# Stochastic Differential Equations Introduction

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## The Problem

Southern German water routes have had several drastic population changes concerning gammarids.

Much of this is due to canal construction.

Native Species:

Gammarus pulex (Gp)

Invasive Species:

Dikerogammarus villosus (Dv) Dikerogammarus haemobaphes (Dh) Dikerogammarus bispinosus (Db) Echinogammarus berilloni (Eb)

# Killer Shrimp

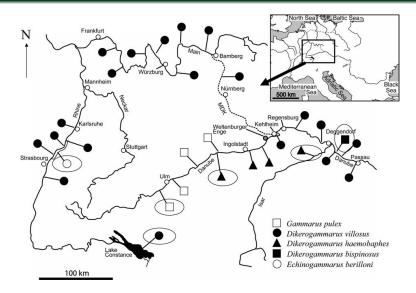


# Killer Shrimp



# Killer Shrimp





(Kinzler, 2008)

## Invasion Time Line

<1976 *Gp* native 1976-1994 *Dh* invades

1992-1995 Dv invades, Dh declines

>1995 All but Dv coexist separate from Dv

# Terminology

Intraguild Predation

Mutual Predation
Mutual Interference

Intraspecific Predation

Cannibalism

# Kinzler, 2008 Study

#### Isolated pairs of specimens in a controlled environment

- One freshly moulted (prey)
- One predator
- Total of 279 experiments
- Grouped by age, sex, and species

#### Results

- Found Dv to be clear strongest predator
- Found Dh to have highest cannibalism rate

## Basic Goals

## Determine long term population trends!

Does *Dv* totally dominate in the end?

Which species survive?

Is there an equilibrium?

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## Markov Process

(Markov Process) is a stochastic process with the following properties:

- 1 The number of possible outcomes or states is finite
- ② The outcome at any stage depends only on the outcome of the previous stage.
- 3 The probabilities are constant over time.

## **Brownian Motion**

#### Definition

(**Brownian Motion**) is a stochastic process that models random continuous motion. The stochastic process  $B = \{B(t), t \ge 0\}$  is standard Brownian Motion if the following holds:

- B has independent increments.
- ② For  $0 \le s < t$ ,

$$B(t) - B(s) \sim N(0, t - s).$$

- $\odot$  The paths of B are continuous with probability 1.
- B(0) = 0

Modeling

If x(t) is a Brownian Motion then  $\frac{x(\lambda t)}{\sqrt{\lambda}}$  is a Brownian motion.

$$\begin{split} P\left(a \leq \frac{x(\lambda t)}{\sqrt{\lambda}} - \frac{x(\lambda s)}{\sqrt{\lambda}} \leq b\right) &= P\left(a\sqrt{\lambda} \leq x(\lambda t) - x(\lambda s) \leq b\sqrt{\lambda}\right), \\ &= \frac{1}{\sqrt{2\pi(\lambda t - \lambda s)}} \int_{a\sqrt{\lambda}}^{b\sqrt{\lambda}} e^{\frac{-x^2}{2}(\lambda t - \lambda s)} dx, \\ &= \frac{1}{\sqrt{2\pi(t - s)}} \int_{a}^{b} e^{\frac{-u^2}{t - s}} du. \end{split}$$

# Riemann-Stieltjes

### (Riemann-Stieltjes Integral):

$$\int_a^b f(g)dg = \lim_{n o \infty} \sum_{i=1}^N f(g(t_i)) \cdot (g(t_{i+1})) - g(t_i)$$

The main motivation for the Riemann-Stieltjes Integral comes from the concept of Cumulative Distribution Function (CDF) of a random variable.

# Weiner Integral

### Weiner Integral

$$\int_a^b f(t)dW(t)$$
 
$$1[t_{i+1},t_i](t) = \begin{cases} 1 & \text{if } t_{i+1} \leq t < t_i \\ 0 & \text{otherwise} \end{cases}$$

Modeling

# Itô's Formula is used in Itô Calculus to find the differential of a time-dependent function of a stochastic process.

#### Differential Form

$$\partial x_t = \left(\frac{\partial x}{\partial t} + \frac{1}{2}\left(\frac{\partial^2 x}{\partial B^2}\right)\right) \cdot dt + \frac{\partial x}{\partial B} \cdot dB$$

#### Integral Form

$$F(t,B(t)) - F(a,B(a)) = \int_{a}^{t} \frac{\partial F}{\partial s} + \frac{1}{2} \frac{\partial^{2} F}{\partial B^{2}} ds + \int_{a}^{t} \frac{\partial F}{\partial B} dB$$

Let 
$$F = tR^2$$

$$\frac{dF}{dt} = B^{2}$$

$$\frac{dF}{dB} = 2t + B$$

$$\frac{d^{2}F}{dB^{2}} = 2t$$

$$tB^{2}(t) - aB^{2}(a) = \int_{a}^{t} B^{s} ds + \int_{a}^{t} 2sBdB + \int_{a}^{t} \frac{1}{2}2sds$$
$$= \int_{a}^{b} B^{2} + sds + \int_{a}^{t} 2sBdB$$
OR

$$tB^{2}(t) - aB^{2}(a) = \int_{a}^{t} B^{s} ds + \int_{a}^{t} 2sBdBt + \frac{1}{2}t^{2} - \frac{1}{2}a^{2}$$

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The governing Equations:

$$\dot{a} = L_1 a + N_1(a, g),$$
  
 $\dot{g} = L_2 g + N_2(a, g).$ 

## Calculating Stochastic Integrals

As an example consider the integral

$$Z_t = \int_0^t B(s)dB(s)$$

This integral can be calculated as

$$\int_0^t B(s)dB(s) = \frac{1}{2}(B^2(t) - B^2(0)) - \frac{1}{2}$$

$$x \rightarrow \bar{X}\xi,$$
 $t \rightarrow \bar{T}s.$ 

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## Nondimensionalization

The initial model is:

$$\frac{dx}{ds} = rx\left(1 - \frac{x}{k}\right) - \alpha xy,$$

$$\frac{dy}{ds} = \rho y\left(1 - \frac{y}{l}\right) - \beta xy.$$

Let

$$x \to A\hat{x}(s)$$
  
 $y \to B\hat{y}(s)$   
 $t \to \tau \cdot s$ 

When you substitute and group terms the system becomes nondimensionalized.

Modeling

The nondimensionalized system is:

$$\frac{dx}{ds} = rx(1-x) - \alpha xy,$$
  
$$\frac{dy}{ds} = y(1-y) - \beta xy.$$

## Heun's Method

- Heun's method is a numerical procedure for approximating ordinary differential equations with a given initial value.
- First you calculate the intermediate value  $\tilde{y}_{i+1}$  and then the final approximation  $y_{i+1}$  at the next generation point.

$$\tilde{y}_{i+1} = y_i + \Delta t \ f(t_i, y_i)$$

$$y_{i+1} = y_i + \frac{\Delta t}{2} \left[ f(y_i, t_i) + f(\tilde{y}_{i+1}, t_{i+1}) \right]$$