

# Mathematical Modelling of Infectious Diseases for Public Health

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- (iii) Throughout the whole study period the population under consideration **is fixed in size**. There are **no births, deaths, immigration or emigration during the whole study period**.



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These assumptions reflect the situation for many diseases, such as measles or influenza, and would seem to be reasonable for computers whose anti-virus software has been updated to recognise the virus.



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An immediate implication of the assumptions is that individuals can only make two moves: from  $S$  to  $I$  and from  $I$  to  $R$ . For this reason the model is said to be an **SIR epidemic model**.





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$$\begin{aligned} \dot{S} &:= \frac{dS}{dt} = f_1(S, I) := -\beta SI \\ \dot{I} &:= \frac{dI}{dt} = f_2(S, I) := \beta SI - \gamma I = I(\beta S - \gamma), \end{aligned}$$

where  $\beta, \gamma > 0$  are positive constants,  $S(t) \geq 0$  and  $I(t) \geq 0$  for all  $t \geq 0$ .



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By potentially substituting  $\beta$  through  $\beta N$  we may assume WLOG that  $S + I + R = 1$ . These ODEs, together with the initial conditions  $I(0) := I_0$  and  $S(0) := S_0 := 1 - I_0$  for some fixed  $0 < I_0 < 1$  define the model.



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Remark (Lotka-Volterra)

*Coupled non-linear ODE systems of this type are very similar to the Lotka-Volterra equations, also known as the predator-prey equations, given by*

$$\begin{aligned}\dot{S} &= \alpha S - \beta SI = S(\alpha - \beta I) \\ \dot{I} &= \gamma SI - \delta I = I(\gamma S - \delta),\end{aligned}$$

where  $\alpha, \beta, \gamma, \delta > 0$  and  $S, I$  are defined on  $[0, \infty)$ .

# Deterministic generalisations of simple SIR

Remark (Some deterministic generalisations of the simple SIR model)

*One can add an inflow of newborns into the class  $S$  of susceptibles to the simple SIR model, at rate  $\mu N$ , and - the births balancing - deaths in the classes at rates  $-\mu S$ ,  $-\mu I$ ,  $-\mu R$  respectively, for some additional parameter  $\mu > 0$ . These models are known as **classic endemic models**.*



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**$\{t : t \geq 0 \text{ and } \beta S(t) - \gamma > 0\}$ .** Moreover,  $\frac{d}{dt}(S + I) = -\gamma I < 0$  on  $(0, \infty)$ , implying that - in any case - also the non-negative function  $S + I$  is strictly decreasing on  $(0, \infty)$ .

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## Definition

$R_0 := \frac{\beta}{\gamma} > 0$  is called **basic reproduction ratio**.





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### Proposition

*The initial value problem*

$$\dot{I} = (\beta S(t) - \gamma) I, I(0) = I_0 \quad (I_0 \in (0, 1])$$

has an **uniquely determined positive** solution on  $[0, \infty)$ . This solution is given by

$$I(t) := I_0 \exp\left(\beta \int_0^t S(u) du\right) \exp(-\gamma t) \stackrel{(!)}{=} I_0 \left(\exp\left(R_0\left(S(\tau) - \frac{1}{R_0}\right)\right)\right)^{\gamma t} \quad (t \geq 0)$$

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Similarly, we can see that also  $S(t) > 0$  for all  $t \geq 0$  (since  $S_0 > 0$  by assumption). Note that *in general* we don't know whether this unique solution  $I$  is bounded from above!

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### Proof.

(i)  $\Rightarrow$  (ii): Assume that  $I(t) \leq I_0$  for all  $t \geq 0$ . Then

$\exp\left(\beta \int_0^t S(u) du - \gamma t\right) \leq 1$  for all  $t \geq 0$ . Hence,  $\frac{1}{t} \int_0^t S(u) du \leq \frac{1}{R_0}$  **for all**  $t \geq 0$ . Consequently,  $S_0 = S(0) = \lim_{t \rightarrow 0} \frac{1}{t} \int_0^t S(u) du \leq \frac{1}{R_0}$ .

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Proof ctd.

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$S_0 = 1 - I_0$ . (i)  $\Rightarrow$  (iii): Let  $S_0 \leq \frac{1}{R_0}$ . Since  $\dot{S} = -\beta I S$  on  $(0, \infty)$  and both,  $I$  and  $S$  are positive it follows that  $\dot{S} < 0$  on  $(0, \infty)$ , implying that  $S$  is a strictly decreasing function on  $(0, \infty)$ .

Hence,  $S(t) < S(0) \leq \frac{1}{R_0}$  for all  $t > 0$ . In particular,  $\beta S - \gamma < 0$  on  $[0, \infty)$ . Consequently,  $\dot{I} = (\beta S - \gamma) I < 0$  on  $(0, \infty)$ , implying that  $I$  is strictly decreasing on  $(0, \infty)$ .

