

# Modelling SDEs in biology

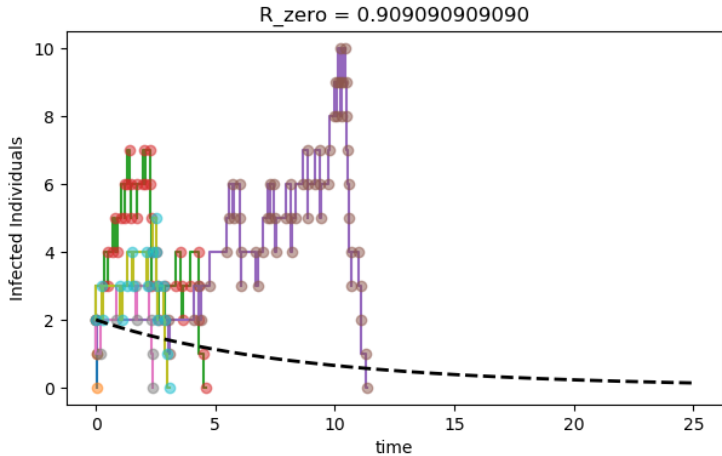
Formulation, Numerical Simulation and Analysis.

**Third day: Analysis of epidemic models**

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Saúl Díaz Infante Velasco

CONACYT-UNIVERSIDAD de SONORA, Cimat, Guanajuato Gto



# Analysis of an SI-SDE model

$$\dot{S}(t) = \Lambda - \mu S(t) - \beta S(t)I(t) - \delta S(t)$$

$$\dot{I}(t) = \beta S(t)I(t) - (\mu + \gamma + \varepsilon)I(t)$$

$$\dot{R}(t) = \gamma I(t) - \mu R(t) + \delta S(t)$$

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## Deterministic threshold

$$\mathcal{R}_0 = \frac{\beta \Lambda}{(\mu + \gamma + \varepsilon)(\mu + \delta)}$$

$$\mathcal{R}_0 < 1 \Rightarrow FDE : \text{ (g.a.s) }$$

$$\mathcal{R}_0 > 1 \Rightarrow EE : \text{ (g.a.s) }$$

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## Stochastic threshold

$$\mathcal{R}_0^S = ?$$

$$\mathcal{R}_0^S < 1 \Rightarrow \text{Extinction}$$

$$\mathcal{R}_0^S > 1 \Rightarrow \text{Persistence}$$

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Check:



Yue Zhang, Yang Li, Qingling Zhang, and Aihua Li.  
**Behavior of a stochastic SIR epidemic model with saturated incidence and vaccination rules.**

*Physica A: Statistical Mechanics and its Applications*, 501:178–187, 2018.

# When apply Stochastic Models?

## When are interested in

- Small population
- Demographic variability
- Environmental variability

## According to



Allen, L. J. (2017).  
**A primer on stochastic epidemic models: Formulation, numerical simulation, and analysis.**  
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## Example

Transmission, births, recovery, deaths

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## Example

Transmission, births, recovery, deaths

Territorial conditions, aquatic:  
diseases vector, zoonotic  
Foodborne

# Alternatives

## Models

- (D/C)-TMCs
- Parameter perturbation
  - Mean reverting processes
  - $\beta_t^H H \in (0.5, 1)$
- Random Diff. Eq.

## MC + ME $\rightarrow$ SDE



L. J. Allen.

**A primer on stochastic epidemic models: Formulation, numerical simulation, and analysis.**

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## Tools

- Gillespie
- Kloeden-Methods
- Hermite-PC

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$$\varphi dt \rightsquigarrow \varphi dt + \sigma dB_t$$



Gray, A., Greenhalgh, D., Hu, L., Mao, X., and Pan, J. (2011).

### **A Stochastic Differential Equation SIS Epidemic Model.**

*SIAM Journal on Applied Mathematics*, 71(3):876–902.

