Stochastic logistic model with environmental noise

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Questions

I. What plausible biological mechanisms, if any, lead to logistic growth?

Derivations of & mechanisms behind logistic

II. How can the logistic be made more useful?

Accounting for stochastic forces \Leftrightarrow Fitting to data and evaluating

$$\frac{dN}{dt} = rN - \left(\frac{r}{N}\right)N^2 = aN - bN^2$$

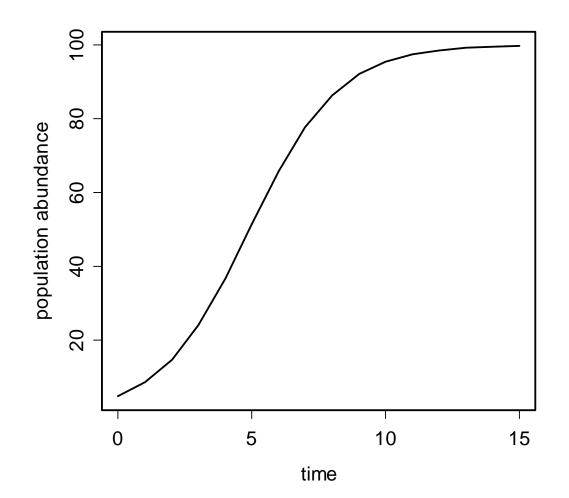
N: population abundance at time t

r: maximum per-unit-abundance growth rate

 \overline{N} : equilibrium abundance

transformation: $Y = \frac{1}{N}$ yields linear DE for Y

solution trajectory:
$$N = \frac{\overline{N}}{1 + \left(\frac{\overline{N} - N_0}{N_0}\right)e^{-rt}}$$



I. Derivations/mechanisms

- A. Verhulst (1838) "logistique" added $-bN^2$ and $-bN^{\alpha}$ to the exponential growth DE as an adjustment
- B. Lotka (1925)

$$\frac{dN}{dt} = m(N) \approx aN + bN^2$$

Handwaves about the sign of b

Taylor series expands around a particular point— what point does he have in mind?

Lotka's derivation is parroted in many ecology textbooks and websites (Hutchinson 1978)

C. Chapman (1928)

$$\frac{dN}{dt} = rN \times (\text{"environmental resistance"}) = rN(1 - \frac{N}{K})$$

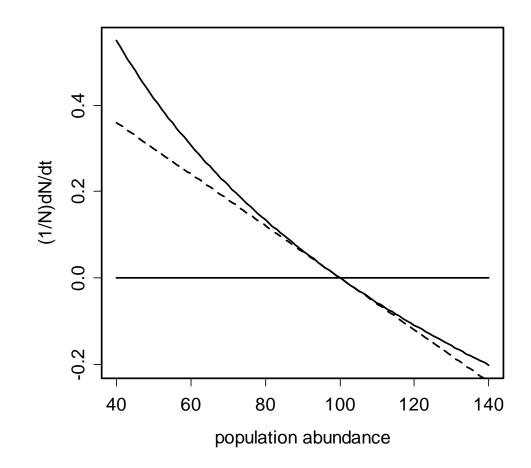
- D. Dennis and Patil (1984), Dennis (1989a) Re-formulation of Lotka
 - $\frac{dN}{dt} = Ng(N)$ g(N) is per-unit-abundance growth rate, presumed decreasing

$$g(\overline{N}) = 0, \quad g'(\overline{N}) < 0$$

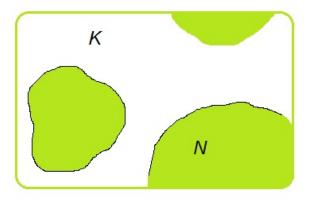
Near \overline{N} ,

$$g(N) \approx g(\overline{N}) + (N - \overline{N})g'(\overline{N}) = a - bN$$

 $a = -\overline{N}g'(\overline{N}) \qquad b = -g'(\overline{N})$



E. Substrate-product model: "something replacing something else"



Invasions: cheat grass replacing native grassland. Epidemics: infecteds replacing susceptibles. Commerce: Wal-Mart replacing K-Mart. Innovation: DVDs replacing VHSs. Dissemination of ideas:

Like an autocatalytic chemical reaction (Pearl and Reed 1920, Reed and Berkson 1929):

$$\frac{dN}{dt} = k_1 N (K - N)$$

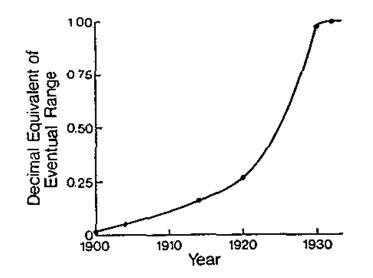
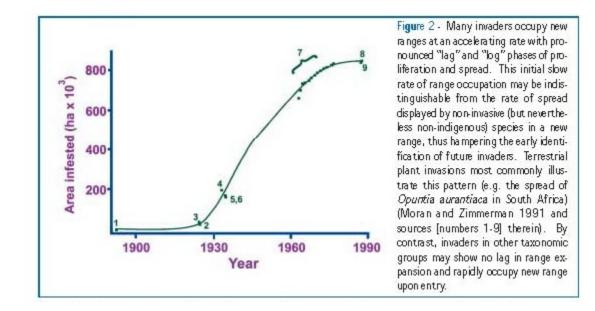
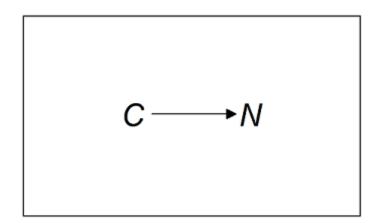


Fig. 2. Progress of *B. tectorum* as a plot of area occupied versus time based on accumulative percentage of eventual range occupied by 1900, 1904, 1914, 1920 and 1930.



- F. (Williams 1972) Explicit limiting nutrient (or substrate)
 - 1. Closed system



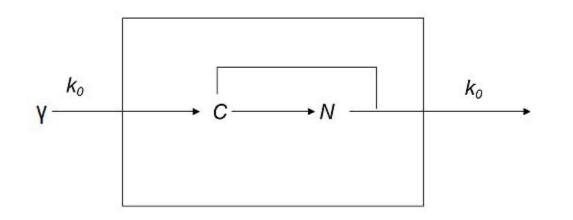
 $\frac{dC}{dt} = -\alpha k_1 C N \qquad \alpha: \text{ conversion (in)efficiency}$

 $\frac{dN}{dt} = k_1 C N$

mass balance: $C + \alpha N = C_0 + \alpha N_0$

$$\Rightarrow C = C_0 + \alpha N_0 - \alpha N$$
$$\frac{dN}{dt} = rN - \frac{r}{N}N^2 \qquad r = k_1(C_0 + \alpha N_0), \qquad \overline{N} = \frac{1}{\alpha}(C_0 + \alpha N_0)$$

