Space-Time modeling II

Infectious diseases

Bmtry 763

Infectious Disease Modeling

Infection: Mechanistic Models

- South Carolina County level
- Influenza C+ notifications
  - Flu season: 6 month period each year
  - Biweekly reports of counts
  - Under-ascertained

- ODC Files:
  - ST_flumodel2_working.odc

Mechanistic Models

- FMD in Cumbria UK 2001
- Infected premises (IPs) are to be modeled
- Within parishes we have counts of IPs and we also have a record of the total number of premises which changes over time.
- 138 parishes and 13 half-monthly time periods (February 2001-August 2001)
- ODC file: FMD_model2a_UH_CAR

Basic SIR model

- Susceptible population (S)
- Infective (I)
- Removed (R)

- Also SEIR includes Exposed group also

How can counts be modelled?

- Observe new incident infections (Infectives)
- We know previous infective numbers
- We know the population (susceptibles)
- Removal?
  - Can assume a given rate

Flu models: Model I

$$y_{ij} \sim bin(\rho, I_{ij})$$

- Model assumes that the observed count is a proportion of the true infectives
- The true infectives depend on the previous true infective count

Flu models: Model II

- Accounting model

$$I_{ij} \sim Pois(S_{ij} f(I_{ij-1}))$$
$$S_{ij+1} \sim N(\mu_{ij+1}, \sigma_s{}^2)$$
$$\mu_{ij+1} = S_{ij} - I_{ij} - R_{ij}$$
$$R_{ij} \sim N(\beta I_{ij}, \sigma_R{}^2)$$

Simpler version: Model 2

$$
\begin{aligned}
&I_{ij} \sim Pois(\pi_{ij}) \\
&\pi_{ij} = S_{ij} f(I_{ij-1})) \\
&S_{ij+1} = \mu_{ij+1} \\
&\mu_{ij+1} = S_{ij} - I_{ij} - R_{ij} \\
&R_{ij} = \beta I_{ij}
\end{aligned}
$$

Model 2

- How to parameterize the dependence on the previous infectives?

