Workshop on R and movement ecology:

Hong Kong University, Jan 2018



Eric Dougherty, Dana Seidel, Wayne Getz



Lecture 7 Epidemiological models





Continuous time susceptible SEIR disease state model

S: suceptible

E: exposed (infected but not infectious)

I: infectious

R=V+D:

(V: immune, D: dead)

 λ : recruitment

 μ : natural mortality

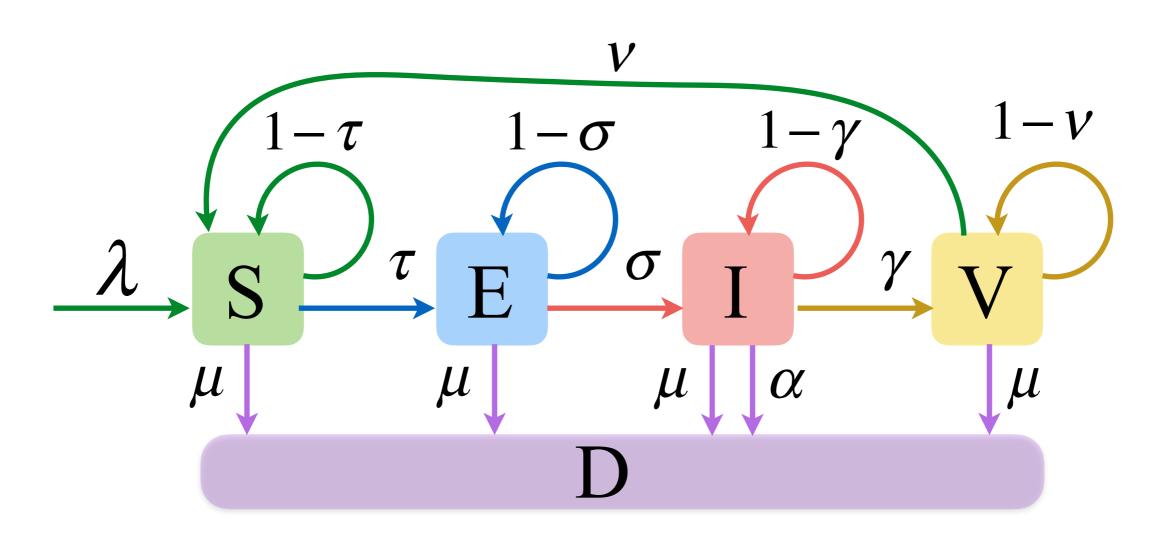
 α : disease-induced mortality

 τ : per-capita S transmission rate

 $1/\sigma$: latent-period

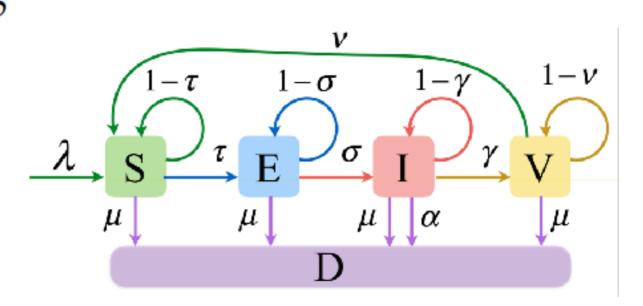
 $1/\gamma$: infectious-period

1/v: immune-period



Continuous time susceptible SEIR disease state model

$$\begin{array}{ll} \frac{dS}{dt} & = & \lambda(t) + \nu V - \left(\tau(I,N) + \mu\right)S \\ \frac{dE}{dt} & = & \tau(I,N)S - \left(\sigma + \mu\right)E \\ \frac{dI}{dt} & = & \sigma E - \left(\gamma + \alpha + \mu\right)I \\ \frac{dV}{dt} & = & \gamma I - \left(\nu + \mu\right)V \end{array}$$