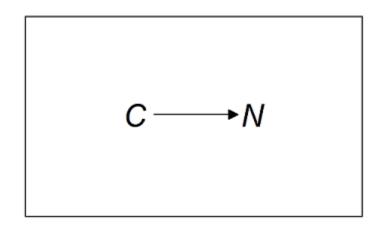
2. Open system (like a laboratory microbial chemostat)



$$\frac{dC}{dt} = k_0 \gamma - \alpha k_1 C N - k_0 C \qquad \gamma: \text{ nutrient concentration in inflow} \\ k_0: \text{ dilution rate} \\ \frac{dN}{dt} = k_1 C N - k_0 N$$

mass balance: $C + \alpha N = \gamma + (C_0 + \alpha N_0 - \gamma)e^{-k_0 t}$

 $\Rightarrow \frac{dN}{dt}$ is a logistic with time-dependent coefficients (Dennis 1978), is exactly logistic if $\gamma = C_0 + \alpha N_0$, and becomes logistic as $t \rightarrow \infty$ 3. Closed system, Michaelis-Menton nutrient uptake

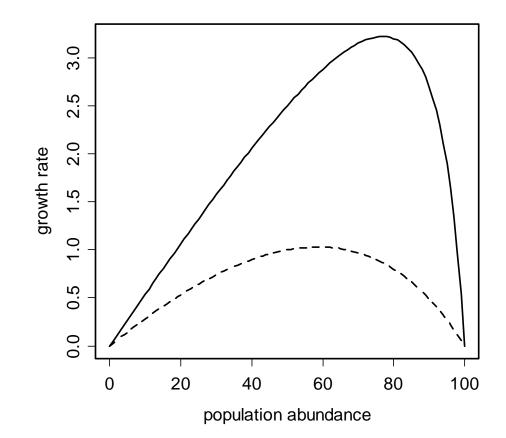


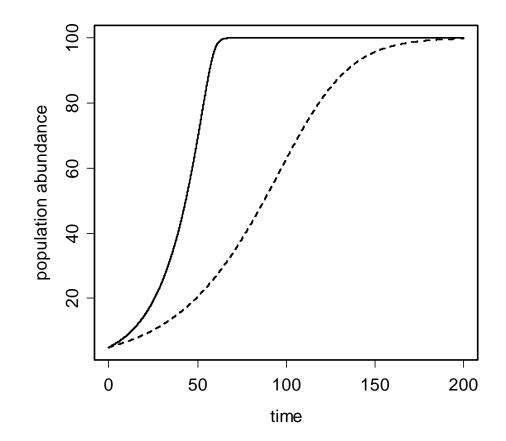
 $C + V \Rightarrow C \sim V \rightarrow V + N$ V: uptake bottleneck (gut volume, cell membrane sites, filter surface, etc.)

⇒ rate of product formation per unit abundance $\approx \frac{FC}{K+C}$ (analogous to Michaelis-Menten enzyme kinetics)

$$\frac{dC}{dt} = -\alpha \frac{FCN}{K+C}$$

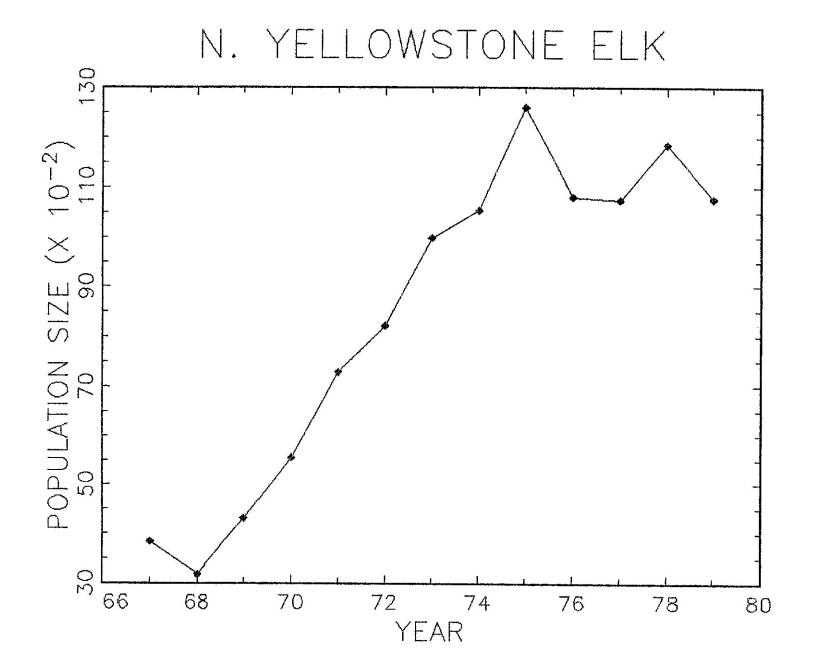
 $\frac{dN}{dt} = \frac{FCN}{K+C}$

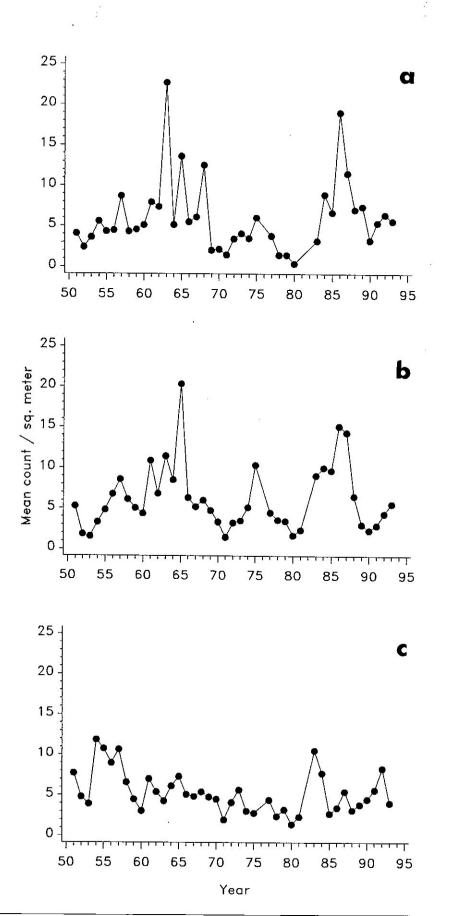




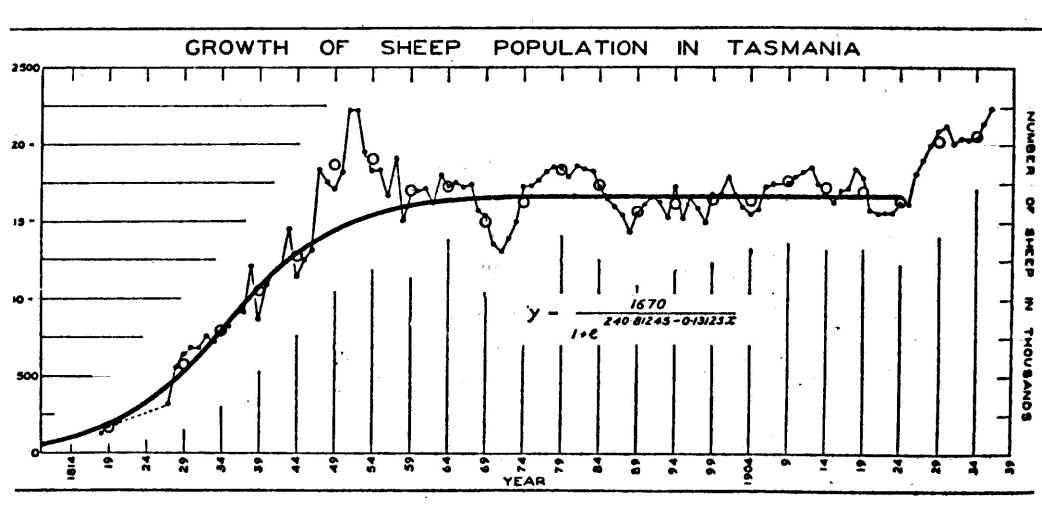
II. Stochastic forces and data analysis

- A. Problems with using the logistic as is.
 - 1. Life is stochastic (data depart from model in noisy ways)
 - 2. How to do inferences (estimation, evaluation)
 - 3. Modeling objectives might require more realistic modeling





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B. Off-the-shelf solution: least squares (Leach 1981)

Data: time series population abundances

Model parameters: r, \overline{N} , σ^2

Minimize departures of observations from logistic trajectory:

$$SS(r, ar{N}, \sigma^2) = \sum_{i=1}^q \left(n_i - rac{ar{N}}{1 + \left(rac{ar{N} - n_0}{n_0}
ight)e^{-rt_i}}
ight)^2$$

This procedure implicitly assumes a stochastic logistic model in which the underlying growth is deterministic and the departures from the trajectory are due to observation or measurement error.