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Schurz, H. and Tosun, K. (2015).  
**Stochastic Asymptotic Stability of SIR Model with Variable Diffusion Rates.**  
*Journal of Dynamics and Differential Equations*, 27(1):69–82.

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## Fractiona BM.: long range memory.



Ma, Y., Zhang, Q., and Ye, M. (2017). **Mean-square dissipativity of numerical methods for a class of resource-competition models with fractional brownian motion.** *Systems Science & Control Engineering*, 5(1):268–277.

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## parameters as r.v.



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To illustrate ideas  $\varphi dt \rightsquigarrow \varphi dt + \sigma dB_t$

- Modelling
- Analysis and simulation
- Perspectives

1. Introduction
2. Perturbación con MB
3. Solution properties
4. Trheshold:  $R_0^S := R_0^D - f(\sigma, \cdot)$
5. Perspectives and fina comments

$$\frac{dS(t)}{dt} = \mu N - \beta S(t)I(t) + \gamma I(t) - \mu S(t),$$

$$\frac{dI(t)}{dt} = \beta S(t)I(t) - (\mu + \gamma)I(t),$$

$$R_0^D = \frac{\beta N}{\mu + \gamma},$$

$$R_0^D < 1 \Rightarrow \lim_{t \rightarrow \infty} I(t) = 0$$

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- $(\Omega, \mathcal{F}, \{\mathcal{F}\}_{t \geq 0}, \mathbb{P})$ ,
- $B_t$  M.B.
- $\beta S(t)I(t)dt$   
nuevas infecciones en  $[t, t + dt)$
- $\beta dt$ , contactos potencialmente infecciosos

$$dI(t) = [\beta S(t)I(t) - (\mu + \gamma)I(t)] dt$$



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# Modelo de juguete

$$\begin{aligned}\frac{dS(t)}{dt} &= \mu N - \beta S(t)I(t) + \gamma I(t) - \mu S(t), \\ \frac{dI(t)}{dt} &= \beta S(t)I(t) - (\mu + \gamma)I(t), \\ R_0^D &= \frac{\beta N}{\mu + \gamma},\end{aligned}$$

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- $\beta dt$ , contactos potencialmente infecciosos

$$dI(t) = [\beta S(t)I(t) - (\mu + \gamma)I(t)] dt$$

$$\beta dt \rightsquigarrow \underbrace{\beta dt + \sigma dB_t}_{:= \tilde{\beta} dt}$$

$$\mathbb{E}[\tilde{\beta} dt] = \beta dt$$

$$\text{Var}[\tilde{\beta} dt] = \sigma^2 dt \xrightarrow{dt \rightarrow 0} 0$$

$$\frac{dS(t)}{dt} = \mu N - \beta S(t)I(t) + \gamma I(t) - \mu S(t),$$

$$\frac{dI(t)}{dt} = \beta S(t)I(t) - (\mu + \gamma)I(t),$$

$$R_0^D = \frac{\beta N}{\mu + \gamma},$$

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$$dS(t) = [\mu N - \beta S(t)I(t) + \gamma I(t) - \mu S(t)]dt - \sigma S(t)I(t)dB_t$$

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$$N = S(t) + I(t) = \text{cte.}$$

$$dI(t) = I(t) ([\beta(N - I(t)) - \mu - \gamma]) dt - \sigma(N - I(t)) dB_t$$

## Theorem

- $\forall I(0) \in (0, N)$

$\exists$  **global positive invariant solution**  
 $I_t$

$$\mathbb{P}[I(t) \in (0, N) \forall t \geq 0] = 1.$$

$$dI(t) = I(t) \{ [\beta(N - I(t)) - \mu - \gamma] dt + \sigma(N - I(t)) dB_t \}$$