$$\tau(I, N) = \frac{\beta I}{N}$$
, where $N = S + E + I + V$

Expected number of new infections from index case

$$R_0 = \frac{\beta \sigma}{(\sigma + \mu)(\gamma + \mu + \alpha)}$$

Outbreak threshold

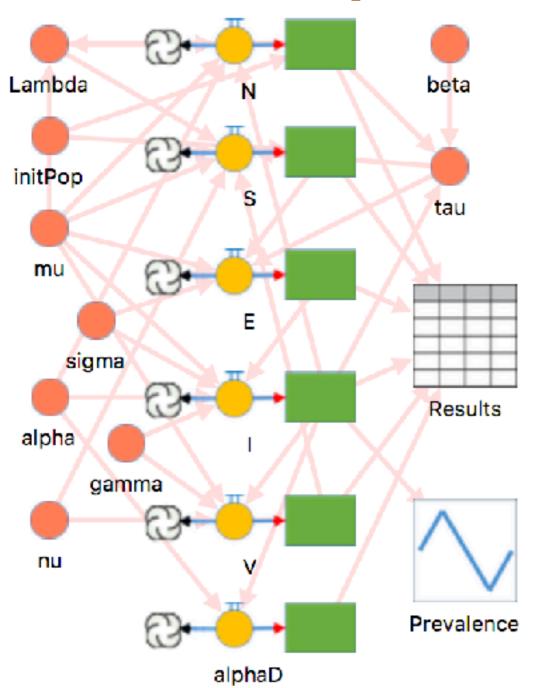
$$\beta > \frac{(\sigma + \mu)(\gamma + \mu + \alpha)}{\sigma}$$

Deaths: natural & disease

$$D^{\mu}(t) = \int_{0}^{t} \mu N(z) dz$$
$$D^{\alpha}(t) = \int_{0}^{t} \alpha I(z) dz$$

Continuous time susceptible SEIR disease state model

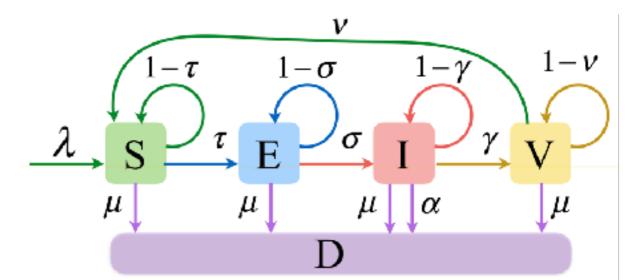
Numerus Model Builder Implementation

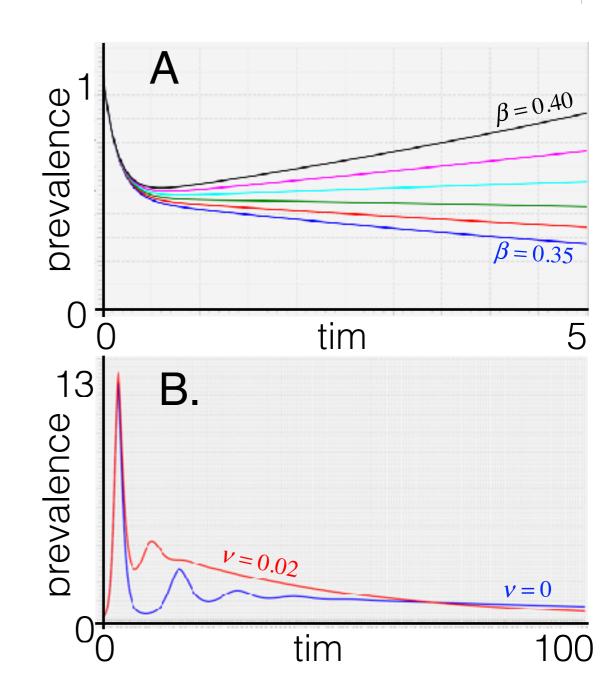


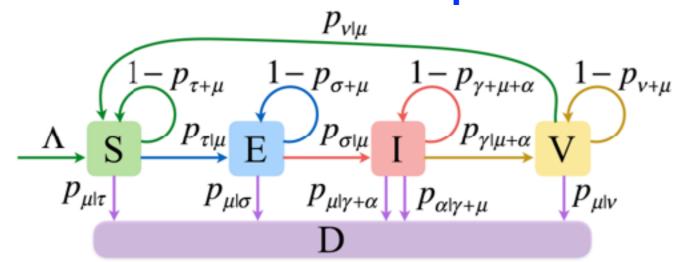
S(0)=999, $E(0)=0,\,I(0)=1,\,\text{and}\,\,V=0$ for the case $\mu=0.01,$ $\alpha=0.05,\,\sigma=\gamma=0.3,$ under the assumption that

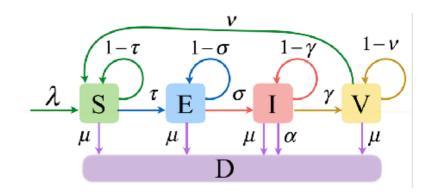
 $\lambda(t) = \mu N(t)$. In addition: in A. $\nu = 0$ and β varies from 0.35 to 0.40 (in steps of 0.01); and in B. $\beta = 1$

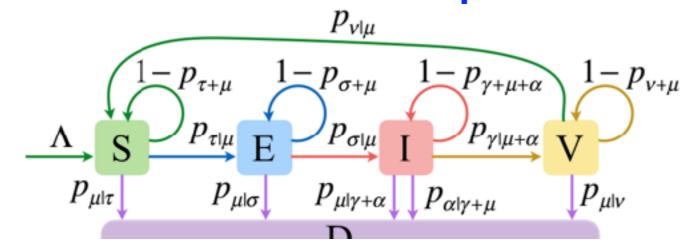
and $\nu = 0.02$ (red) and $\nu = 0$ (blue).