Ecological populations themselves are stochastic (process noise).

C. Models of process noise

Seek: a useful, general stochastic version of

dN = m(N)dt

Answer: a diffusion process is in the form

 $dN_t = m(N_t)dt + \sqrt{v(N_t)} \, dW_t,$

where:

 N_t is population abundance at time t, $dW_t \sim \text{normal}(0, dt)$ m(n) is the infinitesimal mean ("skeleton") v(n) is the infinitesimal variance D. Stochastic logistic with "environmental noise":

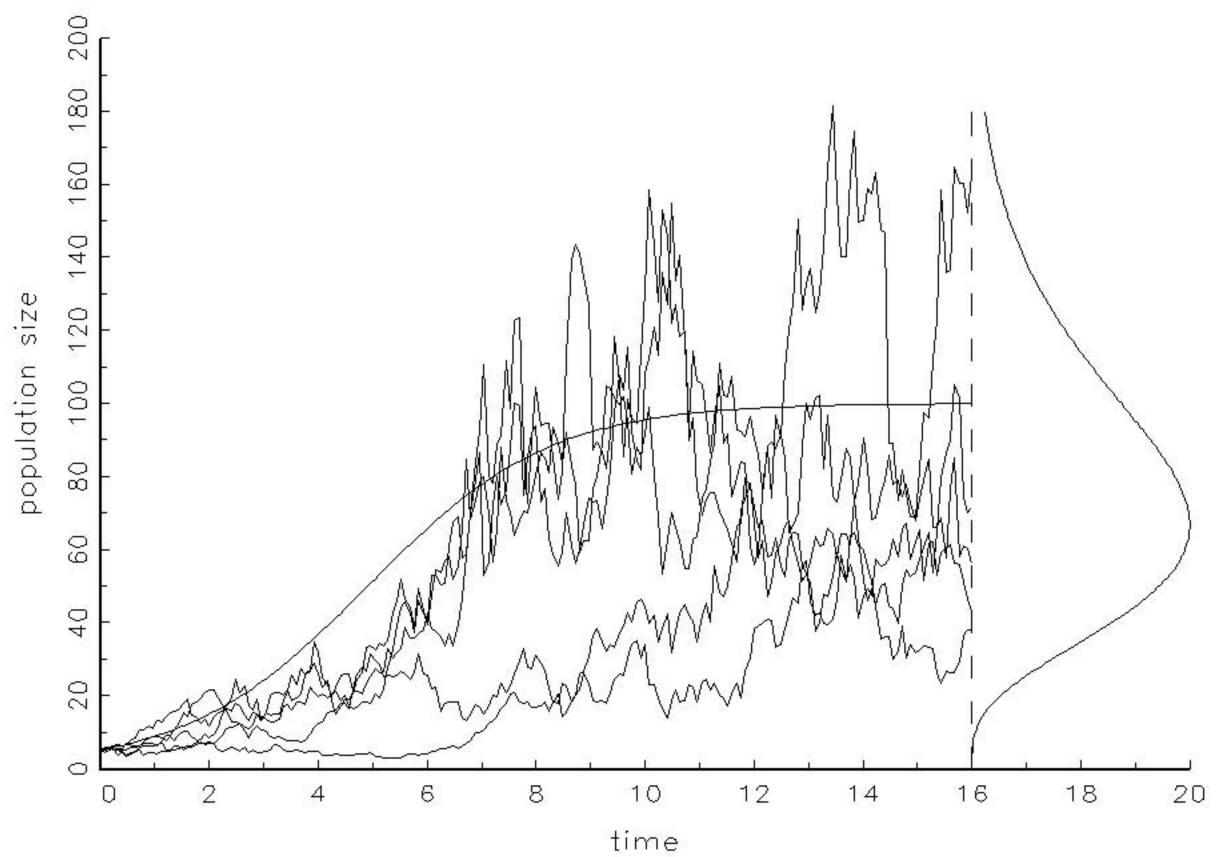
$$m(n) = rn + \left(\frac{r}{k}\right)n^2$$

$$v(n)\,=\,\sigma^2 n^2$$

(I'll use "k" instead of \overline{N} from here on... "equilibrium" of the stochastic model will be seen to be a probability distribution)

this form of $v(n) \Rightarrow \ln(N_t)$ has a constant infinitesimal variance

 \Rightarrow substantial fluctuations at all population sizes, not just at low population sizes



Transition probability density function: $p(n, t | n_0)$

$$\begin{aligned} \Pr[a < N_t \le b] &= \int_a^b p(n, t \mid n_0) dn \\ &\int_0^\infty p(n, t \mid n_0) dn \ = \ \mathbf{1} \\ &\frac{\partial p}{\partial t} \ = \ \mathbf{\frac{1}{2}} \frac{\partial^2 [vp]}{\partial n^2} \ - \ \frac{\partial [mp]}{\partial n} \end{aligned}$$

(Fokker-Planck equation)

The FP for the stochastic logistic has been solved!

$$p(n,t \mid n_0) = p(n) \sum_{\lambda \in A} \phi_{\lambda}(n) \phi_{\lambda}(n_0) e^{-\lambda t}$$

 ϕ_{λ} is related to a confluent hypergeometric function

Stationary pdf of a diffusion process:

$$p(n, t \mid n_0) \xrightarrow[as t \to \infty]{as t \to \infty} p(n)$$

 $p(n) = \frac{C}{v(n)} e^{2\int \frac{m(n)}{v(n)} dn}$

stationary pdf exists if

$$\int_0^\infty p(n) dn = 1$$

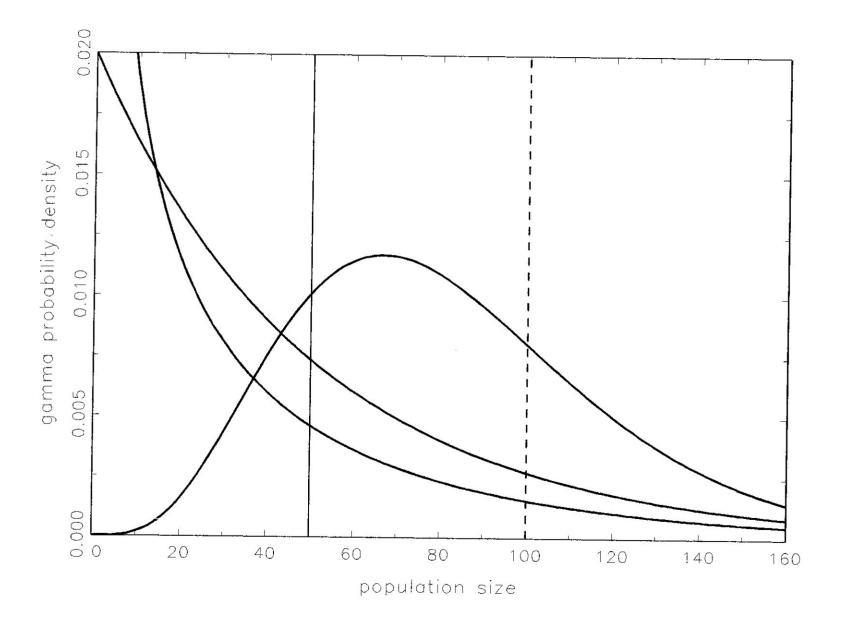
Stationary pdf for stochastic logistic:

$$p(n) = rac{eta^lpha}{\Gamma(lpha)} n^{lpha-1} e^{-eta n}$$

(gamma distribution)

$$lpha = rac{2r}{\sigma^2} - 1$$
, $eta = rac{2r}{k\sigma^2}$

stationary pdf exists if $\alpha > 0$



Moments of N_t :

$$u_{\nu}(n_0, t) = \mathsf{E}[(N_t)^{\nu} | N_0 = n_0]$$
$$\frac{\partial u_{\nu}}{\partial t} = \frac{v(n_0)}{2} \frac{\partial^2 u_{\nu}}{\partial n_0^2} + m(n_0) \frac{\partial u_{\nu}}{\partial n_0}$$

(backward equation)

$$u_{\nu}(n_0, \mathbf{0}) = n_0^{\nu}$$

Approximation for the transition pdf (Dennis 1989b)

- 1. Find approximations for $u_1(n_0, t)$ and $u_2(n_0, t)$
- 2. Use a gamma pdf with those moments

1. Singular perturbation (small noise expansion) of backward equation: write

$$u_{\nu}(n_0,t) = w_0(n_0,t) + \sigma w_1(n_0,t) + \sigma^2 w_2(n_0,t) + \cdots$$

substitute into the PDE, equate coefficients of like powers of σ , solve resulting PDEs for $w_0, w_1, ...,$ subject to initial condition (laborious)

Wieszak (1988) proved that this perturbation is asymptotically correct

$$u_{1}(n_{0},t) \approx k / \left[1 + \left(\frac{k - n_{0}}{n_{0}} \right) e^{-rt} \right] \\ + \frac{k\sigma^{2}}{2r} \left\{ \left[1 - \frac{2k}{n_{0}} \right] e^{-2rt} + \frac{2k}{n_{0}} e^{-rt} - 1 - 2r \left[\frac{k - n_{0}}{n_{0}} \right] t e^{-rt} \right\} \\ \times \left[1 + \left(\frac{k - n_{0}}{n_{0}} \right) e^{-rt} \right]^{-3}$$

$$\begin{aligned} u_2(n_0,t) &\approx \frac{k^2}{\left[1 + \left(\frac{k-n_0}{n_0}\right)e^{-rt}\right]^2} \\ &+ \left(\frac{\sigma^2}{2}\right)\left(\frac{k}{r}\right)^2 2r\left\{\left[-\frac{4k}{n_0} + \frac{5}{2}\right]e^{-2rt} + \left[\frac{4k}{n_0} - 2\right]e^{-rt} - \frac{1}{2} \\ &+ r\left(\frac{k-n_0}{n_0}\right)te^{-rt}\left[\left(\frac{k-n_0}{n_0}\right)e^{-rt} - 2\right]\right\}\left[1 + \left(\frac{k-n_0}{n_0}\right)e^{-rt}\right]^{-4} \end{aligned}$$

2. Use a gamma distribution w/ matching moments as transition pdf: $p(n, t \mid n_0) \approx \frac{\beta_t}{\Gamma(\alpha_t)} n^{\alpha_t - 1} e^{-\beta_t n}$

$$\alpha_t \equiv \alpha(n_0, t) = \frac{u_1^2}{u_2 - u_1^2}$$
$$\beta_t \equiv \beta(n_0, t) = \frac{u_1}{u_2 - u_1^2}$$

E. Simulations: does the approximation work?

 $dN_t = \left[rN_t + \left(\frac{r}{k}\right)N_t^2 \right] dt + \sigma N_t dW_t$

1000 realizations ending at each time t ($t = 1, 2, 3, \dots$ until stationarity)

Density probability plot:

excellent graphical tool for assessing goodness of fit for a continuous distribution (related to the probability plot)

Y, r.v. with continuous distribution

F(y), f(y): cdf & pdf models to be assessed

 $y_{(1)}$, $y_{(2)}$, ..., $y_{(q)}$ data (ordered)

usual "probability plot":

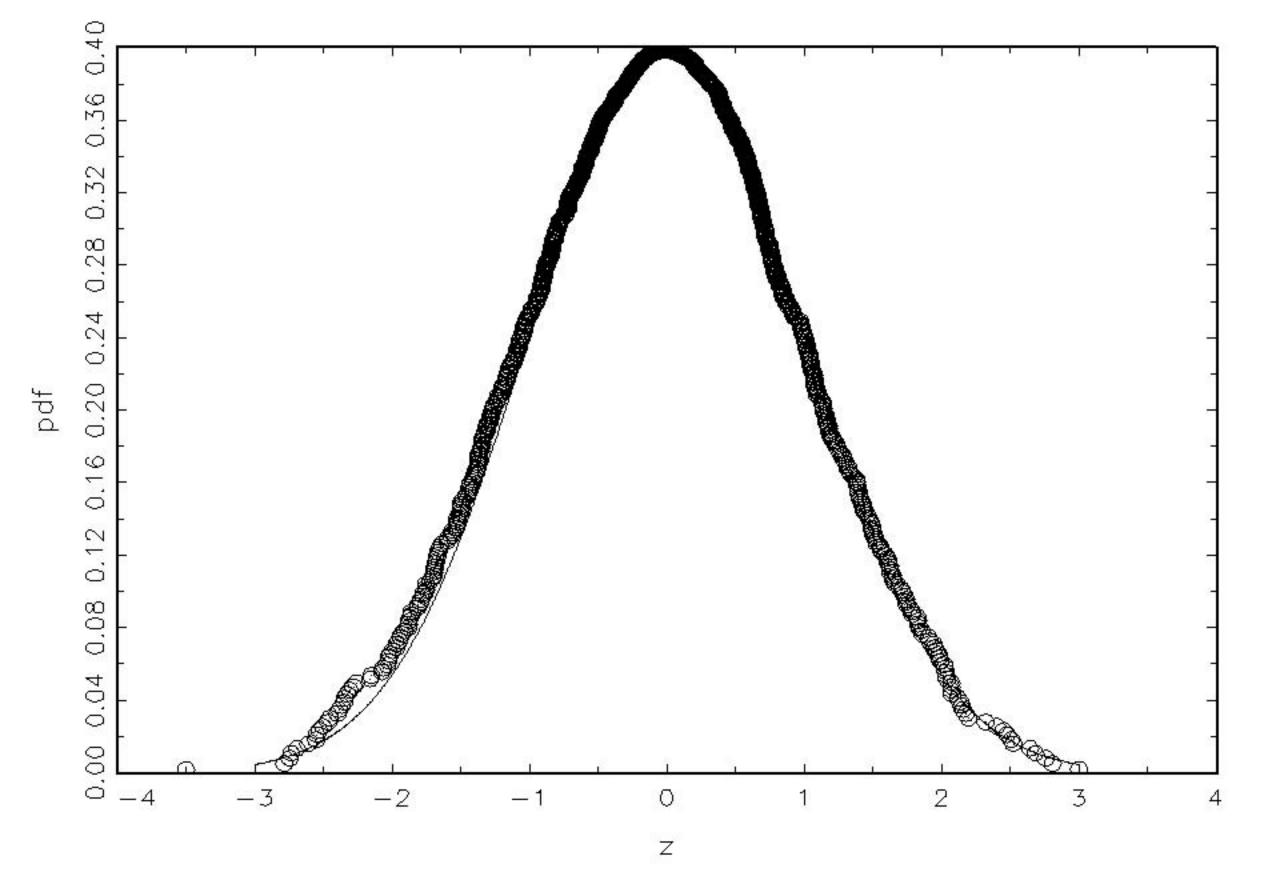
plot
$$F^{-1} \Big(rac{i - rac{1}{2}}{q} \Big)$$
 vs. $y_{(i)}$