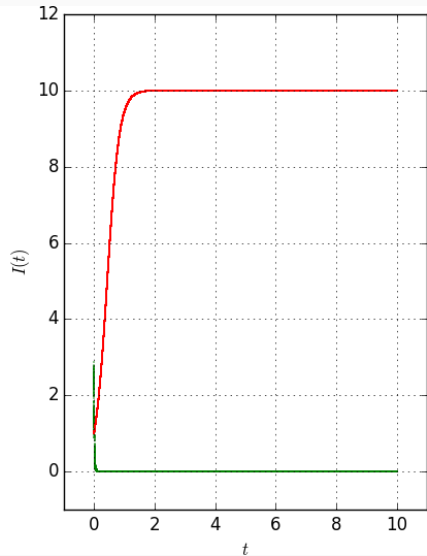
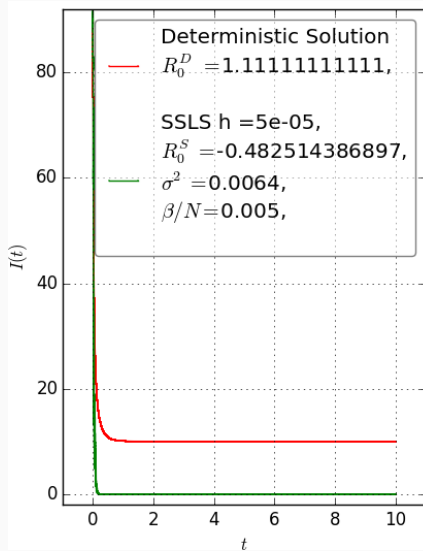
## Theorem

- $\sigma^2 > \max \left\{ \frac{\beta}{N}, \frac{\beta^2}{2(\mu + \gamma)} \right\}$

for all  $I(0) \in (0, N)$  the solution to SDE(\*) satisfies

$$\limsup_{t \rightarrow \infty} \frac{1}{t} \log I(t) \leq \underbrace{-\mu - \gamma + \frac{\beta^2}{2\sigma^2}}_{< 0}$$

# Simulación: Extinción por ruido ambiental



## Theorem (Extinction)

- $R_0^S := R_0^D - \frac{\sigma^2}{2(\mu + \gamma)} < 1$
- $\sigma^2 \leq \frac{\beta}{N}$

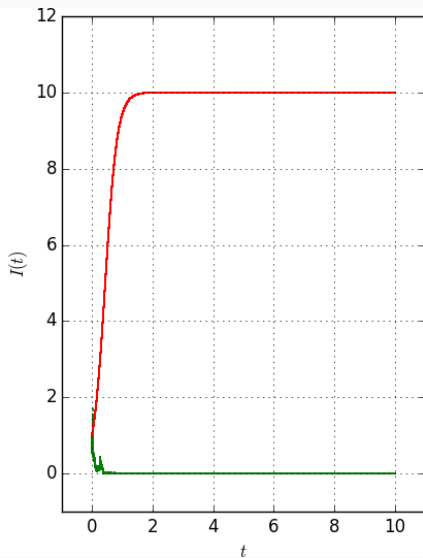
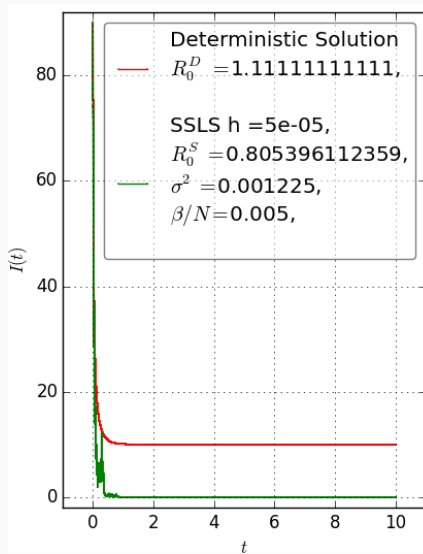
for all  $I(0) \in (0, N)$

$$\limsup_{t \rightarrow \infty} \frac{1}{t} \log I(t) \leq \kappa, \quad \text{c.s.}$$

$$\kappa := \beta N - \mu - \gamma - \frac{\sigma^2 N^2}{2\sigma^2} < 0$$

$$dI(t) = I(t) \{ [\beta(N - I(t)) - \mu - \gamma] dt + \sigma(N - I(t)) dB_t \} \quad (*)$$