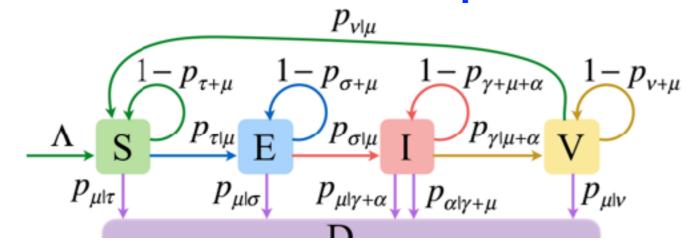








$$\Lambda_t = \int_t^{t+1} \lambda(s) ds$$
 and $\tau_t = \tau(I(t), N(t))$



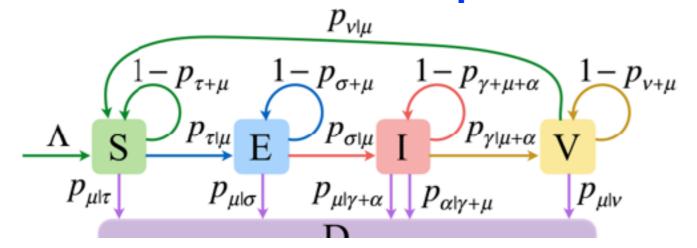
$$\Lambda_t = \int_t^{t+1} \lambda(s) ds$$
 and $\tau_t = \tau(I(t), N(t))$

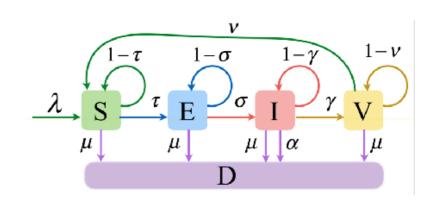
$$S(t+1) = \Lambda_t + p_{\nu|\mu}V(t) + S(t)(1 - p_{\tau_t+\mu})$$

$$E(t+1) = p_{\tau_t|\mu}S(t) + E(t)(1 - p_{\sigma+\mu})$$

$$I(t+1) = p_{\sigma|\mu}E(t) + I(t)(1 - p_{\gamma+\alpha+\mu})$$

$$V(t+1) = p_{\gamma|\mu+\alpha}I(t) + V(t)(1-p_{\nu+\mu})$$





$$\Lambda_t = \int_t^{t+1} \lambda(s) ds$$
 and $\tau_t = \tau(I(t), N(t))$

$$S(t+1) = \Lambda_t + p_{\nu|\mu}V(t) + S(t)(1 - p_{\tau_t+\mu})$$

$$E(t+1) = p_{\tau_t|\mu}S(t) + E(t)(1 - p_{\sigma+\mu})$$

$$I(t+1) = p_{\sigma|\mu}E(t) + I(t)(1 - p_{\gamma+\alpha+\mu})$$

$$V(t+1) = p_{\gamma|\mu+\alpha}I(t) + V(t)(1 - p_{\nu+\mu})$$

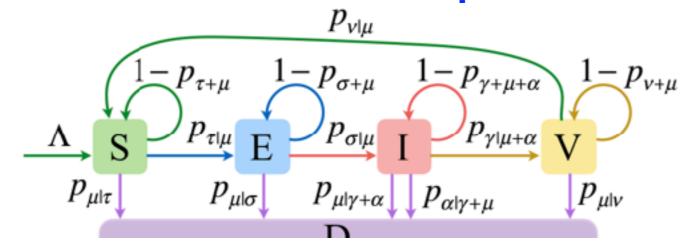
$$p_{\gamma|\alpha+\mu} = \frac{\gamma \left(1 - e^{-(\gamma + \alpha + \mu)}\right)}{\gamma + \alpha + \mu}$$

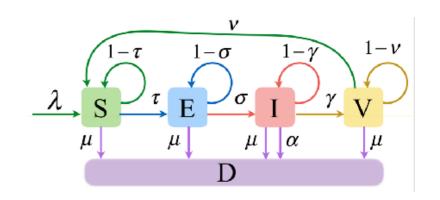
$$p_{\alpha|\gamma+\mu} = \frac{\alpha \left(1 - e^{-(\gamma+\alpha+\mu)}\right)}{\gamma + \alpha + \mu}$$

$$p_{\mu|\gamma+\alpha} = \frac{\mu \left(1 - e^{-(\gamma+\alpha+\mu)}\right)}{\gamma + \alpha + \mu}$$