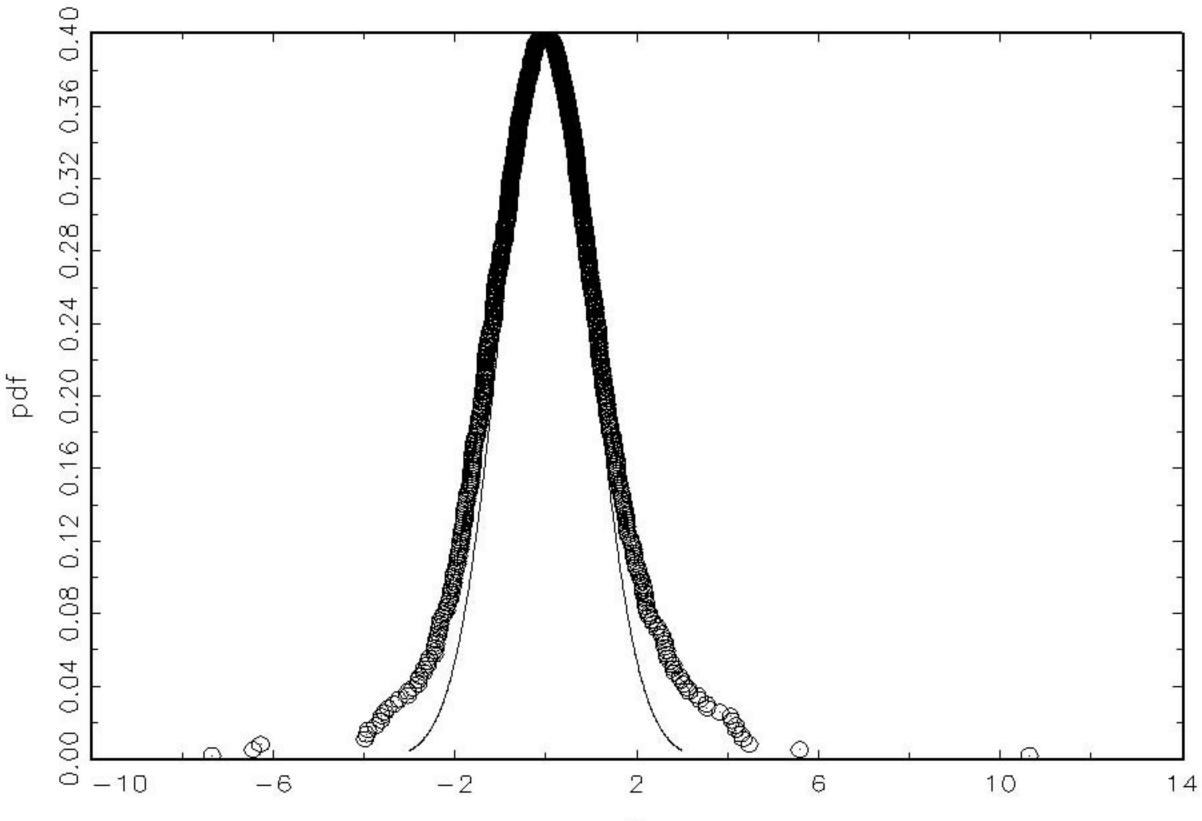
straight line indicates good fit, but the interpretations of departures from fit are not transparent

density probability plot (Jones and Daly 1995, Jones 2004):

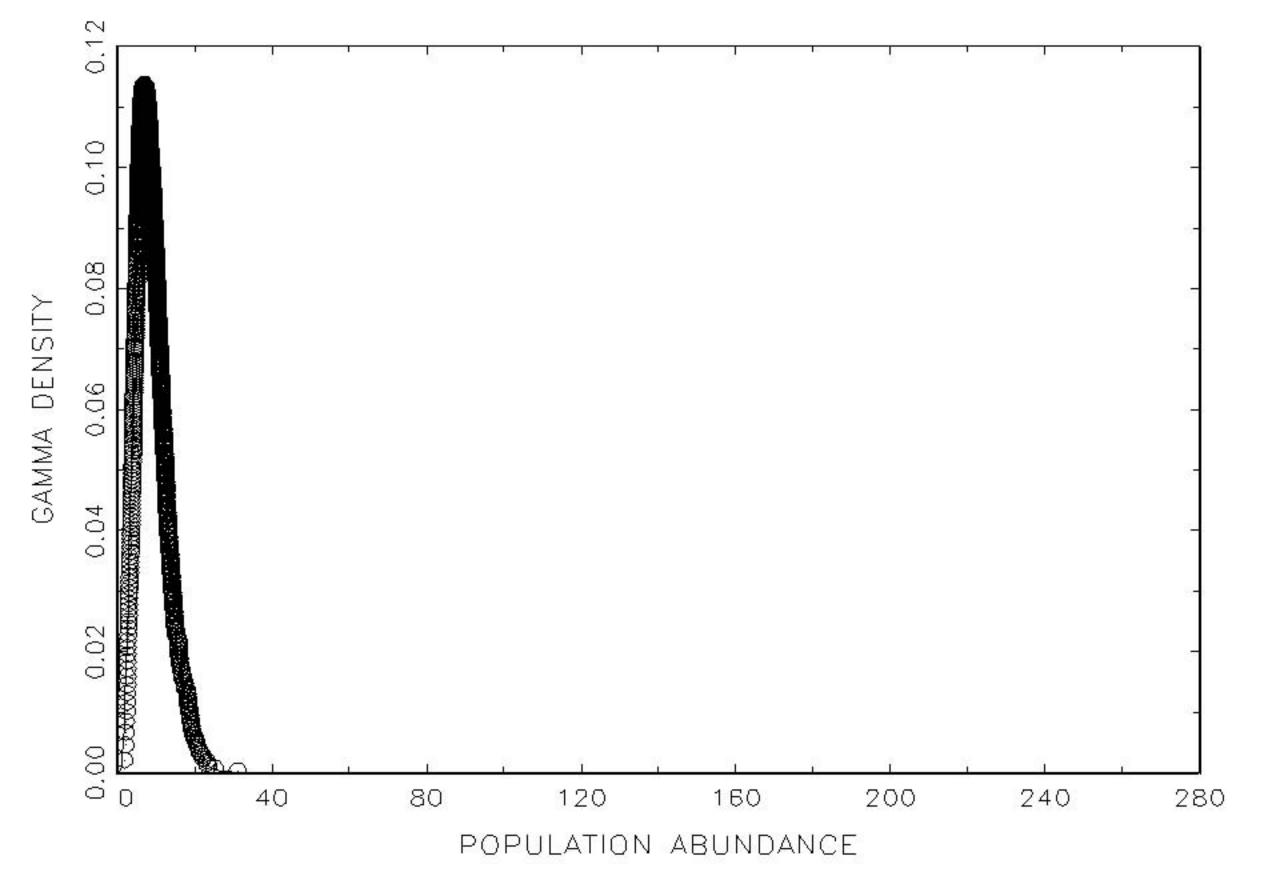
plot
$$f\!\left(F^{-1}\!\left(rac{i-rac{1}{2}}{q}
ight)
ight)$$
 vs. $y_{(i)}$