$$\log \pi_{ij} = \log S_{ij} + \log f(I_{ij-1})$$

Dependencies

$$1)\log f(I_{ij-1}) = \log I_{ij-1} + b_0 + b_i$$

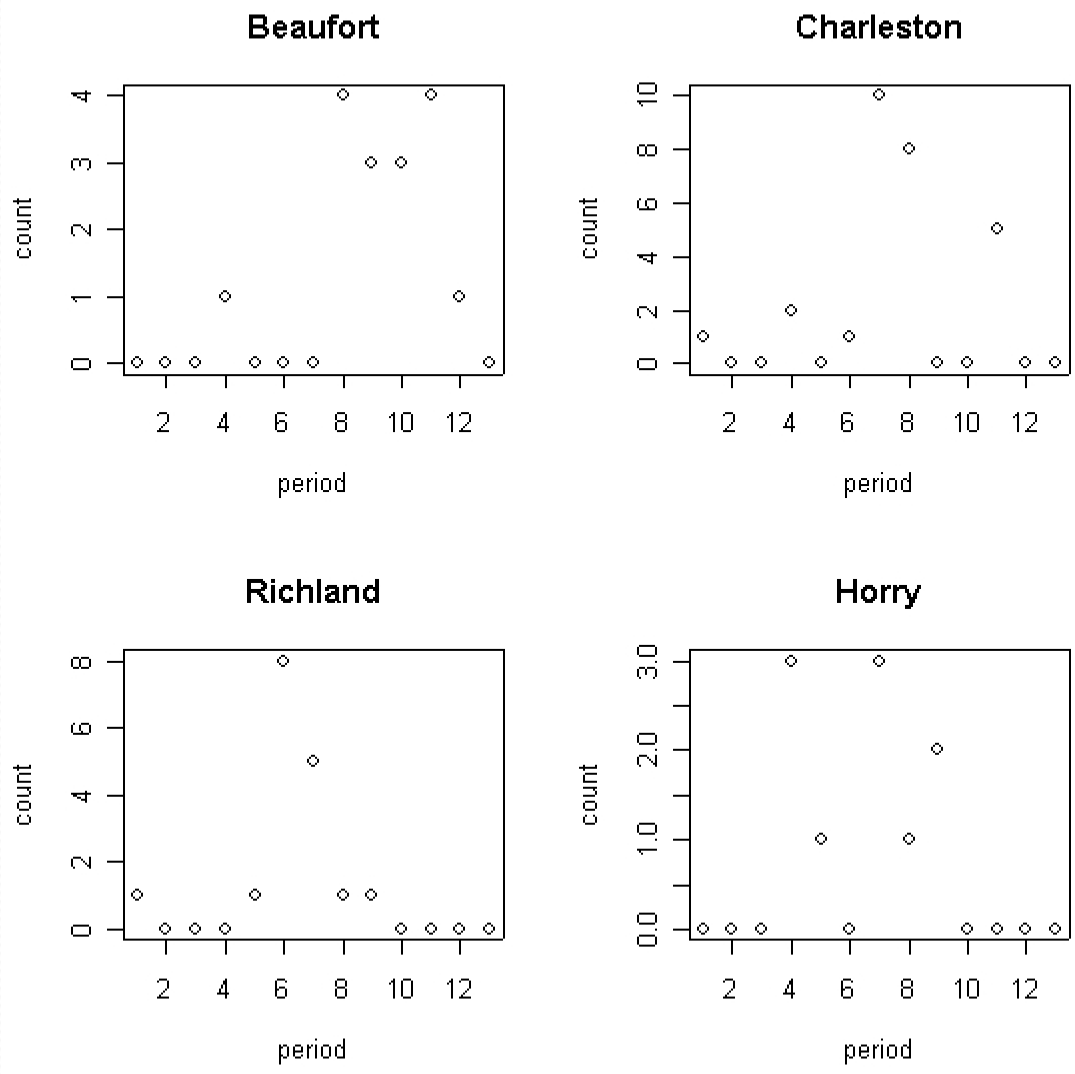
$$OR$$

$$2)\log f(I_{ij-1}) = b_0 + \log[I_{ij-1} + \sum_{l\in\delta_i} I_{lj-1}]$$

Flu Model in WinBUGS

- ST_flumodel2_working

Data: 4 counties



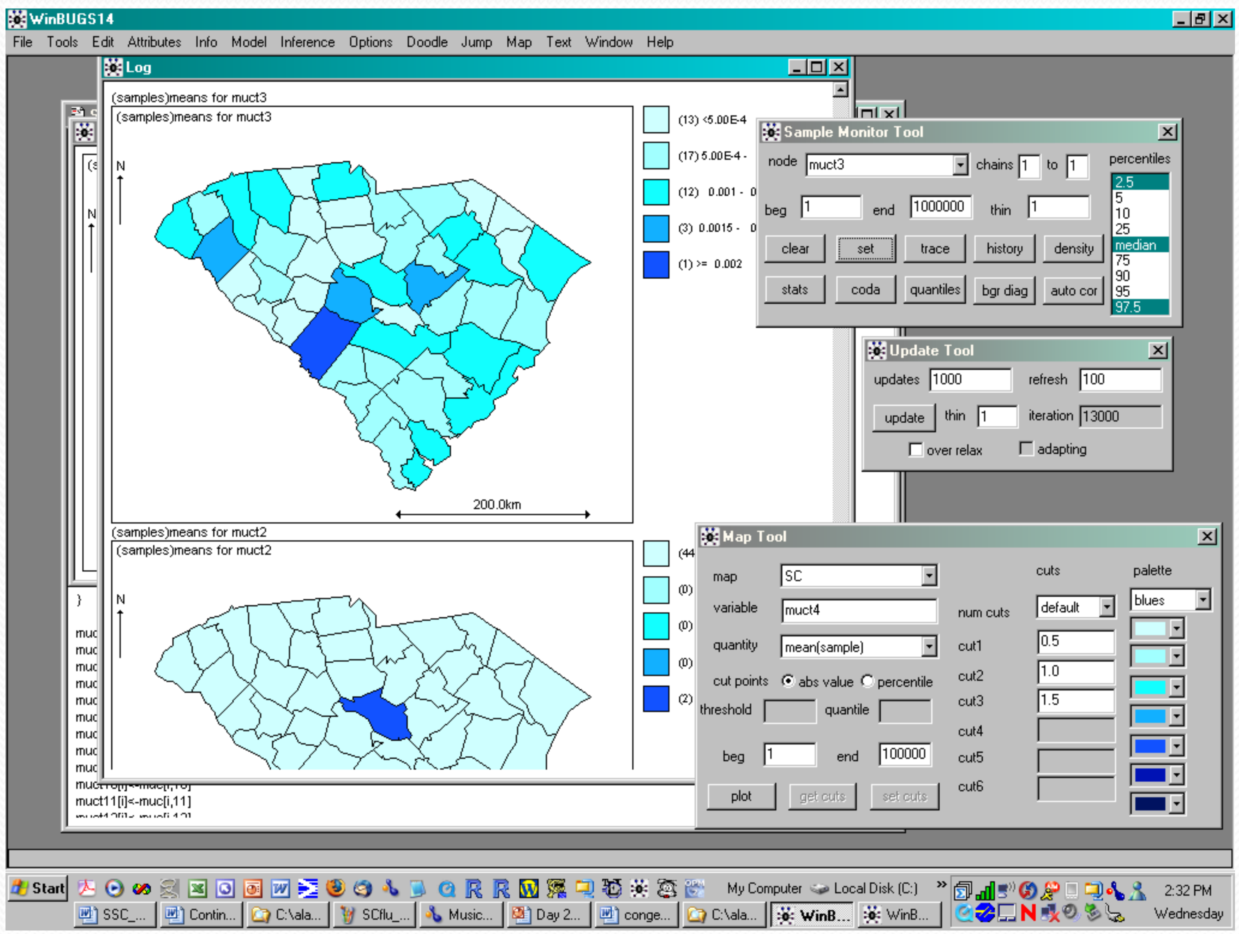
Model I

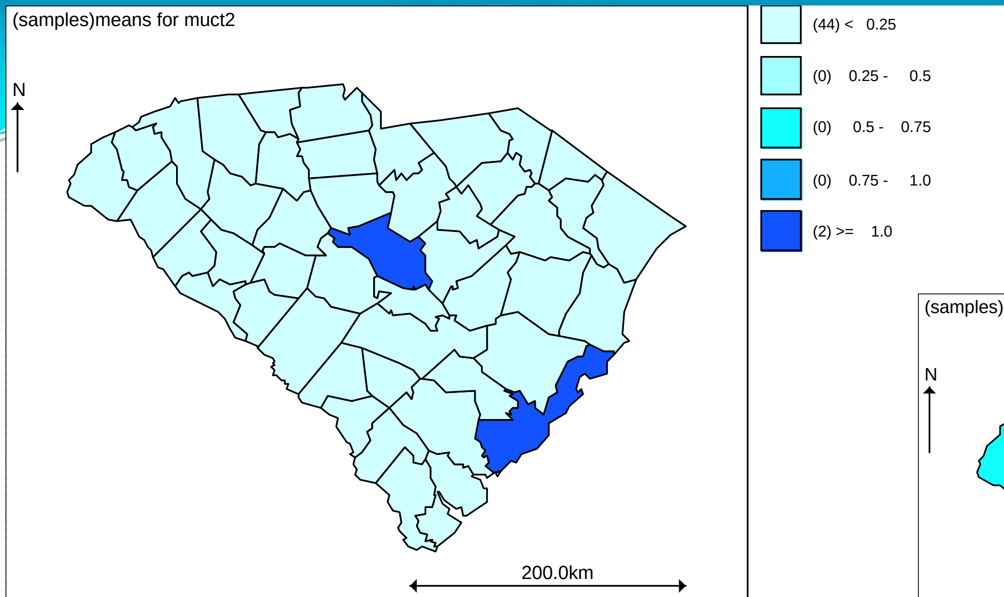
```
model{

for (i in 1:M){
rem[i,1]<-0
susc[i,1]<-susint[i]
muc[i,1]<-susc[i,1]
cpos[i,1]~dpois(muc[i,1])
cpred[i,1]~dpois(muc[i,1])
diff[i,1]<-pow(cpred[i,1]-cpos[i,1],2)
}
for (i in 1:M){

for (j in 2: T){
rem[i,j]<-betaR*cpos[i,j]
susc[i,j]<-susc[i,j-1]-cpos[i,j-1]-rem[i,j-1]
cpos[i,j]~dpois(muc[i,j])
cpred[i,j]~dpois(muc[i,j])
diff[i,j]<-pow(cpred[i,j]-cpos[i,j],2)
log(muc[i,j])<-bet0+log(susc[i,j]+0.001)+log(cpos[i,j-1]+0.001)+b1[i]

#ddiffvariable(fromdata2)canbe includedhereto producea dailyrate

}
```