# Extinction by a threshold condition



## Theorem (persistence)

$$\bullet R_0^S := R_0^D - \frac{\sigma^2}{2(\mu + \gamma)} > 1$$

para toda  $I(0) \in (0, N)$

$$\limsup_{t \rightarrow \infty} \frac{1}{t} \log I(t) \geq \varepsilon,$$

$$\liminf_{t \rightarrow \infty} \frac{1}{t} \log I(t) \leq \varepsilon, \quad \text{c.s.}$$

$$\varepsilon = \frac{1}{\sigma^2} \left( \sqrt{\beta^2 - 2\sigma^2(\mu + \gamma) - (\beta - \sigma^2 N)} \right)$$

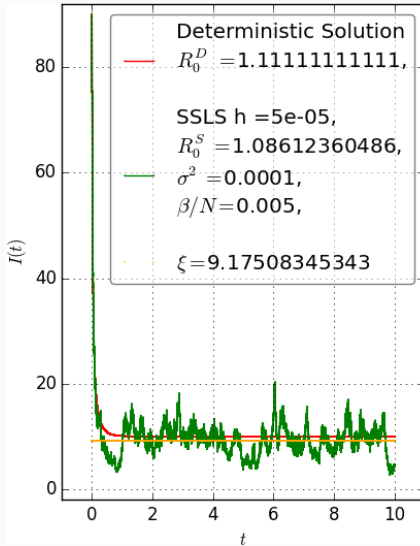
$$dI(t) = I(t) \{ [\beta(N - I(t)) - \mu - \gamma] dt + \sigma(N - I(t)) dB_t \} \quad (*)$$

$$R_0^D : \beta N / (\mu + \gamma)$$

$$R_0^D < 1 \Rightarrow \lim_{t \rightarrow \infty} I(t) = 0$$

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# Simulation: Persistence)



# Stationary distribution

## Stationary distribution

- $P_{l_0,t}(A) = \mathbb{P}[I(t) \in A],$   
 $A \in \mathcal{B}((0, N))$
- $\lim_{t \rightarrow \infty} P_{l_0,t}(\cdot) = \mathbb{P}_\infty(\cdot)$   
in distribution.

# Stationary distribution

## Stationary distribution

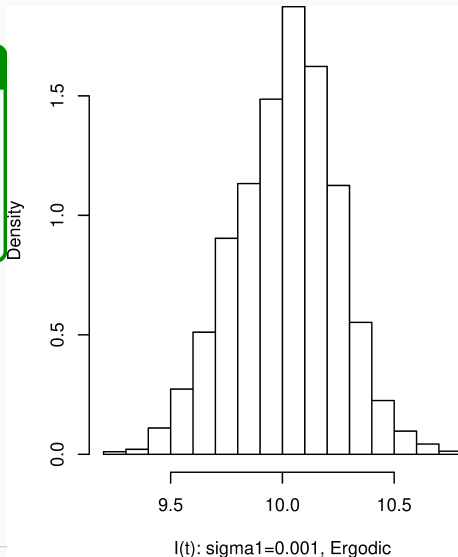
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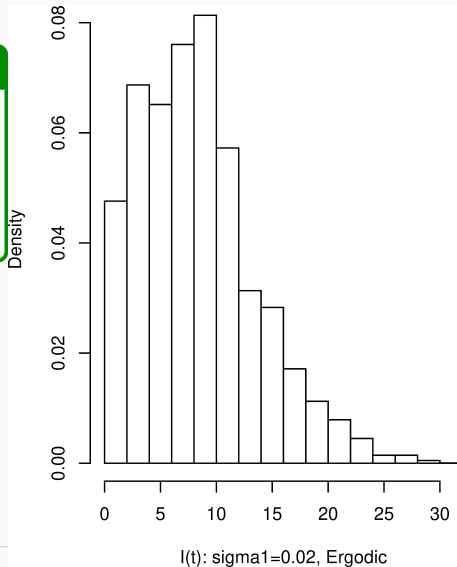
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Manuel Adrian Acuña-Zegarra and Saúl Díaz-Infante.

