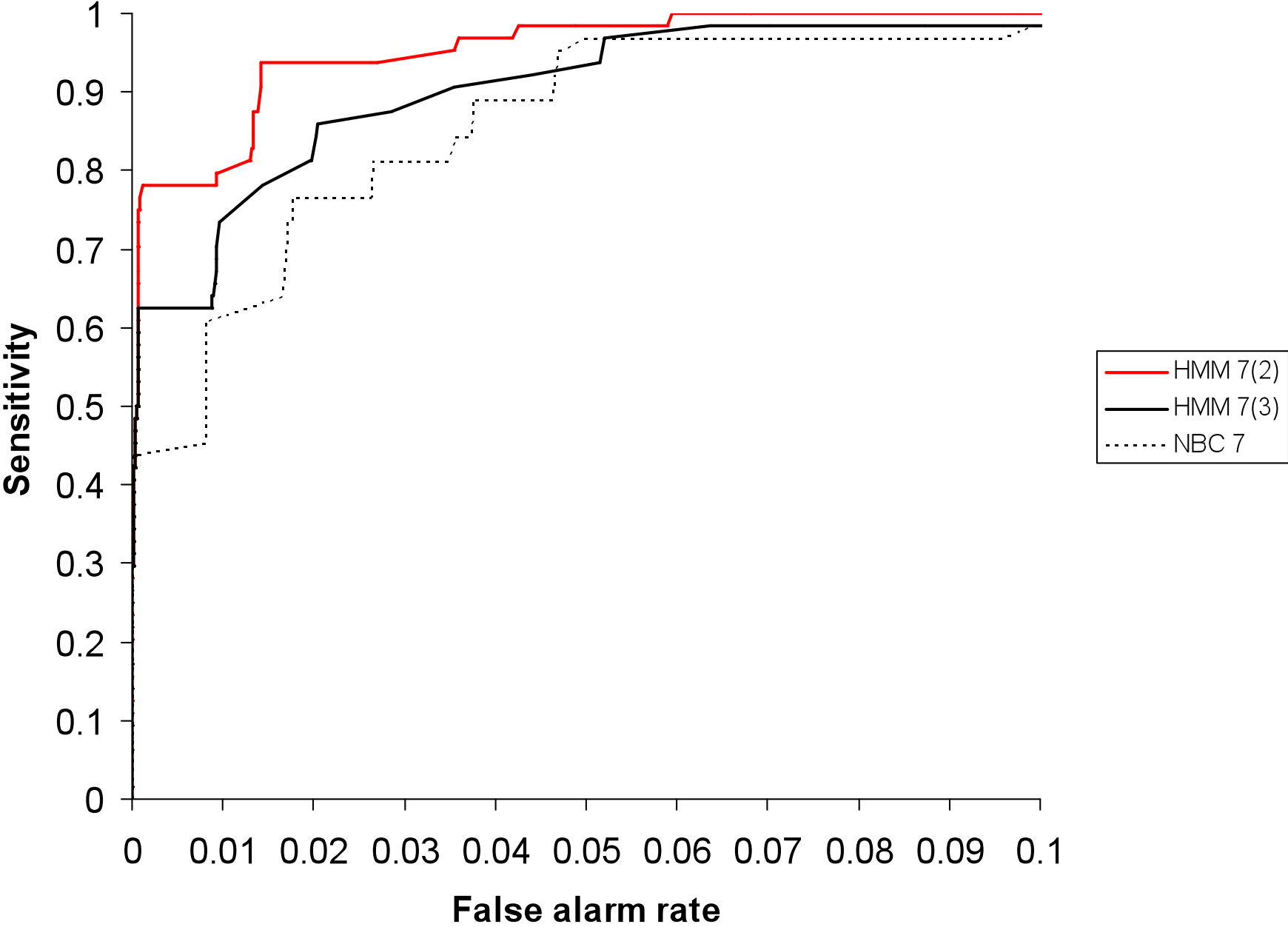
# Small outbreak



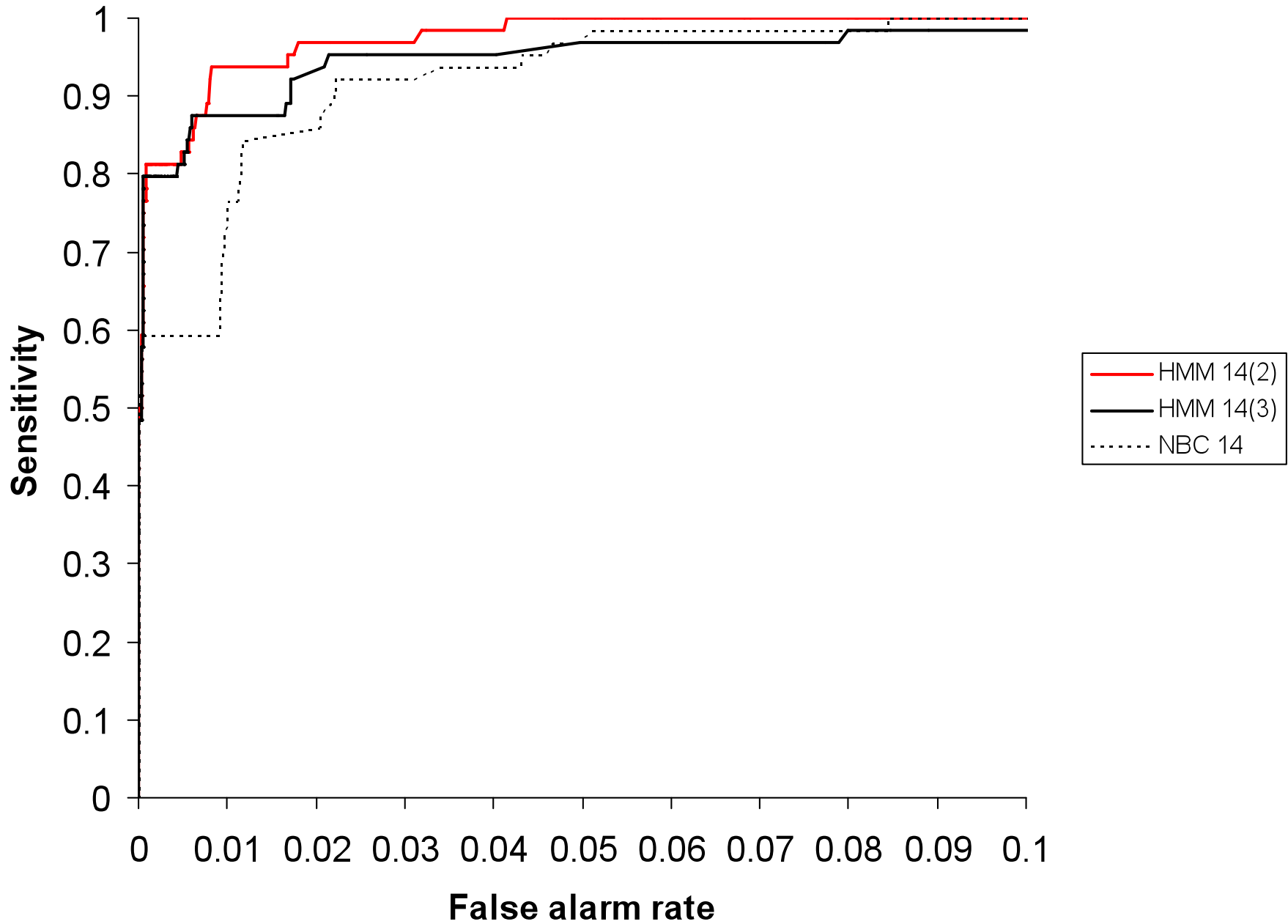
# Large outbreak



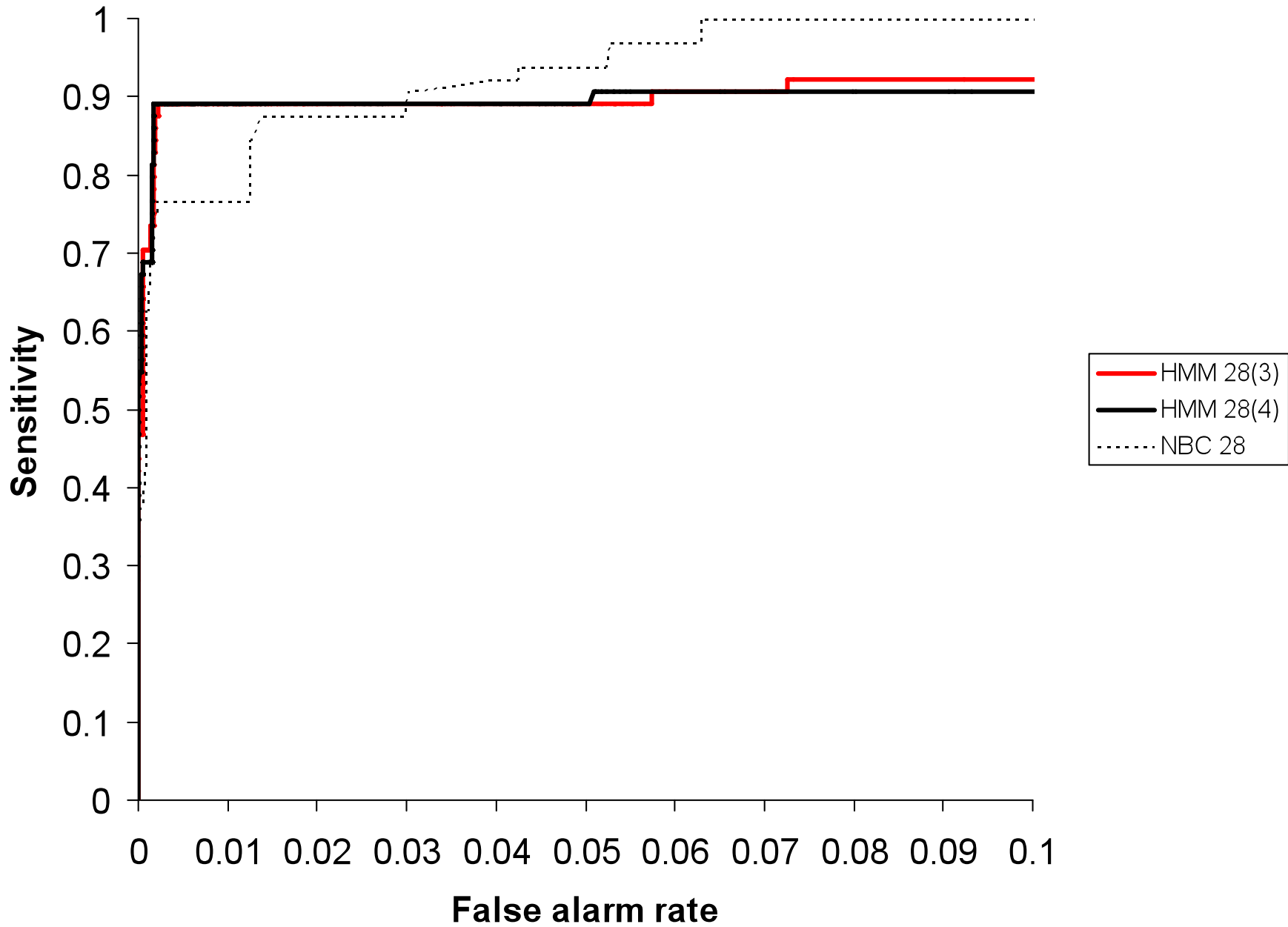
# Small less clustered – 7 day