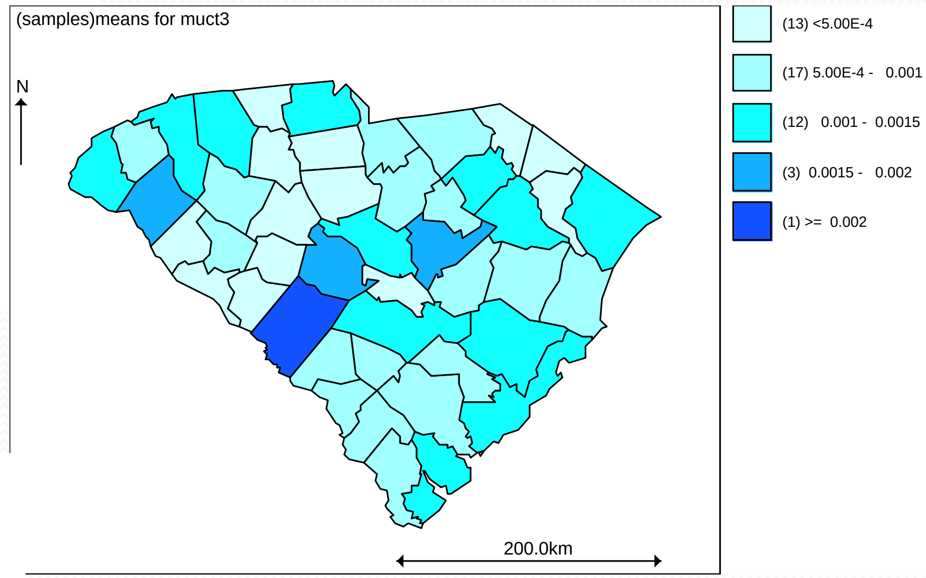
Model II

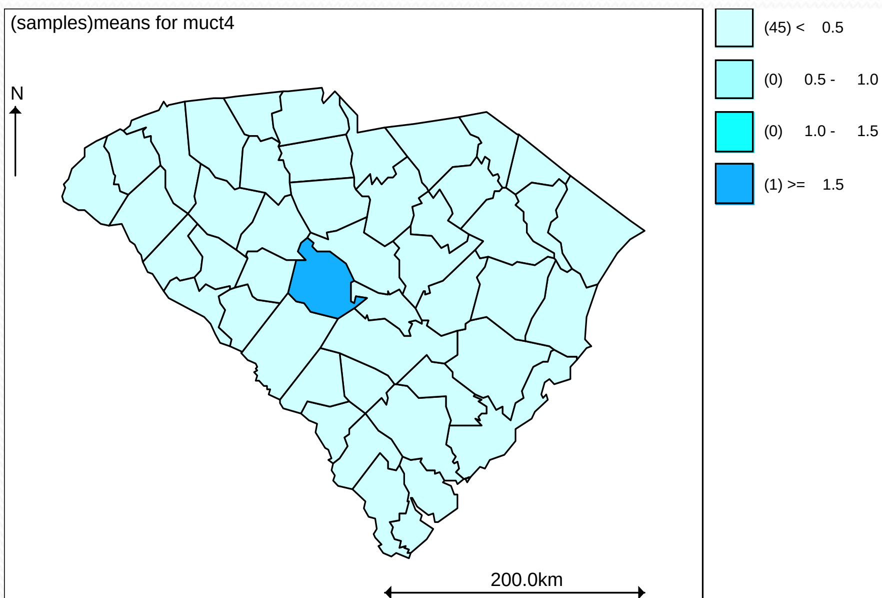
```
mspe<-mean(smean[])
for (j in 1:T){
mucrich[j]<-muc[40,j]
mucchar[j]<-muc[10,j]
muchor[j]<-muc[26,j]
mucbea[j]<-muc[7,j]}

b1[1:46] ~ car.normal(adj[],weights[],num[],tau.b1)


 for(k in 1:sumNumNeigh){
    weights[k] <- 1 }

bet0~dflat()
tau.b1~dgamma(0.01,0.01)
#betaR~dgamma(0.01,1.0)
betaR<-0.001
}
```

Results




(samples)means for muct2
N
200.0km
(44) < 0.25
(0) 0.25 - 0.5
(0) 0.5 - 0.75
(0) 0.75 - 1.0
(2) >= 1.0


(samples)means for muct3
N
200.0km
(13) <5.00E-4
(17) 5.00E-4 - 0.001
(12) 0.001 - 0.0015
(3) 0.0015 - 0.002
(1) >= 0.002


(samples)means for muct4
N
200.0km
(45) < 0.5
(0) 0.5 - 1.0
(0) 1.0 - 1.5
(1) >= 1.5

Example Statistics

b1[37]	-0.314	1.308	0.01457	-2.938	-0.3071	2.288	1001	12000
b1[38]	0.2892	0.6359	0.007557	-0.9778	0.284	1.557	1001	12000
b1[39]	-0.1624	0.3587	0.005918	-0.8883	-0.1603	0.5316	1001	12000
b1[40]	-1.098	0.2925	0.005173	-1.687	-1.091	-0.534	1001	12000
b1[41]	-0.1641	0.906	0.01186	-1.977	-0.167	1.681	1001	12000
b1[42]	-0.8427	0.5607	0.006181	-2.026	-0.8159	0.176	1001	12000
b1[43]	0.1814	0.7448	0.007666	-1.328	0.1906	1.647	1001	12000
b1[44]	-0.3763	0.7467	0.008189	-1.876	-0.3728	1.093	1001	12000
b1[45]	0.3089	0.7012	0.00793	-1.133	0.3228	1.662	1001	12000
b1[46]	-0.5301	0.592	0.00656	-1.798	-0.4909	0.5375	1001	12000
muct2[1]	2.8E-4	3.998E-4	5.888E-6	2.568E-5	1.791E-4	0.001154	1001	12000
muct2[2]	0.002318	0.0029	4.432E-5	2.051E-4	0.001469	0.009549	1001	12000
muct2[3]	6.191E-4	4.569E-4	6.719E-6	1.114E-4	4.983E-4	0.001828	1001	12000
muct2[4]	0.001688	0.002109	2.744E-5	1.787E-4	0.001116	0.006598	1001	12000
muct2[5]	7.32E-4	4.478E-4	6.389E-6	1.806E-4	6.278E-4	0.001898	1001	12000
muct2[6]	8.29E-4	0.001226	1.555E-5	6.891E-5	4.918E-4	0.003715	1001	12000
muct2[7]	0.001085	3.387E-4	5.576E-6	5.444E-4	0.001045	0.001868	1001	12000
muct2[8]	0.001207	5.796E-4	8.519E-6	3.899E-4	0.001106	0.002625	1001	12000
muct2[9]	2.052E-4	2.552E-4	3.274E-6	2.354E-5	1.378E-4	7.694E-4	1001	12000
muct2[10]	1.044	0.2858	0.004913	0.5802	1.014	1.703	1001	12000
muct2[11]	5.484E-4	0.001248	1.377E-5	2.855E-5	2.84E-4	0.002643	1001	12000
muct2[12]	4.252E-4	7.721E-4	9.12E-6	2.634E-5	2.362E-4	0.001913	1001	12000
muct2[13]	9.692E-4	0.001443	2.284E-5	9.142E-5	6.093E-4	0.004085	1001	12000
muct2[14]	7.928E-4	3.503E-4	5.621E-6	3.041E-4	7.279E-4	0.001644	1001	12000
muct2[15]	7.591E-4	5.123E-4	6.859E-6	1.774E-4	6.341E-4	0.00207	1001	12000
muct2[16]	0.001514	0.001876	2.687E-5	1.557E-4	9.931E-4	0.006016	1001	12000
muct2[17]	4.102E-4	5.416E-4	6.749E-6	3.23E-5	2.527E-4	0.001719	1001	12000
muct2[18]	9.892E-4	5.164E-4	6.512E-6	2.8E-4	8.958E-4	0.002254	1001	12000