Competing rates formulation and so on for rest of *p*'s

$$p_{\gamma|\alpha+\mu} + p_{\alpha|\gamma+\mu} + p_{\mu|\gamma+\alpha} = p_{\gamma+\alpha+\mu}$$





$$\Lambda_t = \int_t^{t+1} \lambda(s) ds$$
 and $\tau_t = \tau(I(t), N(t))$

$$S(t+1) = \Lambda_t + p_{\nu|\mu}V(t) + S(t)(1 - p_{\tau_t+\mu})$$

$$E(t+1) = p_{\tau_t|\mu}S(t) + E(t)(1 - p_{\sigma+\mu})$$

$$I(t+1) = p_{\sigma|\mu}E(t) + I(t)(1 - p_{\gamma+\alpha+\mu})$$

$$V(t+1) = p_{\gamma|\mu+\alpha}I(t) + V(t)(1-p_{\nu+\mu})$$

$$p_{\gamma|\alpha+\mu} = \frac{\gamma \left(1 - e^{-(\gamma + \alpha + \mu)}\right)}{\gamma + \alpha + \mu}$$

$$p_{\alpha|\gamma+\mu} = \frac{\alpha \left(1 - e^{-(\gamma+\alpha+\mu)}\right)}{\gamma + \alpha + \mu}$$

$$p_{\mu|\gamma+\alpha} = \frac{\mu \left(1 - e^{-(\gamma+\alpha+\mu)}\right)}{\gamma + \alpha + \mu}$$

Competing rates formulation and so on for rest of *p*'s

$$p_{\gamma|\alpha+\mu} + p_{\alpha|\gamma+\mu} + p_{\mu|\gamma+\alpha} = p_{\gamma+\alpha+\mu}$$

$$S(t+1) = \hat{S}(t) + \hat{\Lambda}_t + \hat{U}^{V}(t) - (\hat{T}(t) + \hat{M}^{S}(t))$$

$$E(t+1) = \hat{E}(t) + \hat{T}(t) - (\hat{U}^{E}(t) + \hat{M}^{E}(t))$$

$$I(t+1) = \hat{I}(t) + \hat{U}^{E}(t) - (\hat{U}^{I}(t) + \hat{M}^{I}(t) + \hat{D}(t))$$

$$V(t+1) = \hat{V}(t) + \hat{U}^{I}(t)$$

 $-\left(\hat{U}^{V}(t)+\hat{M}^{V}(t)\right)$

$$S(t+1) = \hat{S}(t) + \hat{\Lambda}_{t} + \hat{U}^{V}(t) - (\hat{T}(t) + \hat{M}^{S}(t))$$

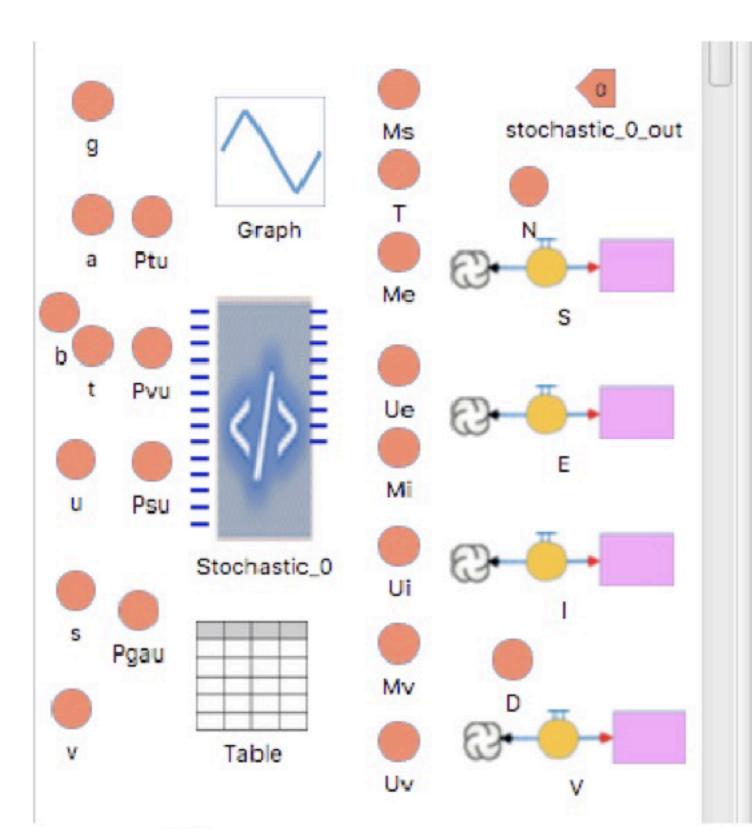
$$E(t+1) = \hat{E}(t) + \hat{T}(t) - (\hat{U}^{E}(t) + \hat{M}^{E}(t))$$

