



Stochastic population modeling

Ola Diserud
01.02.2016

Fig 2.2

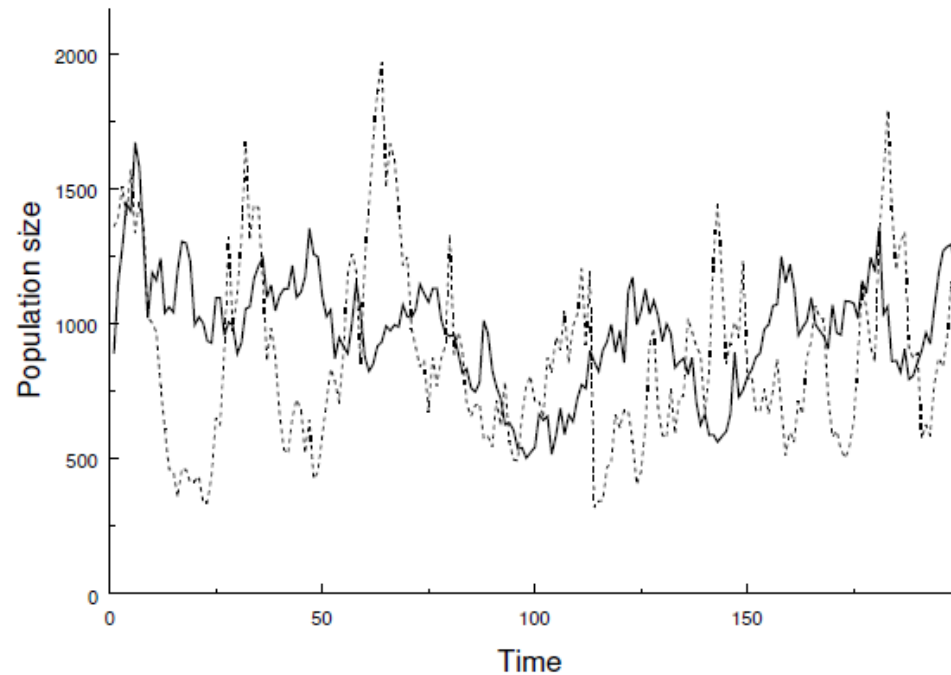
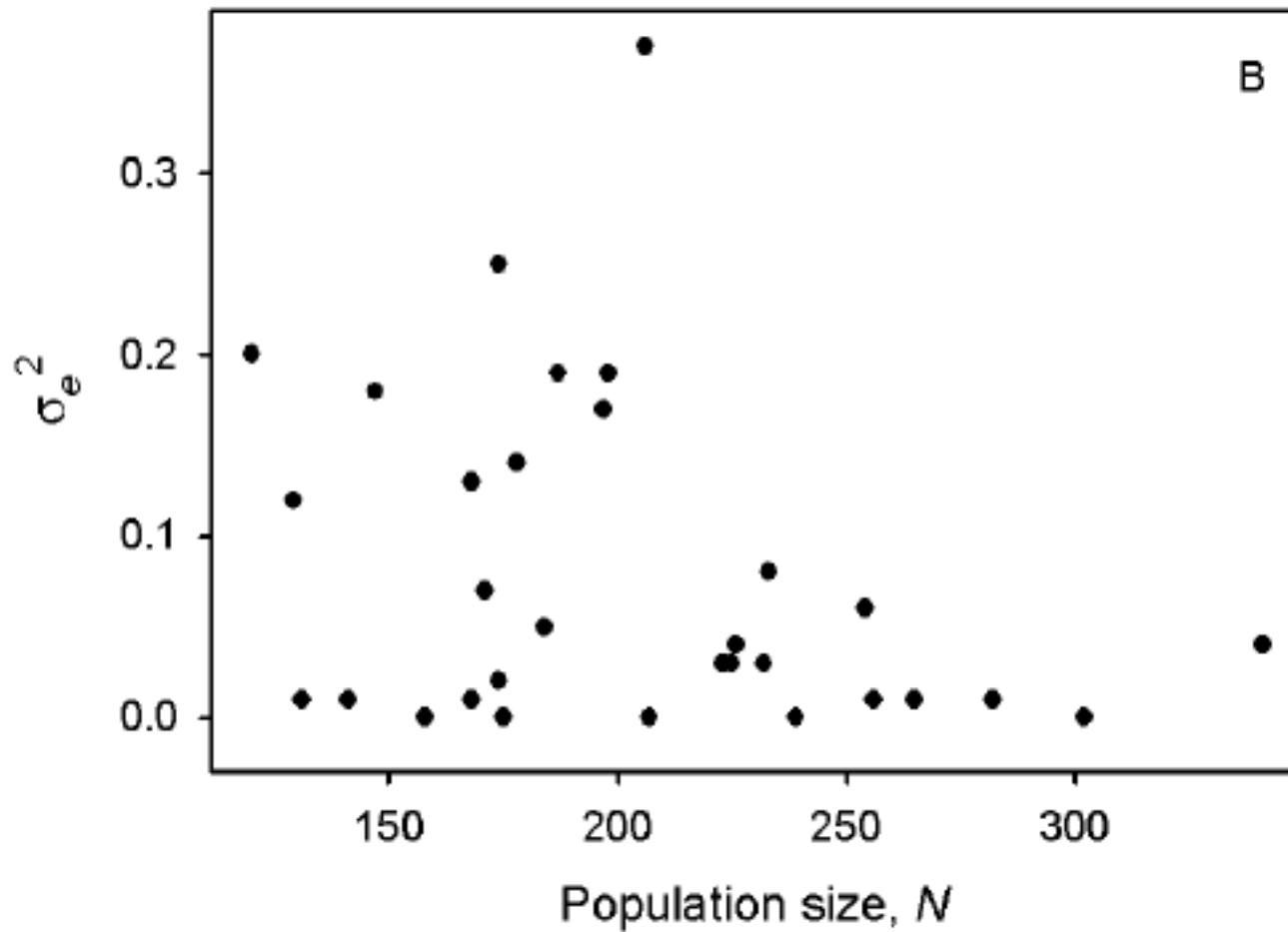