Summary

Node statistics

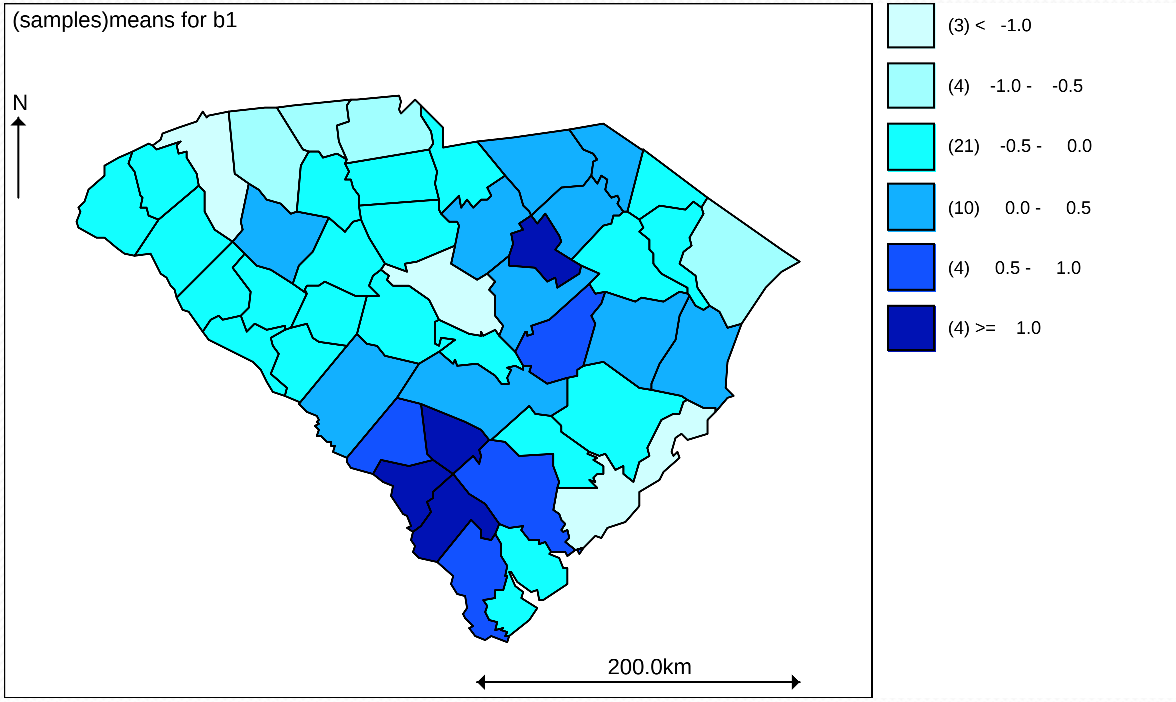
node	mean	sd	MC error	2.5%	median	97.5%	start	sample
deviance	8.025E+6	11.34	0.4564	8.025E+6	8.025E+6	8.025E+6	13001	1000

DIC

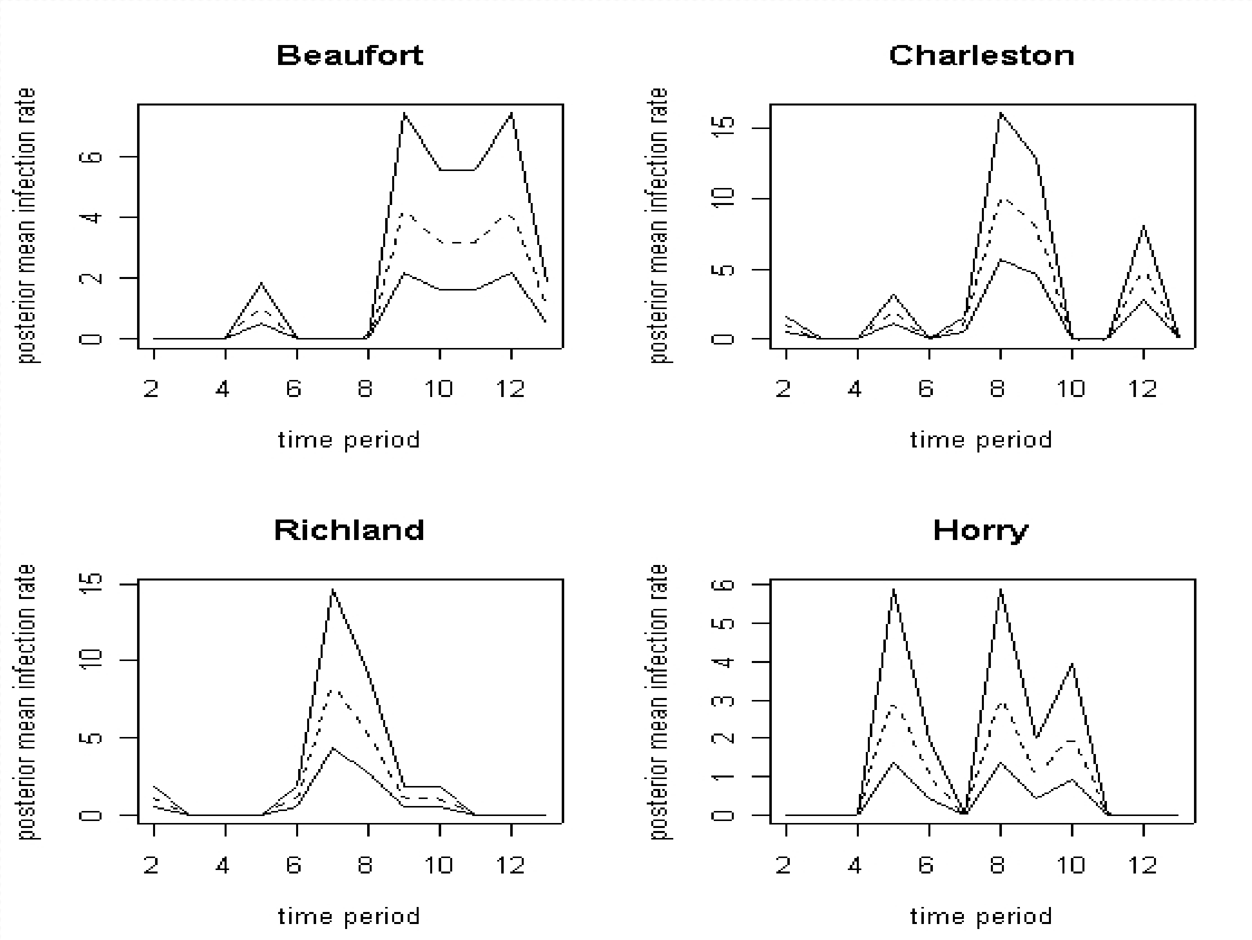
Dbar = post.mean of -2logL; Dhat = -2LogL at post.mean of stochastic nodes