$$I(t+1) = \hat{I}(t) + \hat{U}^{E}(t) - (\hat{U}^{I}(t) + \hat{M}^{I}(t) + \hat{D}(t))$$

$$V(t+1) = \hat{V}(t) + \hat{U}^{I}(t) - (\hat{U}^{V}(t) + \hat{M}^{V}(t))$$

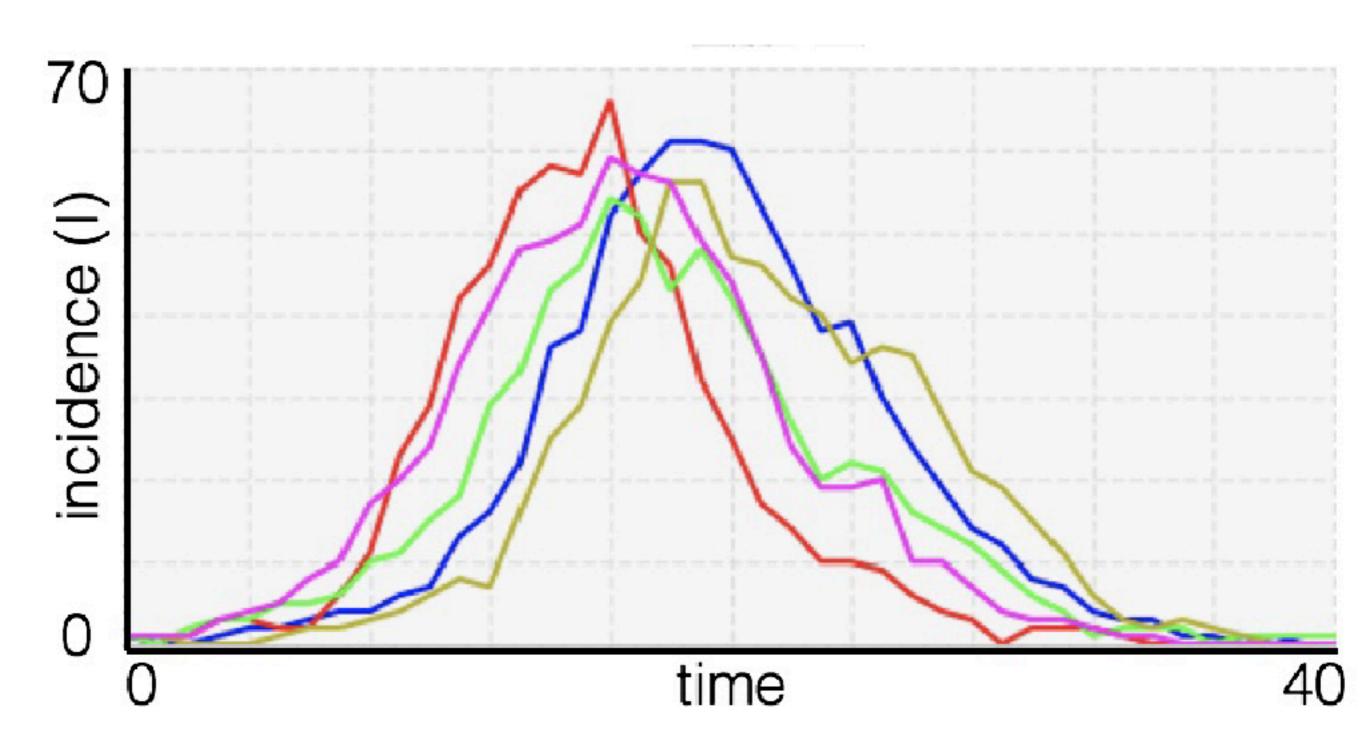
$$\begin{array}{lll} \left(\hat{S}(t), \hat{T}(t), \hat{M}^{\rm S}(t) \right) & := & {\rm MULTINOMIAL} \left[S(t); 1 - p_{\tau_t + \mu}, \, p_{\tau_t \mid \mu}, \, p_{\mu \mid \tau_t} \right] \\ \left(\hat{E}(t), \hat{U}^{\rm E}(t), \hat{M}^{\rm E}(t) \right) & := & {\rm MULTINOMIAL} \left[E(t); 1 - p_{\sigma + \mu}, \, p_{\sigma \mid \mu}, \, p_{\mu \mid \sigma} \right] \\ \left(\hat{I}(t), \hat{U}^{\rm I}(t), \hat{M}^{\rm I}(t), \hat{D}(t) \right) & := & {\rm MULTINOMIAL} \left[I(t); 1 - p_{\gamma + \alpha + \mu}, \, p_{\mu \mid \alpha + \mu}, \, p_{\gamma \mid \alpha + \mu}, \, p_{\alpha \mid \gamma \mid + \mu} \right] \\ \left(\hat{V}(t), \hat{U}^{\rm V}(t), \hat{M}^{\rm V}(t) \right) & := & {\rm MULTINOMIAL} \left[V(t); 1 - p_{\nu + \mu}, \, p_{\mu \mid \nu}, \, p_{\nu \mid \mu} \right] \\ \end{array}$$