Figure 2.2: Simulations of the multiplicative process with $\sigma^2 = 0.01$ (solid line) and 0.04 (dotted line). The other parameters are $K = 1000$ and $\gamma = r = 0.1$, corresponding to a return time to equilibrium $T_R = 1/\gamma = 10$.



3.2 Mean and variance for discrete processes

- ▶ No density dependence

$$X_t = X_0 + \sum_{i=0}^{t-1} S_i, \quad X_t | X_0 \sim N(X_0 + \mu t, \nu t)$$

- ▶ Density regulation

$$E(S_t | X_t = x) = \mu(x), \quad \text{Var}(S_t | X_t = x) = \nu(x)$$

Fig 3.1

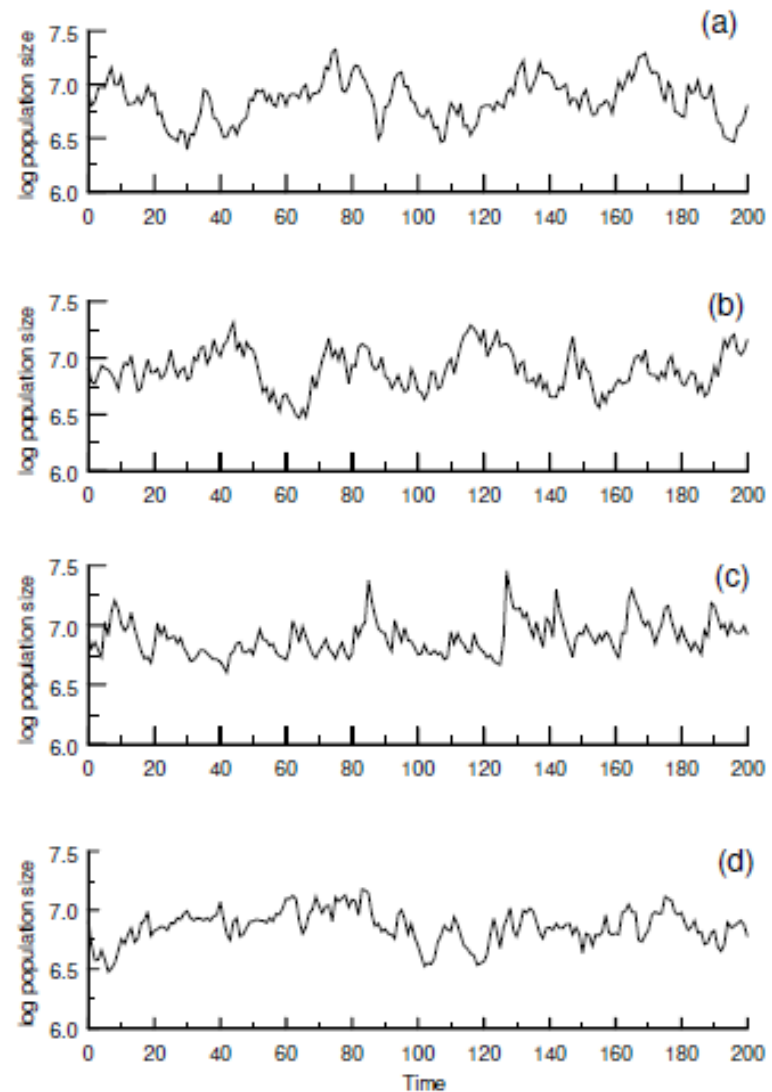


Figure 3.1: Population fluctuations for three models with the same discrete logistic type of dynamics with parameters $r = 0.2$, $K = 1000$, $\sigma_e^2 = 0.01$. The increments are modelled by different distributions: Normal distribution (a), Rectangular distribution (b), Exponential distribution (c) and the diffusion approximation recorded at discrete values with increments 1 (d).

3.3 Diffusion – infinitesimal mean and variance

- ▶ For constant $\mu(x) = \mu$ and $\nu(x) = \nu$ we have for all t :

$$E(X_t - X_0 | X_0) = \mu t$$