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$\exp(\beta \int_0^t S(u) du) \exp(-\gamma t) \leq \exp(\beta S(0) t) \exp(-\gamma t) = \exp(-\alpha t)$ ,  
 where  $\alpha := -(\beta S_0 - \gamma) > 0$ . Hence,  $I(t)$  decreases to 0 if  $t \rightarrow \infty$ .

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(iii)  $\Rightarrow$  (i): trivial. □

## Discussion on the role of $R_0$ III

Observation (Shape of the function  $I$  if  $R_0 > 1$ )

Let  $R_0 > 1$  and  $0 < t^*$  such that  $S(t^*) = \frac{1}{R_0}$ . Then  $I$  is strictly increasing on  $(0, t^*)$ .  $I$  attains its single maximum at  $t^*$ .  $I$  is strictly decreasing on  $(t^*, \infty)$ .



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Proof.

Elementary differentiation and a bit of elementary algebra induced by the structure of the SIR ODE system shows us that  $\dot{I}(t) = 0$  if and only if  $t = t^*$  and

$$\ddot{I} \stackrel{\checkmark}{=} I (\beta S - \gamma)^2 - \beta^2 I^2 S - \gamma I$$

on  $(0, \infty)$ . Consequently, at  $t^*$   $I$  attains its single (and hence global) maximum.

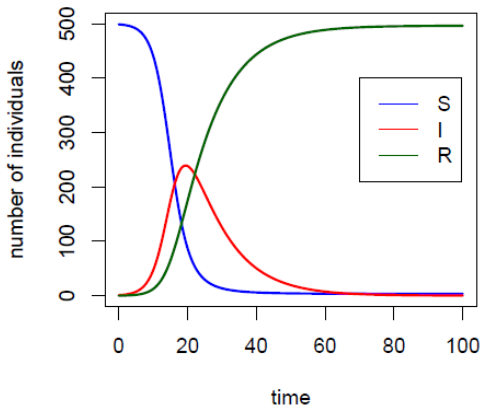
## Discussion on the role of $R_0$ III

Proof ctd.

Let  $0 < t < t^*$ . Then  $\frac{1}{R_0} = S(t^*) < S(t)$ , implying that in fact  $I$  is strictly increasing on  $(0, t^*)$ . Now let  $t^* < t$ . Then  $S(t) < S(t^*) = \frac{1}{R_0}$ . Hence,  $I$  is strictly decreasing on  $(t^*, \infty)$ .  $\square$

# Shape of the functions $S, I$ and $R$ in the case $R_0 > 1$

Here,  $N := 500$  and  $S, I, R : [0, \infty) \rightarrow (0, N]$  (not the percentages!).



## Discussion on the role of $R_0$ IV

Even if the basic reproduction ratio  $R_0$  is not known to us the number of susceptibles today (i.e.,  $S_0$ ) and the percentage of remaining susceptibles  $S_\infty := \lim_{t \rightarrow \infty} S(t) \leq 1$  when the epidemic is over already allows us to retrieve  $R_0$  **at least if  $S_0 \leq \frac{1}{R_0}$** , since:

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### Proposition

*Let  $S_0 \leq \frac{1}{R_0}$  and  $S_0 + I_0 = 1$ . Then*

$$\ln \left( \frac{S_0}{S_\infty} \right) = R_0 (1 - S_\infty) .$$

## Discussion on the role of $R_0$ IV

Proof.

Since  $\dot{S}(t) = -\beta S(t)I(t)$  for all  $t \in (0, \infty)$  and  $S(0) = S_0 = 1 - I_0$  we have

$$S(t) = S_0 \exp\left(-\beta \int_0^t I(u) du\right) \quad (t \geq 0).$$

Hence,

$$S(t) \stackrel{(!)}{=} S_0 \exp\left(R_0 \int_0^t (-\gamma I(u)) du\right)$$

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Hence,

$$\begin{aligned} S(t) &\stackrel{(!)}{=} S_0 \exp\left(R_0 \int_0^t (-\gamma I(u)) du\right) \\ &= S_0 \exp(R_0 (I(t) + S(t) - 1)) \quad (\text{why?}). \end{aligned}$$

# Discussion on the role of $R_0$ IV

Proof ctd.

Equivalently written:

$$\ln \left( \frac{S(0)}{S(t)} \right) = R_0 (1 - S(t) - I(t)) .$$

Now we take limits on both sides of the latter equation (as  $t \rightarrow \infty$ ). Since  $S_0 \leq \frac{1}{R_0}$  by assumption we know that  $I_\infty = \lim_{t \rightarrow \infty} I(t) = 0$  - and the claim follows. □



## 1 Revisiting Deterministic Epidemic Models

## 2 Catching a Glimpse of Stochastic Epidemic Models



# A glimpse of the continuous time Markov chain SIR model I

View the class of susceptibles, respectively the class of infected as stochastic random variables, changing randomly in time.

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View the class of susceptibles, respectively the class of infected as stochastic random variables, changing randomly in time.