**Stochastic asymptotic analysis of a multi-host model with vector transmission.**

*Physica A: Statistical Mechanics and its Applications*, 510:243 – 260, 2018.



S. Jerez, S. Díaz-Infante, and B. Chen.

**Fluctuating periodic solutions and moment boundedness of a stochastic model for the bone remodeling process.**

*Mathematical Biosciences*, 299:153 – 164, 2018.



S. Díaz-Infante and S. Jerez.

**The linear steklov method for sdes with non-globally lipschitz coefficients: Strong convergence and simulation.**

*Journal of Computational and Applied Mathematics*, 309:408 – 423, 2017.

## Modelos

- Mean reverting processes
- $\beta_t^H$   $H \in (0.5, 1)$
- Random Diff. Eq.
- Random Dynamical Systems

$$d\varphi_t = (\varphi_e - \varphi_t)dt + \sigma_\varphi dB_t$$



Allen, E. (2016).

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## Long time memory: fBM



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## Parameters as r.v



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Rafail Khasminskii.

***Stochastic Stability of Differential Equations.***

Stochastic Modelling and Applied Probability 66. Springer-Verlag Berlin Heidelberg, 2 edition, 2012.



Alexander D. Wentzell Mark I. Freidlin.

***Random Perturbations of Dynamical Systems (Grundlehren der mathematischen Wissenschaften).***

Springer, 2nd edition, 1998.





Peter E. Kloeden.

***Random Ordinary Differential Equations and Their Numerical Solution.***

Probability Theory and Stochastic Modelling 85. Springer Singapore, 1 edition, 2017.



Eckhard Platen Peter E. Kloeden.

***Numerical solution of stochastic differential equations.***

Stochastic Modelling and Applied Probability. Springer, corrected edition, 1995.

## About the policies

- $u = u(t)$ , possible improvement
- $u = (x)$ , or  $u = u(t, x)$
- uncertainty

Tool: Dynamical Programing-HJB, MDP .

## About the policies

$$\min_{u \in \mathcal{U}} \mathbb{E} \left[ \int_0^T f(t, x, u) dt \right]$$

$$\text{s.t.} \quad dx_t = a(t, x, u)dt + b(t, x, u)dw_t$$

Tools: Dynamic Programming - HJB, MDP, Viscosity Solution,

# Towards Stochastic Control

## About the policies

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$$\text{s.t.} \quad dx_t = a(t, x, u)dt + b(t, x, u)dw_t$$

Tools: Dynamic Programming - HJB, MDP, Viscosity Solution,



Peter Grandits, Raimund M. Kovacevic, and Vladimir M. Veliov.  
**Optimal control and the value of information for a stochastic epidemiological SIS-model.**  
*J. Math. Anal. Appl.*, 476(2):665–695, 2019.

# Towards Stochastic Control

## About the policies

$$\min_{u \in \mathcal{U}} \mathbb{E} \left[ \int_0^T f(t, x, u) dt \right]$$

$$\text{s.t.} \quad dx_t = a(t, x, u)dt + b(t, x, u)dw_t$$

Tools: Dynamic Programming - HJB, MDP, Viscosity Solution,



Tony Huschto and Sebastian Sager.  
**Solving stochastic optimal control problems by a Wiener chaos approach.**

*Vietnam J. Math.*, 42(1):83–113, 2014.

**Code:** \*.tex, \*.py

<https://github.com/SaulDiazInfante/Modelling-Simulation-with-SDE>

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## Gracias!!!