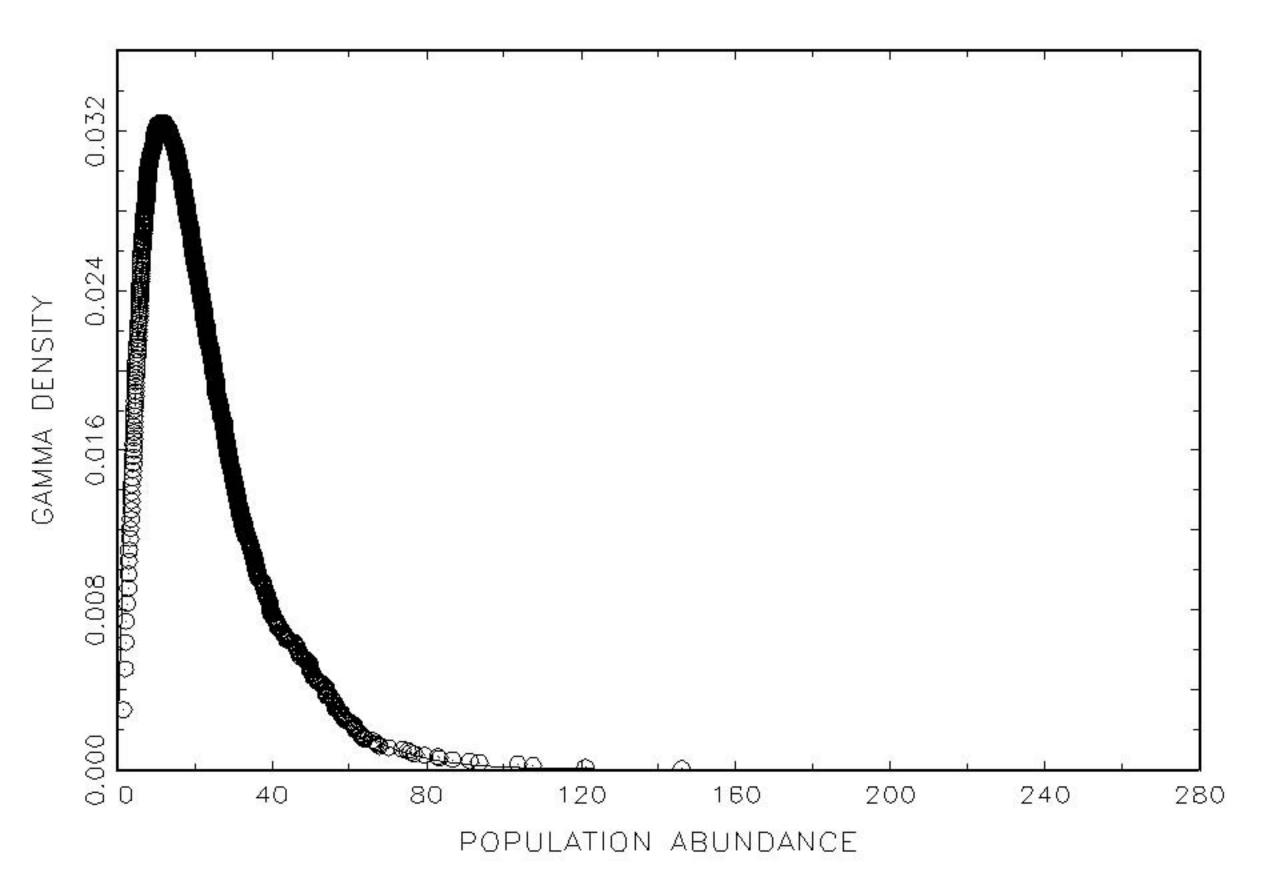
superimposed with plot of $f(\boldsymbol{y})$

