

Foundations of dynamic modeling: The SIR Model Family

Jonathan Dushoff, McMaster University

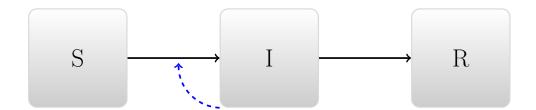
Goals

- This lecture will:
 - introduce the idea of dynamical modeling
 - explain why dynamical modeling is a key tool for understanding infectious disease
 - discuss and demonstrate simple dynamical models from the SIR model family
 - investigate some insights that can be gained from these models

Dynamical modeling connects scales

- Start with rules about how things change in short time steps
 - Usually based on *individuals*
- Calculate results over longer time periods
 - Usually about *populations*

Compartmental models Divide people into categories:



• Susceptible \rightarrow Infectious \rightarrow Recovered

What determines transition rates?

- People get better independently
- People get infected by infectious people

Conceptual modeling

- What is the final result?
- When does disease increase, decrease?

Dynamic implementation

- Requires assumptions about recovery and transmission
- The conceptually simplest implementation uses Ordinary Differential Equations (ODEs)
 - Other options may be more realistic
 - Or simpler in practice

Recovery

- Infectious people recover at per capita rate γ
 - Total recovery rate is γI
 - Mean time infectious is $D = 1/\gamma$

Transmission

- Susceptible people get infected by:
 - Going around and contacting people (rate c)
 - Some of these people are infectious (proportion I/N)
 - Some of these contacts are effective (proportion p)
- Per capita rate of becoming infected is $cpI/N \equiv \beta I/N$
- Population-level transmission rate is $\mathcal{T} = \beta SI/N$

Another perspective on transmission

- Infectious people infect others by:
 - Going around and contacting people (rate c)
 - Some of these people are susceptible (proportion S/N)
 - Some of these contacts are effective (proportion p)
- Per capita rate of infecting others is $cpS/N \equiv \beta S/N$
- Population-level transmission rate is $\mathcal{T} = \beta SI/N$

The basic reproductive number

- \mathcal{R}_0 is the number of people who would be infected by an infectious individual in a fully susceptible population.
- $\mathcal{R}_0 = \beta/\gamma = \beta D = (cp)D$
 - c: Contact Rate
 - − p: Probability of transmission (infectivity)
 - D: Average duration of infection
- A disease can invade a population if and only if $\mathcal{R}_0 > 1$.

ODE implementation

$$\begin{array}{rcl} \frac{dS}{dt} & = & -\beta \frac{SI}{N} \\ \frac{dI}{dt} & = & \beta \frac{SI}{N} - \gamma I \\ \frac{dR}{dt} & = & \gamma I \end{array}$$

 $\frac{d\widetilde{R}}{dt} = \gamma I$ Spreadsheet implementation

http://tinyurl.com/grp.ur

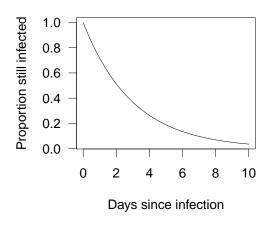
ODEs and mechanistic models

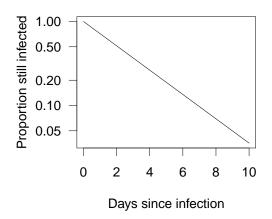
• What is the relationship between the spreadsheet and the ODE model we started with?

ODE assumptions

- Lots and lots of people
- Perfectly mixed

ODE assumptions





- Waiting times are exponentially distributed
- Rarely realistic
 - but sometimes OK for a particular application

Scripts vs. spreadsheets

- Scripts are more transparent, less redundant
- Spreadsheets are more intuitive for simple problems

More about transmission

- $\beta = pc$
 - What is a contact?
 - What is the probability of transmission?
- Sometimes this decomposition is clear
- But usually it's not
- So we often start by estimating β directly

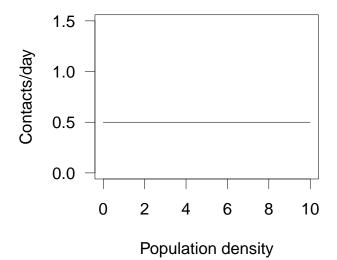
Population sizes

- How does β change with population size?
- We can make different assumptions about this
 - It may increase with population size, or not
- If population size changes we have to *consider* the question