	Dbar	Dhat	pD	DIC
cpos	8025290.000	8025270.000	19.516	8025310.000
total	8025290.000	8025270.000	19.516	8025310.000

Spatial heterogeneity



Results


Beaufort
Charleston
Richland
Horry
posterior mean infection rate
time period
2 4 6 8 10 12
0 2 4 6
0 5 10 15
0 1 2 3 4 5 6

Model Criticism

- Poisson (exact) assumption
  - Could use binomial
  - Imputation of true count would be time-consuming
- Binomial model more realistic
- C+ is a subset of total flu?
  - What to do about that ?
- Lawson and Song (2010) SSTE

FMD modeling

- Similar to Flu example BUT with some differences also
- We know the removal due to culling
- We have the (almost) fully ascertained infectives (IPs)
- Finite population of premises which varies in time.
- Also want to estimate termination

FMD Models

Notation

I_{ij} : infective premise count

y_{ij} : true IP count

n_{ij} : total number of premises

Underascertainment

$y_{ij} = \beta I_{ij}$

Initial Model

$I_{ij} \sim bin(p_{ij}, n_{ij})$

However the rate is low and so a Poisson approximation may be useful: $I_{ij} \sim Pois(\mu_{ij})$ where $\mu_{ij} = S_{ij}.f(I_{i,j-1})$ and where $S_{ij} = n_{ij}$

FMD Model Dependencies

- We will model the rate of infection:
  - Model I: dependence on previous IPs
  - Model II: dependence on IPs and counts
  - Model III/IV: dependence on lagged neighbors

- Note: the SIR accounting equation is fixed in this case:

$$n_{ij} = n_{i,j-1} - R_{i,j-1} - I_{i,j-1}$$

Poisson SIR

Model I: log f($I_{i,j-1}$)=$\alpha_0+\alpha_c I_{i,j-1}+v_i+u_i$

Model II: log f($I_{i,j-1}$)=$\alpha_0+\alpha_c I_{i,j-1}+\alpha_p n_{i,j-1}+v_i+u_i$

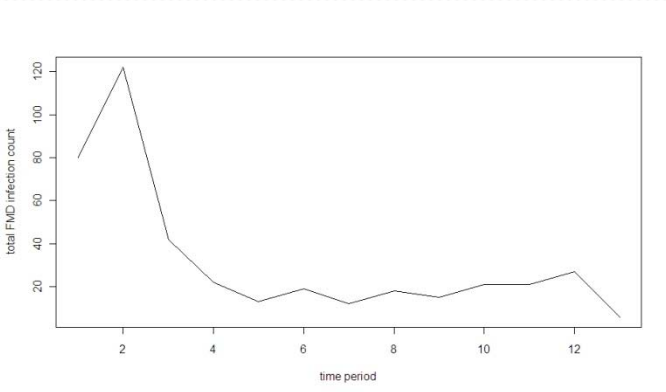
Model III: log f($I_{i,j-1}$)=

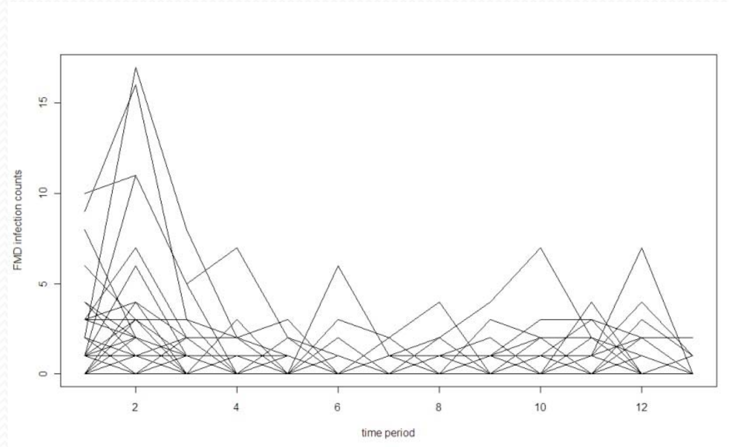
$$\alpha_0+\alpha_{c1}I_{i,j-1}+\alpha_{c2}\sum_{k\in\delta_i}I_{k,j-1}+v_i+u_i$$

Model IV:log f($I_{i,j-1}$)=

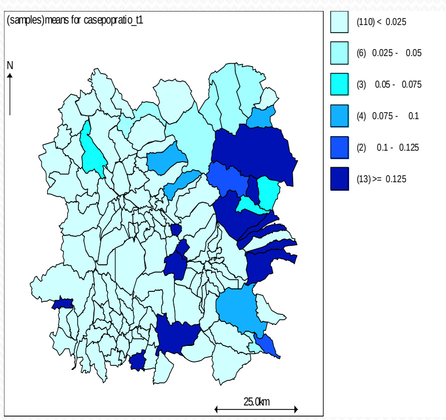
$$\alpha_0+\alpha_{c1}I_{i,j-1}+\alpha_{c2}\sum_{k\in\delta_i}I_{k,j-1}+\alpha_p n_{i,j-1}+v_i+u_i$$