$$\text{Var}(X_t - X_0 | X_0) = \nu t$$

- ▶ Diffusion = this hold for $t \rightarrow 0$

$$E(\Delta X_t | X_t = x) = \mu(x) \Delta t$$

$$\text{Var}(\Delta X_t | X_t = x) = \nu(x) \Delta t$$

Diffusion process - definition

- ▶ Infinitesimal mean:

$$\lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} E(\Delta X_t | X_t = x) = \mu(x)$$

- ▶ Infinitesimal variance:

$$\lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} E((\Delta X_t)^2 | X_t = x) = \nu(x)$$

- ▶ and some boundary conditions (e.g. absorbing barrier at extinction).

Diffusion process

Ito approach:

Choose the expectation and variance functions of the discrete process as infinitesimal mean and variance.

Diffusion approximation for N_t ?

$$\mu_N(n) = E(\Delta N | N = n)$$

$$\nu_N(n) = \text{Var}(\Delta N | N = n) \approx E(\Delta N^2 | N = n)$$

These two diffusions not quite equal!

Fig 3.2

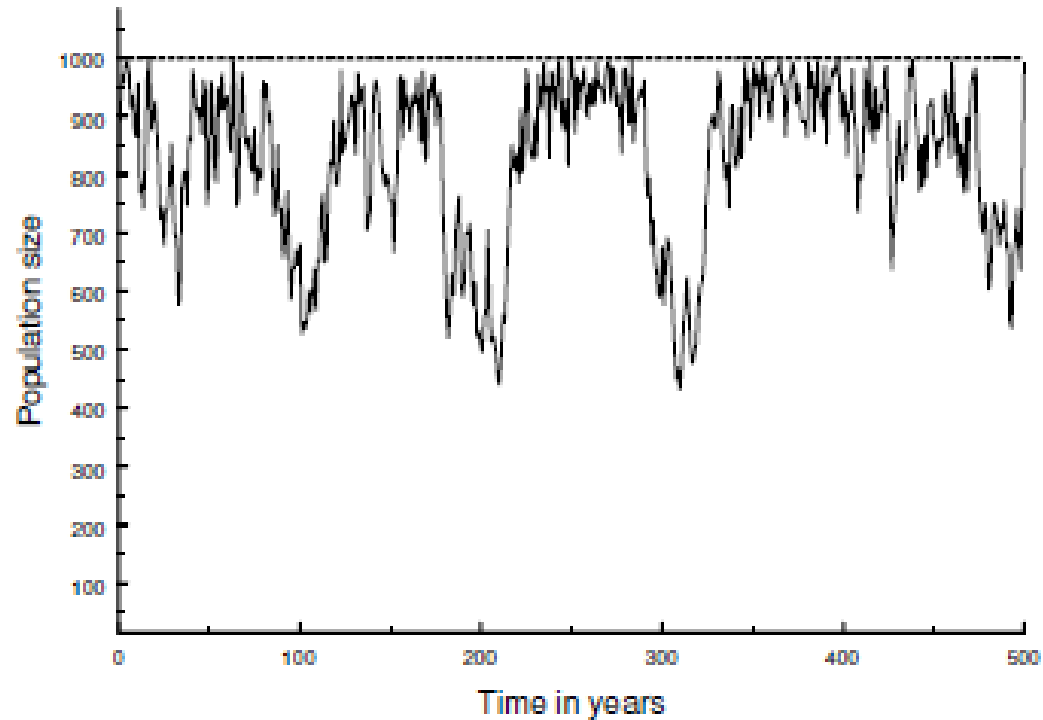


Figure 3.2: Simulation of the ceiling model with reflecting barrier at population size 1000. The parameters are $r_1 = 0.02$, $\sigma_e^2 = 0.01$.