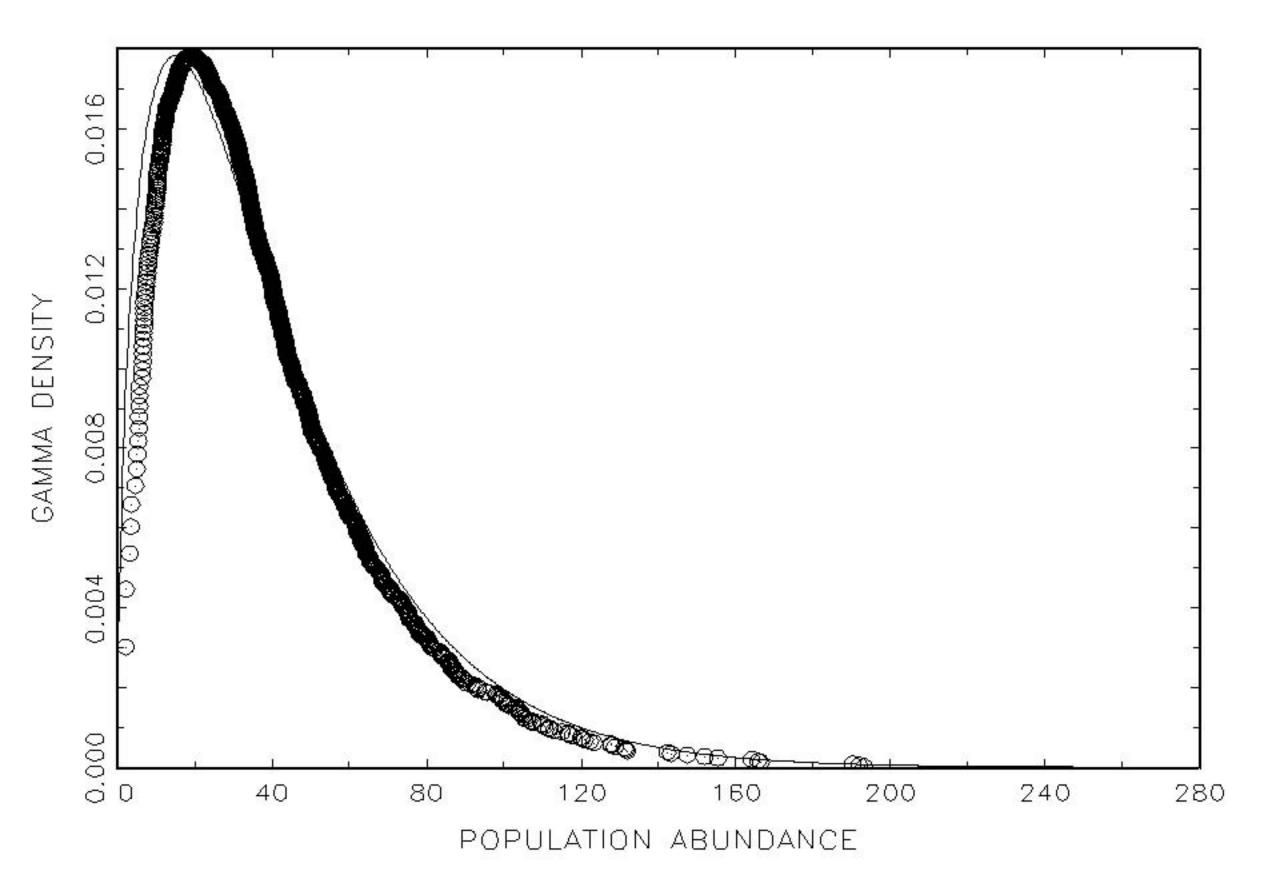


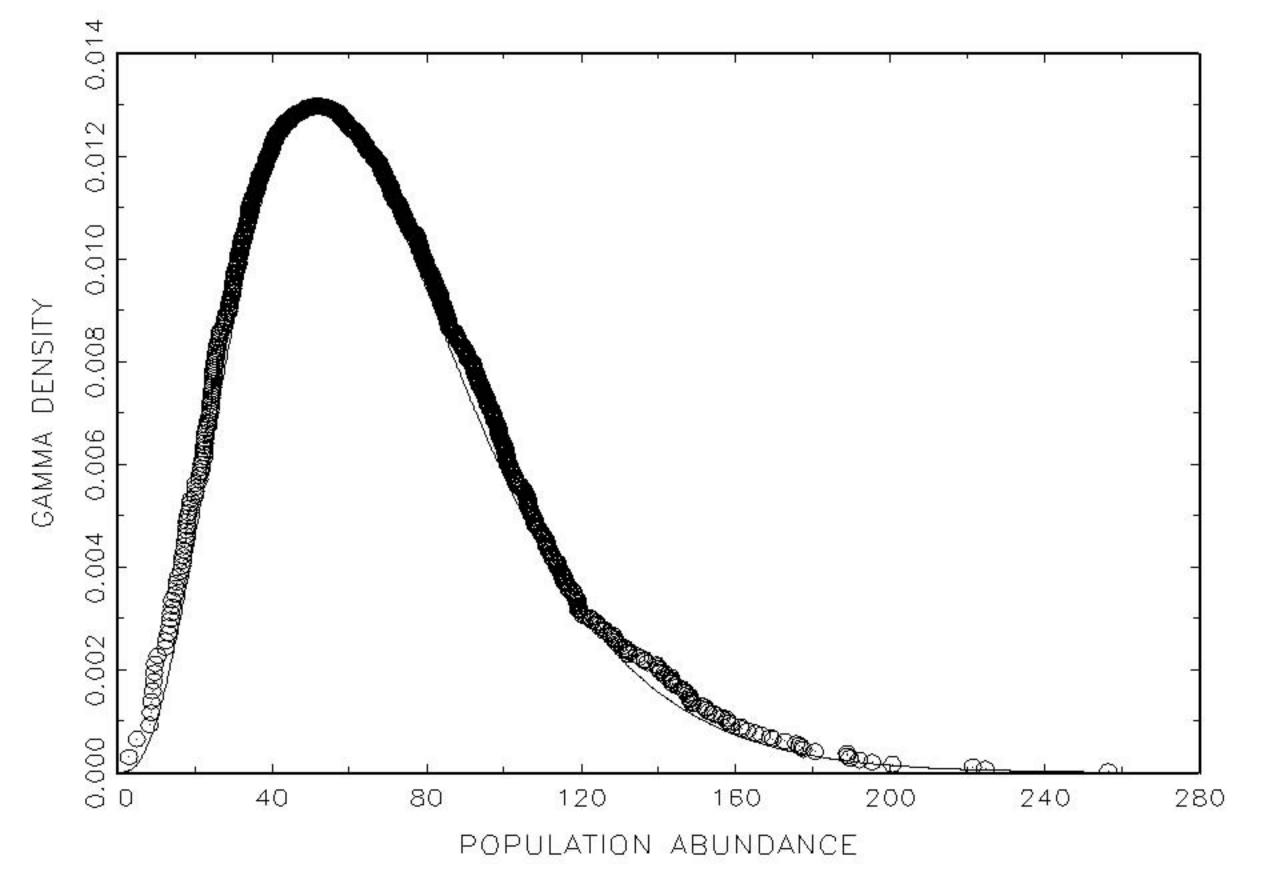


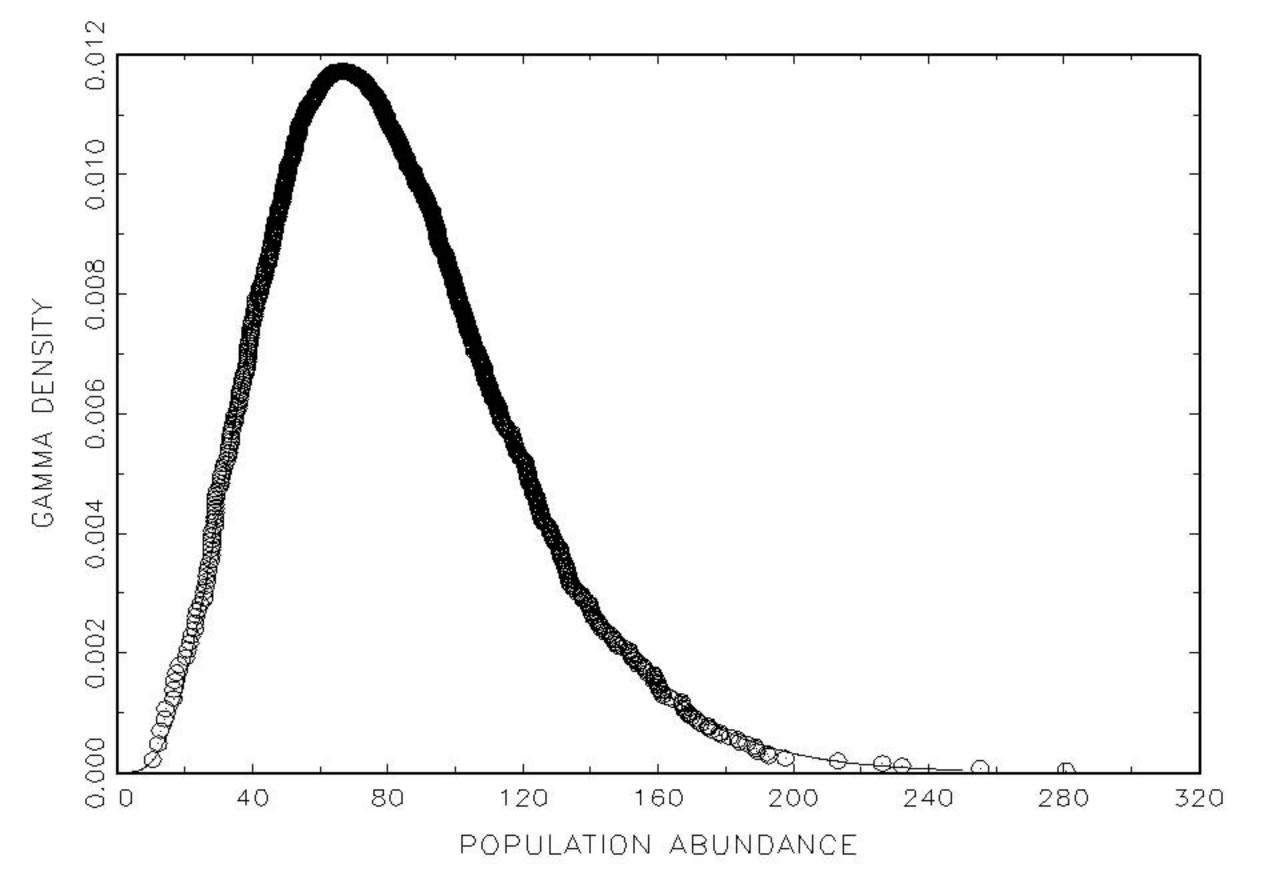
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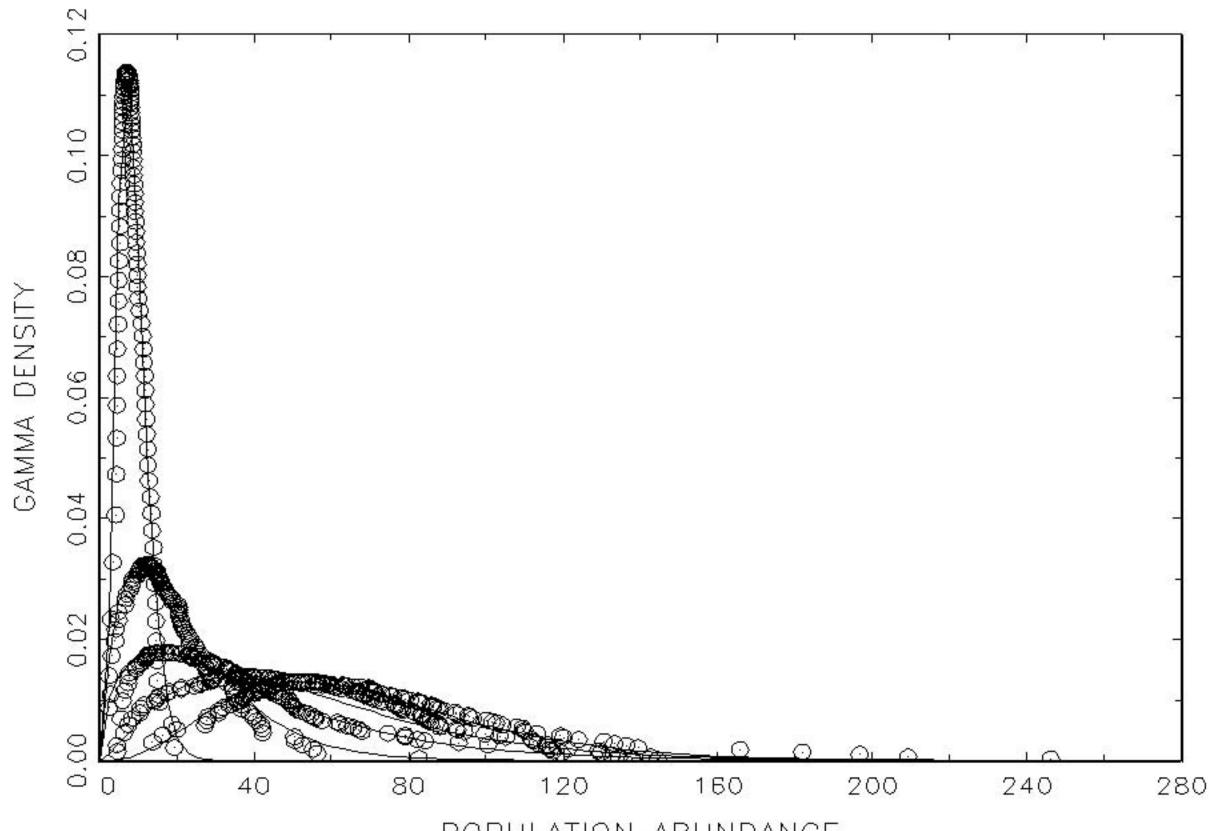












POPULATION ABUNDANCE

Uses of the stochastic logistic: data analysis!

r, k, σ^2 unknown parameters

 $egin{array}{ccccccccc} 0 & t_1 & t_2 & \cdots & t_q \ n_0 & n_1 & n_2 & \cdots & n_q \ time \ {
m series} \ {
m data} \ ({