Numerus Model Builder Implementation

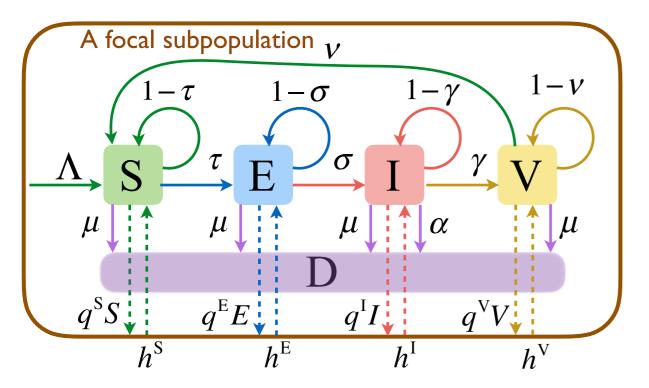


```
Sset = MULTINOMIAL(S,[(1-Ptu),
   (t/(t+u))*Ptu,(u/(t+u))*Ptu])
  T = Sset[1]
  Ms = Sset[2]
  Eset = MULTINOMIAL(E, [(1-Psu),
   (s/(s+u))*Psu,(u/(s+u))*Psu])
  Ue = Eset[1]
  Me = Eset[2]
   Iset = MULTINOMIAL(I,[(1-Pgau),
12 (g/(g+a+u))*Pgau, (u/(g+a+u))*Pgau,
   (a/(g+a+u))*Pgau])
  Ui = Iset[1]
  Mi = Iset[2]
  D = Iset[3]
  Vset = MULTINOMIAL(V,[(1-Pvu),
   (v/(v+u))*Pvu,(u/(v+u))*Pvu])
  Uv = Vset[1]
  Mv = Vset[2]
22
```

Stochastic solutions highly variable for small populations: expectation very close to deterministic solution

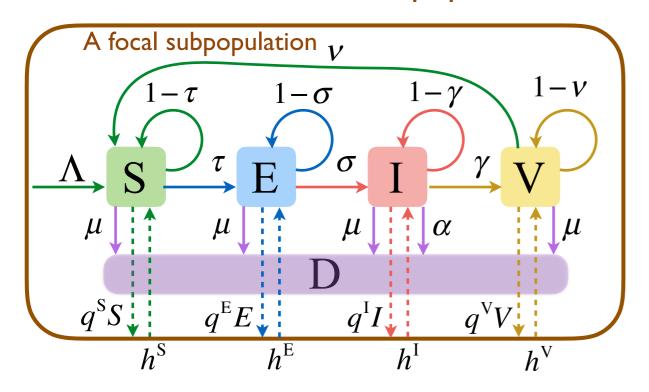


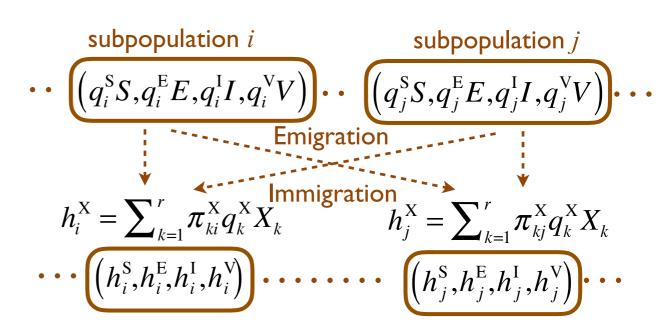
A. Continuous SEIR in a metapopulation setting



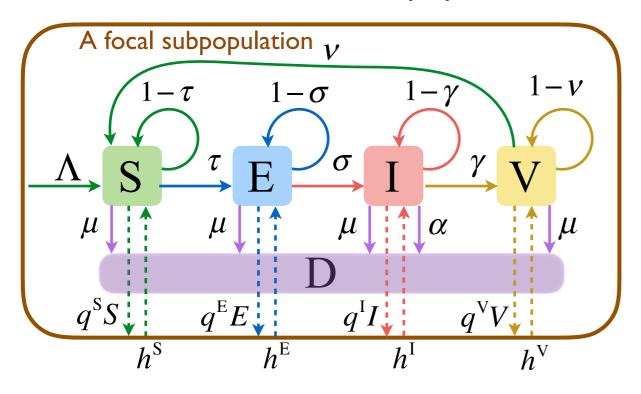
A. Continuous SEIR in a metapopulation setting