3.5 Transformations

If N_t is a diffusion process, then also $X_t = g(N_t)$ is a diffusion for any function $g(\cdot)$ that is twice differentiable.

Infinitesimal mean for $X_t = g(N_t)$:

$$\mu_X(x) = g'(n)\mu_N(n) + \frac{1}{2}g''(n)v_N(n), \quad n = g^{-1}(x)$$

Infinitesimal variance:

$$v_X(x) = \text{Var}(\Delta X_t | X_t = x) = g'(n)^2 v_N(n)$$

Brownian motion and OU-process

- ▶ Brownian motion: Diffusion process with constant infinitesimal mean and variance.
- ▶ Ornstein-Uhlenbeck:
 - ▶ Infinitesimal mean linear expression
 - ▶ Infinitesimal variance constant (ignore σ_d^2)

Fig 3.3

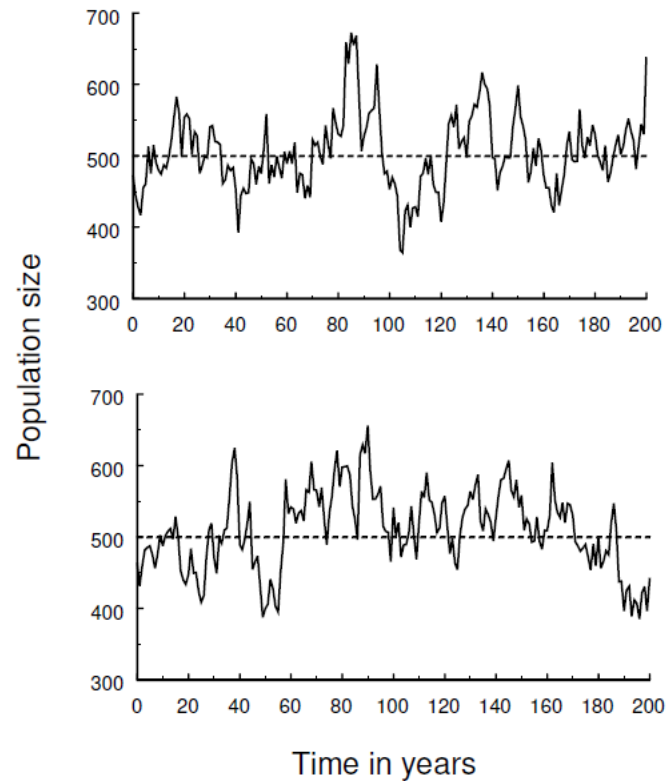


Figure 3.3: Simulation of the theta-logistic model with $r_1 = 0.1$, $K = 500$, $\sigma_e^2 = 0.005$ and $\theta = 2$ (upper panel) and the same process approximated by an Ornstein-Uhlenbeck process (lower panel).

3.8.1 The Green function $G(x, x_0)$ for a diffusion process

The expected time the process is in $(x, x + \Delta x)$ before reaching an absorbing barrier is $G(x, x_0)\Delta x$ when $\Delta x \rightarrow 0$.

Expected time in $[c, d]$: $\int_c^d G(x, x_0) dx$

Mathematical expressions for $G(x, x_0)$

$$s(x) = \exp\left[-2\int^x \frac{\mu(z)}{\nu(z)} dz\right] \quad \text{and} \quad S(x) = \int^x s(z) dz$$

Help function (to simplify notation): $m(x) = \frac{1}{\nu(x)s(x)}$,

$$G(x, x_0) = \begin{cases} 2 \frac{[S(x) - S(a)][S(b) - S(x_0)]}{S(b) - S(a)} m(x) & a \leq x \leq x_0 \leq b \\ 2 \frac{[S(b) - S(x)][S(x_0) - S(a)]}{S(b) - S(a)} m(x) & a \leq x_0 \leq x \leq b \end{cases}$$