FMD data and Model I fitting

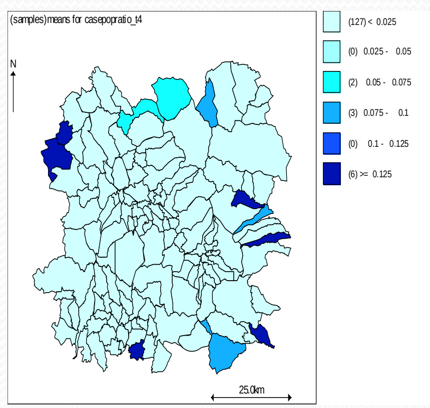




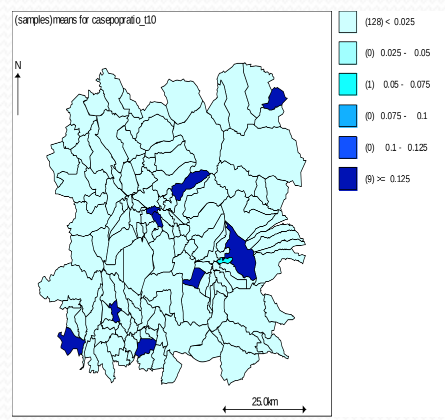
1



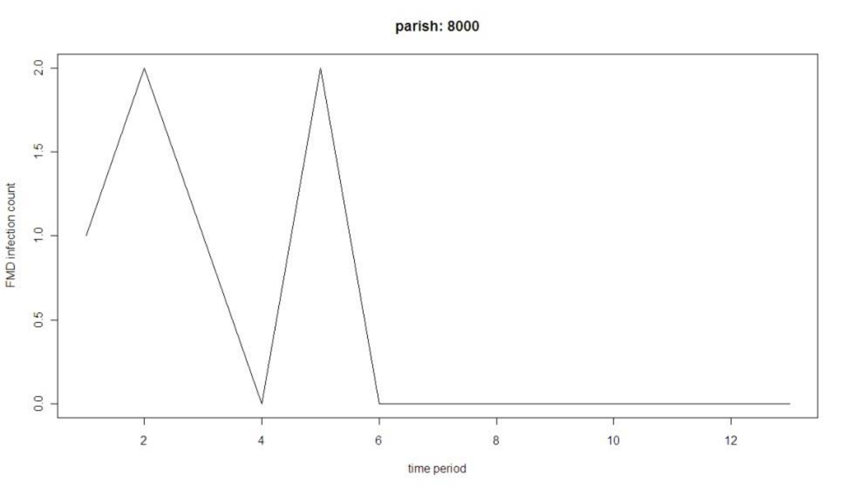
4

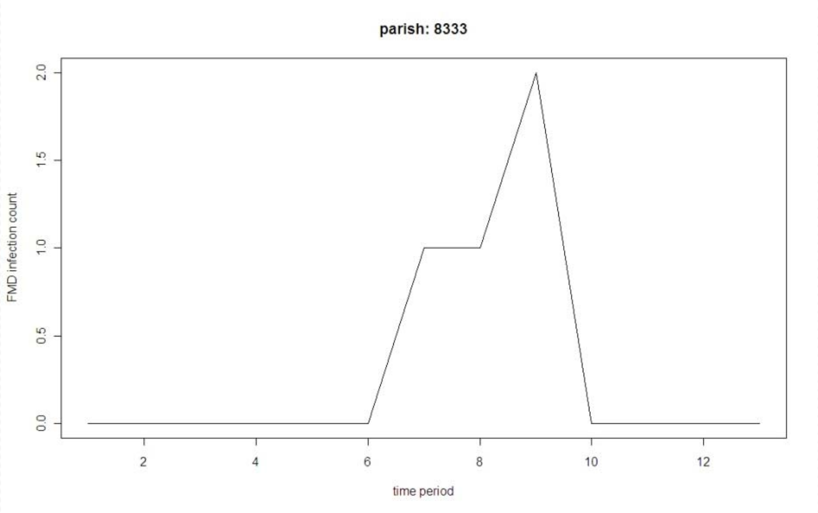


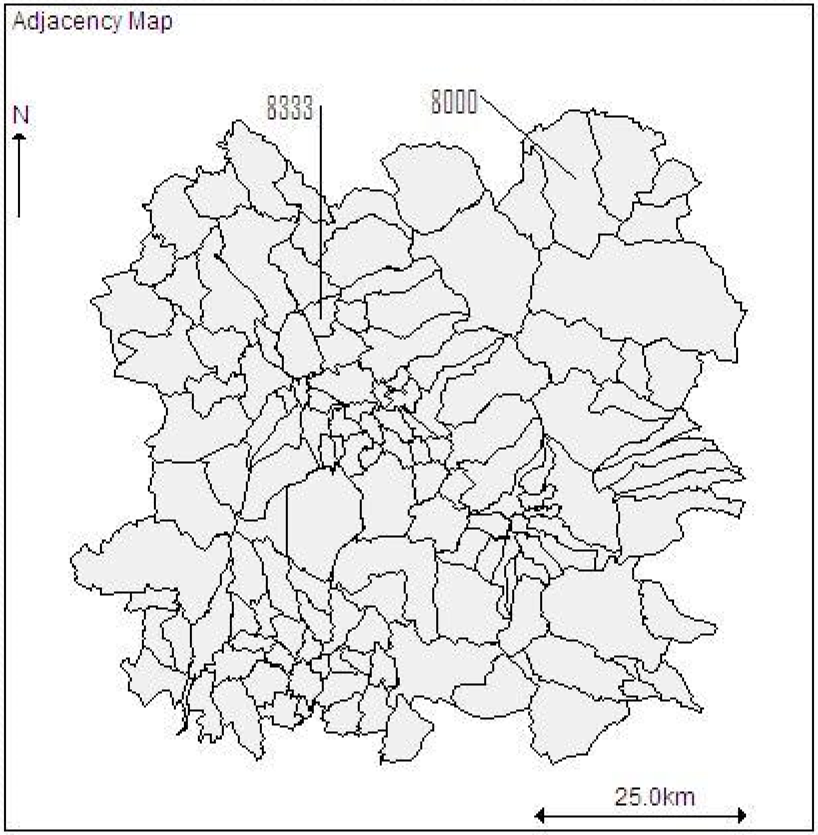
10



Parish 8000 & 8333







Results for all FMD Models

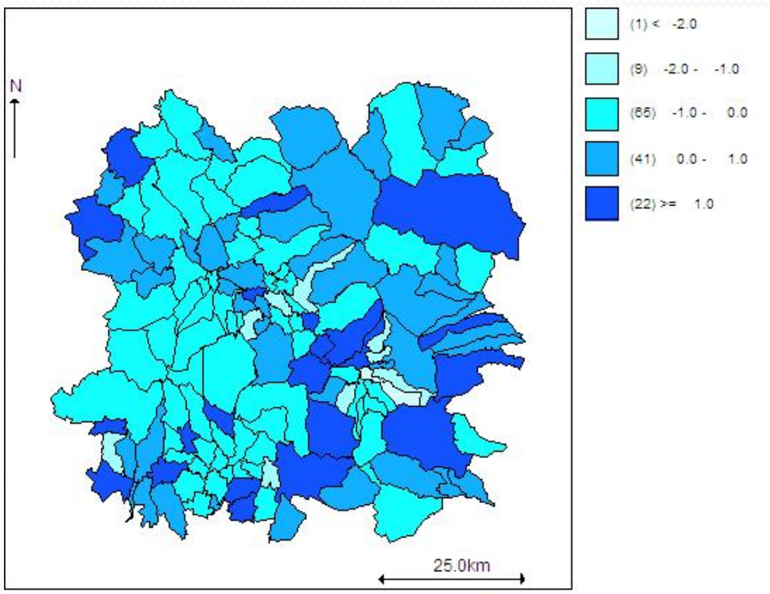
Model	random effects	DIC	Deviance	pD
Model 1	UH+CAR	1660.21	1580.58	79.63
	UH only	1665.71	1582.99	82.72
	CAR only	1665.51	1589.37	76.14
	No RE	1917.58	1914.52	3.059
Model 2	UH+CAR	1625.53	1540.80	84.74
	UH only	1625.57	1537.72	87.85
	CAR only	1632.03	1550.20	81.82
	No RE	1910.79	1906.75	4.04
Model 3	UH+CAR	1658.21	1577.28	80.93
	UH only	1662.75	1578.97	83.78