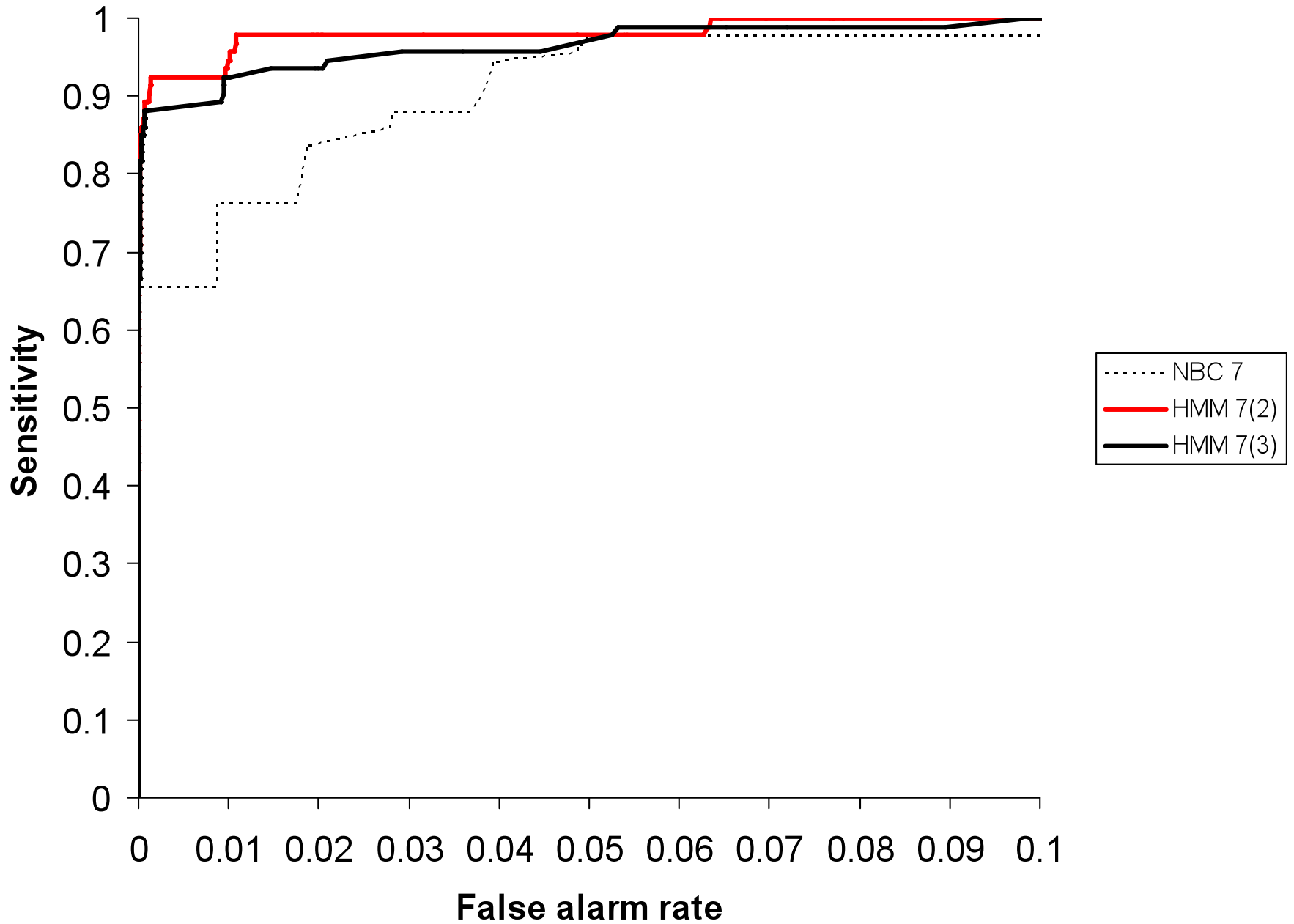
# Small less clustered – 14 day



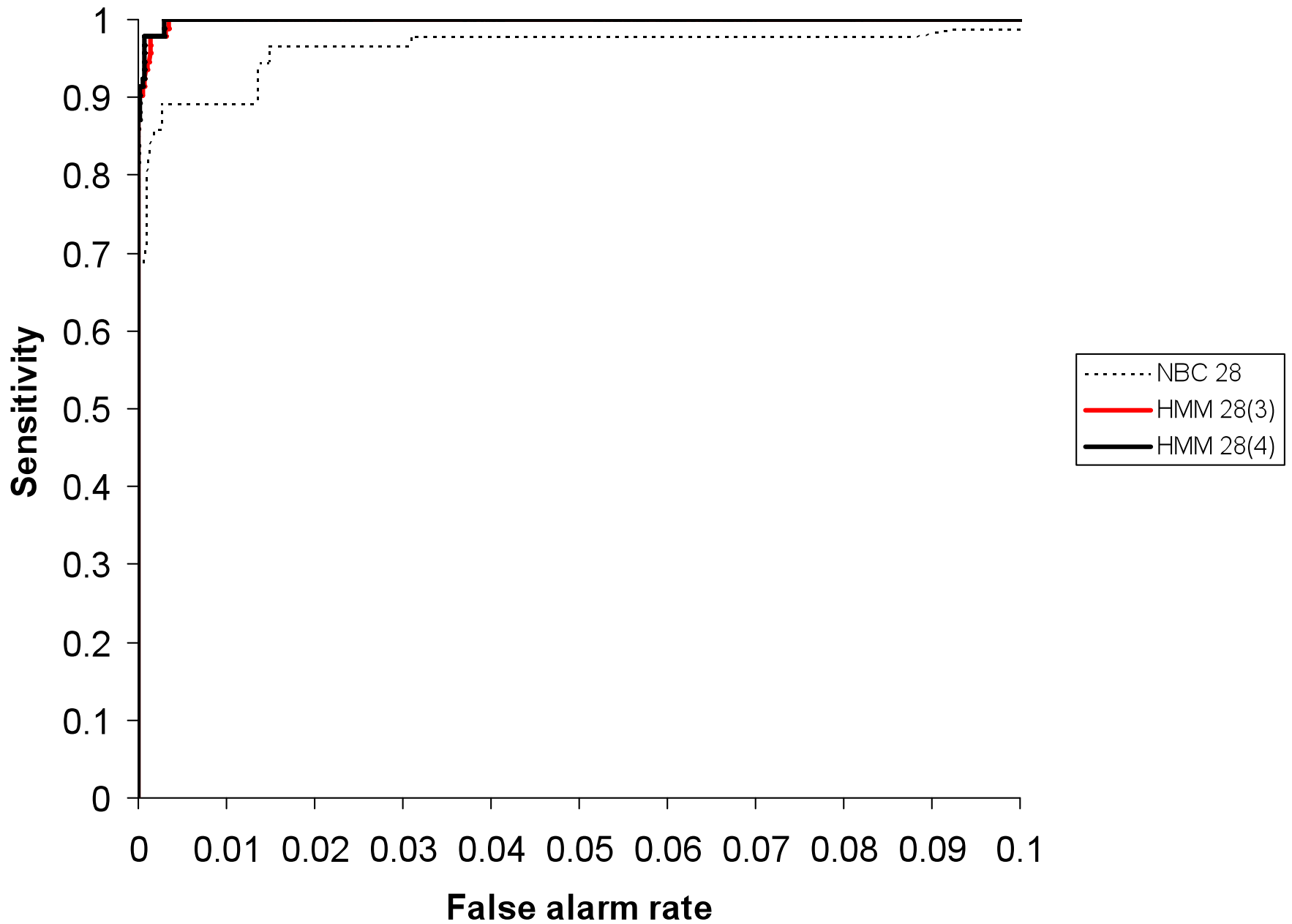
# Small less clustered – 28 day



# Large more clustered – 7 days



# Large more clustered – 28 days





# Summary

**Higher prior means were generally associated with decreased model sensitivity**

- depends on the amount of data analysed

**Relative algorithm performance depends on the desired false alarm level**

**Short-baseline models are unlikely to be the best performing models**

**More work to be done...**

- optimal analysis window length
- distance-based model
- other comparisons

**further details: 'Disease surveillance using a hidden Markov model' [www.biomedcentral.com/1472-6947/9/39](http://www.biomedcentral.com/1472-6947/9/39)**

**Thank you**