B. Metapopulation network

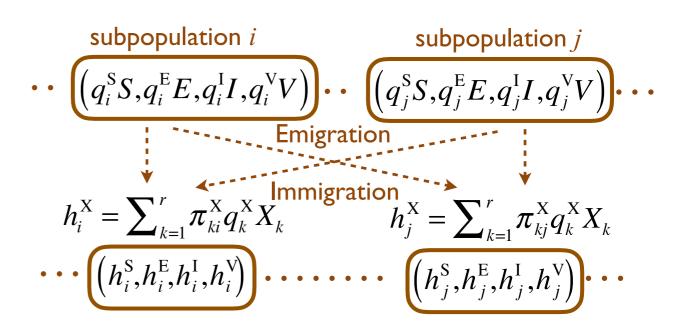




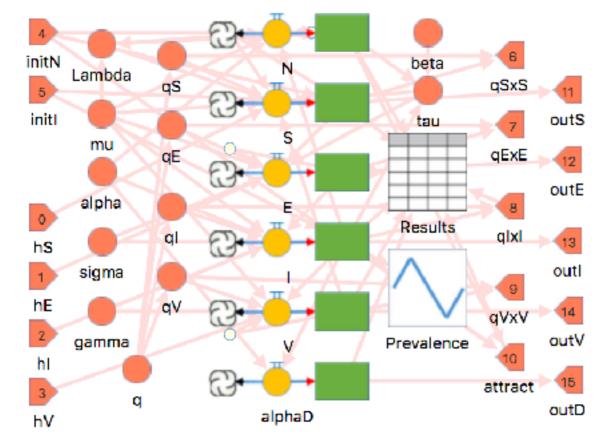
A. Continuous SEIR in a metapopulation setting



B. Metapopulation network

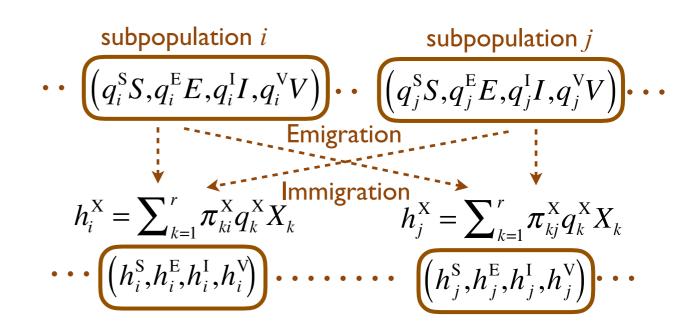


C. Nova Homogeneous SEIR Model with pins

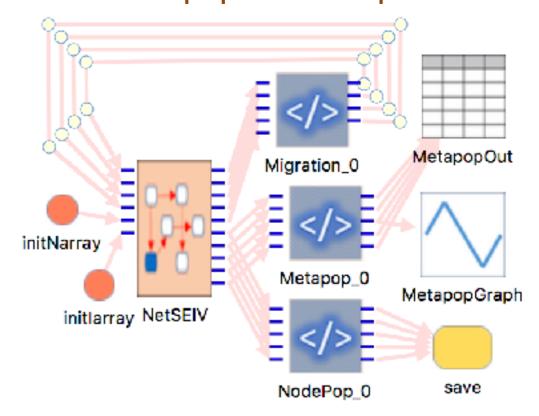


- A. Continuous SEIR in a metapopulation setting

B. Metapopulation network



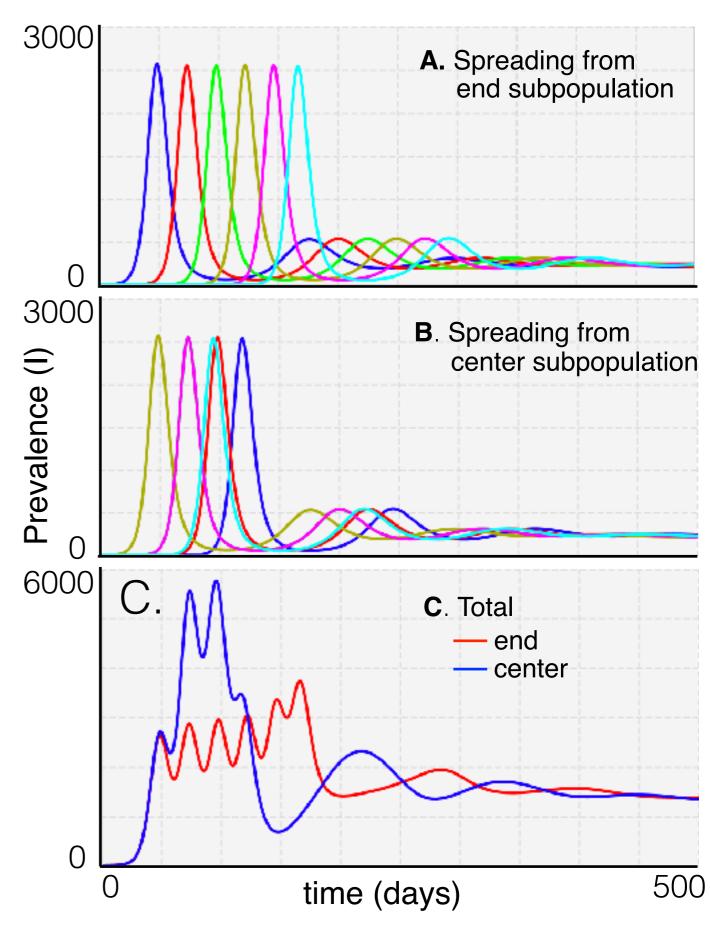
- C. Nova Homogeneous SEIR Model with pins
 - initN beta Lambda qSxS initI outS tau qExE outE alpha Results qlxl sigma outl aVxV gamma outV Prevalence attract outD alphaD hV
- D. Nova Metapopulation Implementation