	CAR only	1664.60	1587.39	77.21
	No RE	1915.33	1911.27	4.061
Model 4	UH+CAR	1625.47	1539.80	85.67
	UH only	1627.96	1539.54	88.42
	CAR only	1634.64	1552.18	82.47
	No RE	1906.70	1901.65	5.05

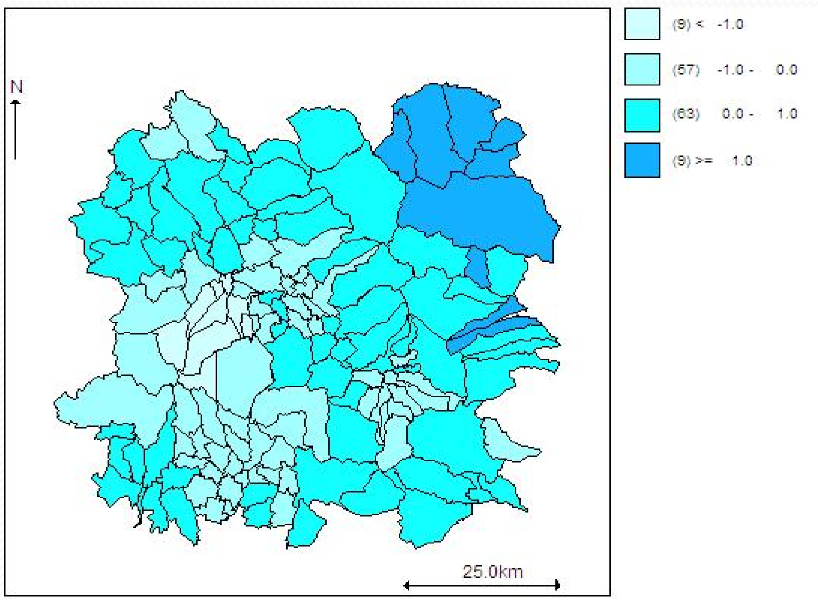
Model 2 results

Parameter name	Estimated mean	95% credible interval	Length of the credible interval
Intercept (time1)	-4.26	(-4.69,-3.87)	0.82
Intercept(time>1)	-4.96	(-5.86, -4.13)	1.73
coefficient log(case)	0.19	(0.16,0.21)	0.05
Coefficient log(pop)	0.41	(0.17,0.66)	0.49
Precision	tauv: 0.78 tauW: 0.64	(0.35,2.089) (0.18,1.78)	1.74 1.60

Model running

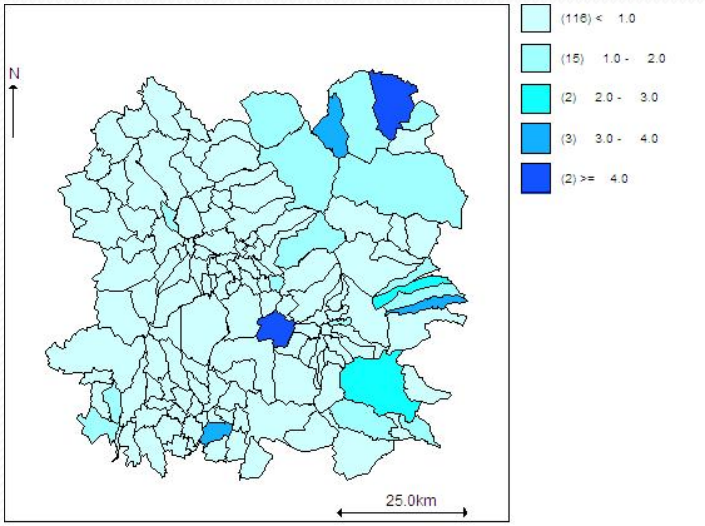
- FMD_poisson_model2a_UH_CAR.odc
- UH and CAR components