Population sizes

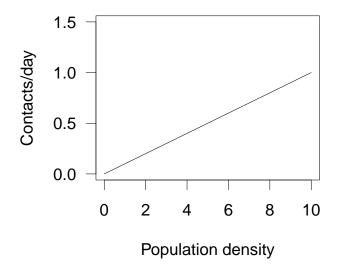
$$\begin{array}{rcl} \frac{dS}{dt} & = & -\beta(N)\frac{SI}{N} \\ \frac{dI}{dt} & = & \beta(N)\frac{SI}{N} - \gamma I \\ \frac{dR}{dt} & = & \gamma I \end{array}$$

Standard incidence



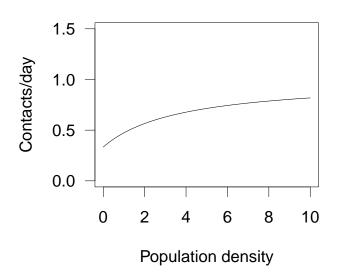
- $\beta(N) = \beta_0$
- $\mathcal{T} = \frac{\beta_0 SI}{N}$
- Also known as frequency-dependent transmission

Mass action



- $\beta(N) = \alpha_0 N$
- $\mathcal{T} = \alpha_0 SI$
- Also known as density-dependent transmission

General



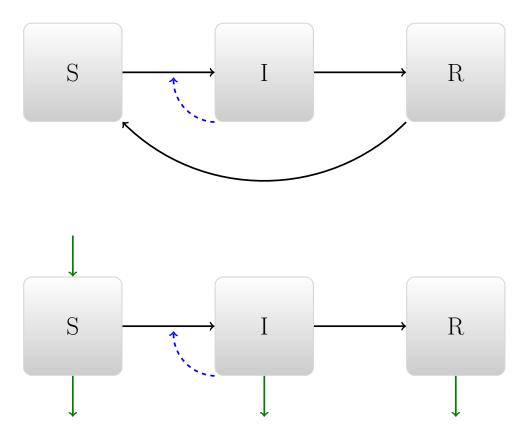
- Per-capita rate:
 - May not go to zero when N does

– May not go to ∞ when N does

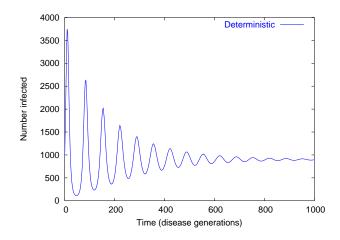
${\bf Digression-units}$

- $\mathcal{T} = \beta SI/N : [ppl/time]$
- $\beta:[1/\text{time}]$
 - The true β always has people in the numerator and the denominator
 - $-\ \beta/\gamma = \beta D: [1]$
- $\mathcal{T} = \alpha SI : [ppl/time]$
 - Mass-action incidence, $\alpha : [1/(\text{people} \cdot \text{time})]$

Closing the circle

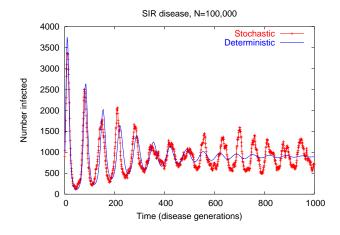


Tendency to oscillate



- Many susceptibles \rightarrow many infections \rightarrow few susceptibles \rightarrow few infections \rightarrow ...
- Oscillations in simple models tend to be "damped"

With individuality



- Treating individuals as individuals can produce substantial oscillations even in large populations
- Interaction between random effects and the different time scales (of infection and recovery)

Summary

- Dynamic models are an essential tool because they allow us to link between scales
- There are many ways to construct and implement dynamic models

- Very simple models can provide useful insights
 - Reproductive numbers and thresholds
 - Tendency for oscillation (and tendency for damping)
- More complex models can provide more detail, but also require more assumptions, and more choices
- Understanding simple models can help guide our understanding of more complicated models