Prevalence plots (SEIV process at each node with migration: individuals flow only to subpopulations that are immediate neighbors.)

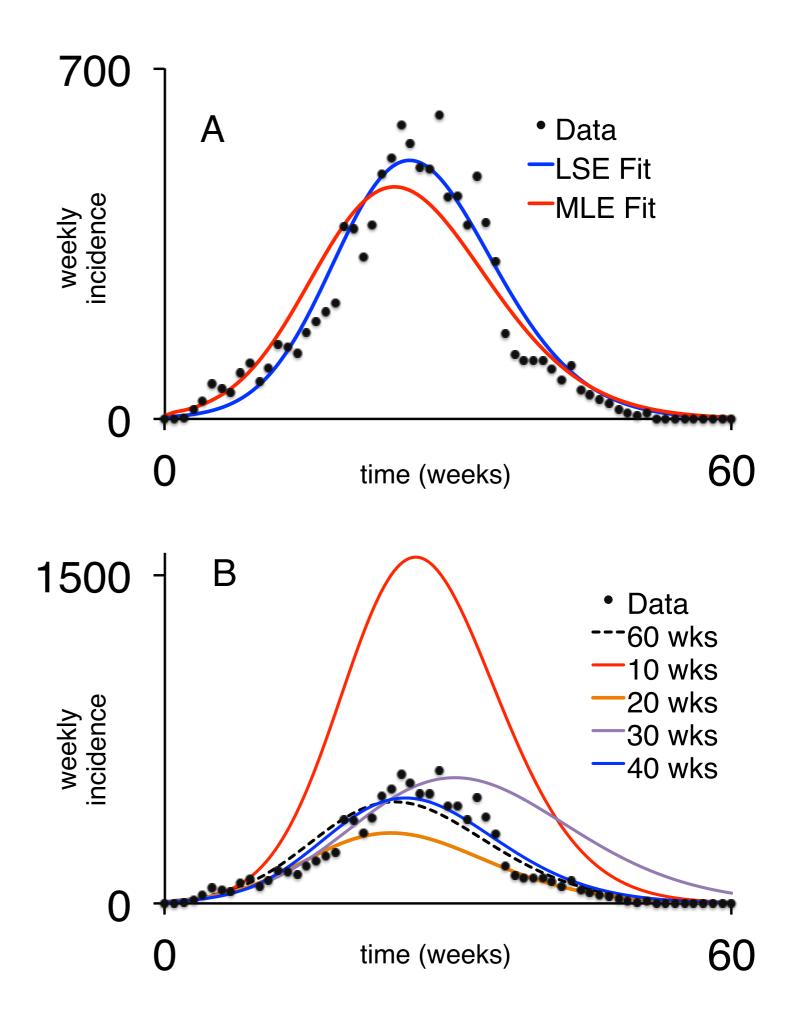
- A. (index case in subpopulation 0)
- B. (index case in subpopulation 2)
- C. Total prevalence for two index cases that are either the end two (red plot, index cases on 0 and 5) or center two (blue plot, index cases in 2 and 3) subpopulations.



Fitting the SEIV model to Ebola data

A. The blue and red curves are the best fit least-square and maximum-likelihood estimate fits of the discrete-time SEIV model to Ebola incidence data from the Sierra Leone 2014

B. The black dotted line is the MLE fit, as in Panel A, with the red, orange, purple and blue plots, being simulations obtained after obtaining the best ML fits to the first 10, 20, 30 and 40 weeks of incidence respectively.



Access Models and Videos

Models available at: https://www.dropbox.com/home/NumerusMB Epi_Models

Videos: search on Youtube using terms: GetzEtAl SEIR