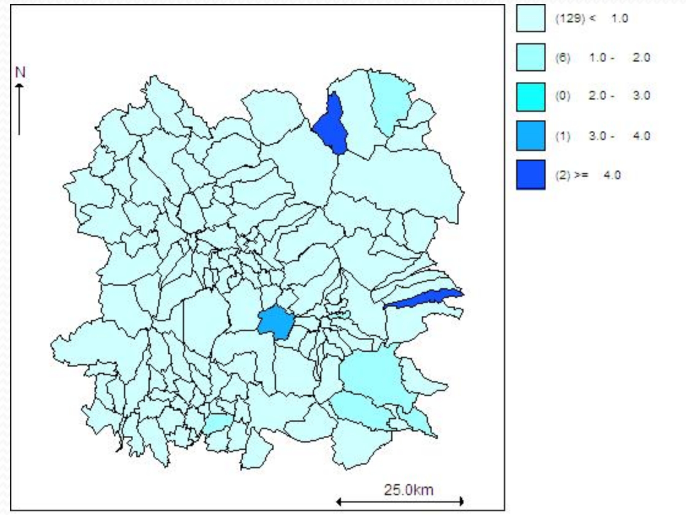


Model II: posterior Mean estimates

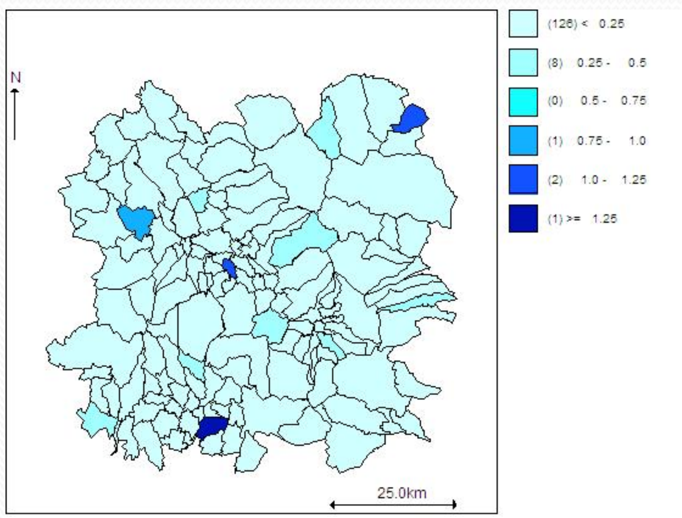
1



4



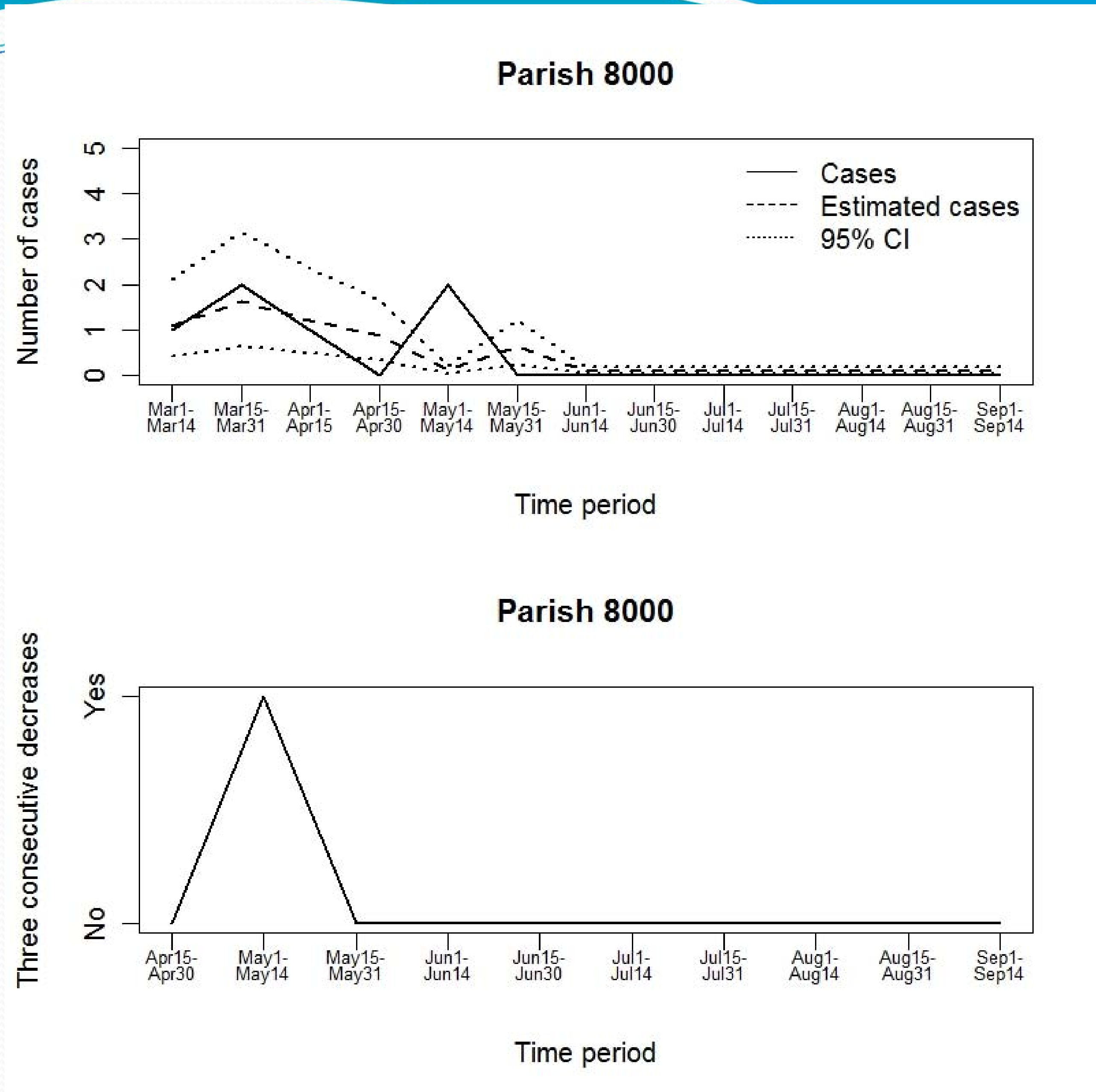
10



Detecting termination

- Can assess termination using monotone means ie continually descending mean estimates flag termination

$$\mu_{ij} < \mu_{i,j-1} < \mu_{i,j-2} < \mu_{i,j-3} \cdots\cdots$$


Parish 8000
Number of cases
0
1
2
3
4
5
Cases
Estimated cases
95% CI
Mar1- Mar14
Mar15- Mar31
Apr1- Apr15
Apr15- Apr30
May1- May14
May15- May31
Jun1- Jun14
Jun15- Jun30
Jul1- Jul14
Jul15- Jul31
Aug1- Aug14
Aug15- Aug31
Sep1- Sep14
Time period
Parish 8000
Three consecutive decreases
No
Yes
Apr15- Apr30
May1- May14
May15- May31
Jun1- Jun14
Jun15- Jun30
Jul1- Jul14
Jul15- Jul31
Aug1- Aug14
Aug15- Aug31
Sep1- Sep14
Time period

References

- Lawson, A. B. and Song, H-R. (2010) Bayesian Hierarchical Modeling of the dynamics of Spatio-temporal influenza season outbreaks. *Spatial and Spatio-temporal Epidemiology*, 1, 2, 187-195
- Lawson, A. B., Onicescu, G., Ellerbe, C. (2011) Foot and mouth disease revisited: Re-analysis using Bayesian spatial susceptible-infectious-removed models, *Spatial and Spatio-temporal Epidemiology, 2, 3, 185-194*