Think e.g. at nodes in a random graph which change colour according to their state. A bit more formally, fix an arbitrary probability space  $(\Omega, \mathcal{F}, \mathbb{P})$  and consider the mappings

$\Omega \times [0, \infty) \ni (\omega, t) \mapsto S_t(\omega)$ , respectively

$\Omega \times [0, \infty) \ni (\omega, t) \mapsto I_t(\omega)$ , **where**

$I_t(\omega), S_t(\omega) \in S := \{0, 1, 2, \dots, N\}$  for all  $\omega \in \Omega$  and  $t \in [0, \infty)$ .

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In addition, given the current state of the  $S \times S$ -valued process  $(S_t, I_t)_{t \geq 0}$  at time  $t$ , we assume that the future state of this process at time  $t + \Delta t$ , for any  $\Delta t > 0$ , does not depend on times **prior to  $t$**  (known as **Markov property**).

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# A glimpse of the continuous time Markov chain SIR model II

Let  $s, i, k, j \in S$  and  $t \in [0, \infty)$ . Then the associated time-homogeneous transition probabilities

$$P_{(s,i),(s+k,i+j)}(\Delta t) := \mathbb{P}((S_{t+\Delta t}, I_{t+\Delta t}) = (s+k, i+j) \mid (S_t, I_t) = (s, i))$$

are modelled as

$$P_{(s,i),(s+k,i+j)}(\Delta t) := \begin{cases} \beta s i \Delta t + o(\Delta t) & \text{if } (k, j) = (-1, 1) \\ \gamma i \Delta t + o(\Delta t) & \text{if } (k, j) = (0, -1) \\ 1 - (\beta s i - \gamma i) \Delta t + o(\Delta t) & \text{if } (k, j) = (0, 0) \\ o(\Delta t) & \text{else} \end{cases}$$

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Unfolding the powerful machinery of Chapman-Kolmogorov equations, respectively time-homogeneous Markov semigroups one can then start to calculate transition probabilities and derived probabilities (think at multiple life insurance mathematics...).



# A glimpse of the SDE SIR model of Allen I

## Coupled SDE SIR Model of Allen

Let  $\beta > 0$ ,  $\gamma > 0$  and  $W^{(1)}$  and  $W^{(2)}$  be two independent standard Brownian motions.

$$\begin{aligned}
 dS_t &= -\beta S_t I_t dt - \sqrt{\beta S_t I_t} dW_t^{(1)} \\
 dI_t &= (\beta S_t I_t - \gamma I_t) dt + \sqrt{\beta S_t I_t} dW_t^{(1)} - \sqrt{\gamma I_t} dW_t^{(2)}.
 \end{aligned}$$

Moreover, the initial conditions are given by  $I(0) := I_0$ ,  $S(0) := S_0 := 1 - I_0$ ,  $0 < I_0 < 1$  (as in the simple deterministic case).



# A glimpse of the SDE SIR model of Allen II

One equivalent formulation of the SDE SIR model of Allen is the following one:

# A glimpse of the SDE SIR model of Allen II

One equivalent formulation of the SDE SIR model of Allen is the following one:

Coupled SDE SIR Model of Allen in Vector Notation

Let  $\beta > 0$ ,  $\gamma > 0$  and  $W^{(1)}$  and  $W^{(2)}$  be two independent standard Brownian motions.

$$d \begin{pmatrix} S \\ I \end{pmatrix} = \begin{pmatrix} -\beta I & 0 \\ \beta I & -\gamma I \end{pmatrix} \begin{pmatrix} S \\ I \end{pmatrix} dt + \begin{pmatrix} -\sqrt{\beta SI} & 0 \\ \sqrt{\beta SI} & -\sqrt{\gamma I} \end{pmatrix} d \begin{pmatrix} W^{(1)} \\ W^{(2)} \end{pmatrix}$$

Moreover, the initial conditions are given by  $\begin{pmatrix} S(0) \\ I(0) \end{pmatrix} := \begin{pmatrix} S_0 \\ I_0 \end{pmatrix}$ , where  $S_0 := 1 - I_0$ ,  $0 < I_0 < 1$  (as in the simple deterministic case).

# A glimpse of the SDE SIR model of Allen III

## Problem

*Is the SDE SIR model of Allen **well-defined**? To answer this non-trivial question we need the whole machinery of (multidimensional) Itô calculus including theory and application of the (vector-valued stochastic) Itô integral! **Actually, SDEs are stochastic integral equations. Brownian motion paths are nowhere differentiable with probability 1!***

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## Problem

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## Problem

Is the SDE SIR model of Allen *well-defined*? To answer this non-trivial question we need the whole machinery of (multidimensional) Itô calculus including theory and application of the (vector-valued stochastic) Itô integral! **Actually, SDEs are stochastic integral equations. Brownian motion paths are nowhere differentiable with probability 1!** Do data reflect whether this model is useful in practice? Why are two independent standard **Brownian motions** used? What about the possibility of Poisson jumps? Are the solution processes  $S$  and  $I$  still semimartingales?

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Thank you for your attention!

*Are there any questions, comments or remarks?*