m pop. \ abundances}) \end{array}$

 $\tau_1 = t_1 - 0, \, \tau_2 = t_2 - t_1, \, ..., \, \tau_q = t_q - t_{q-1}$ intervals

Likelihood function:

$$L(r, k, \sigma^2) = p(n_1, \tau_1 | n_0) p(n_2, \tau_2 | n_1) \cdots p(n_q, \tau_q | n_{q-1})$$

 $\hat{r}, \hat{k}, \hat{\sigma}^2$ maximum likelihood estimates (values of r, k, σ^2 that jointly maximize $L(r, k, \sigma^2)$)

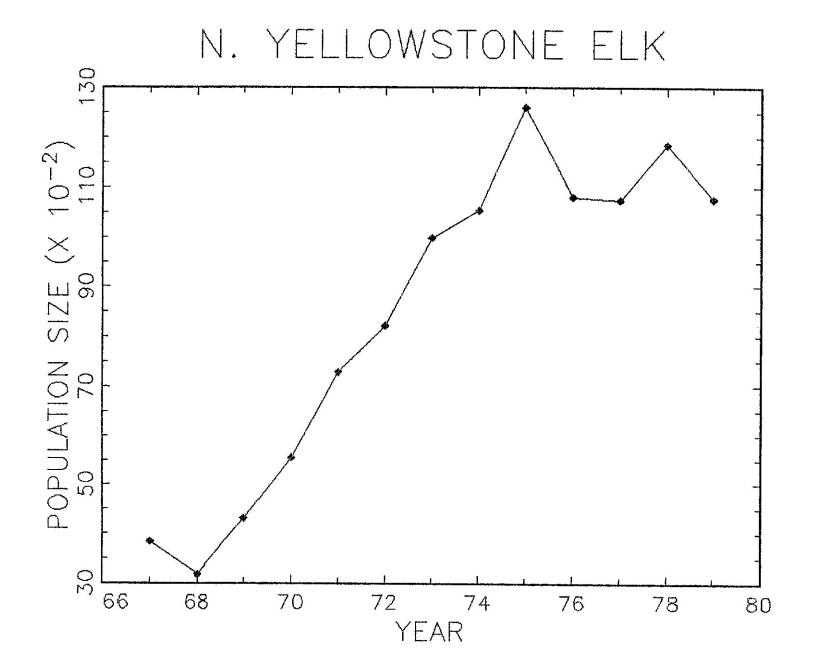
requires numerical maximization: optim() function in R, etc.

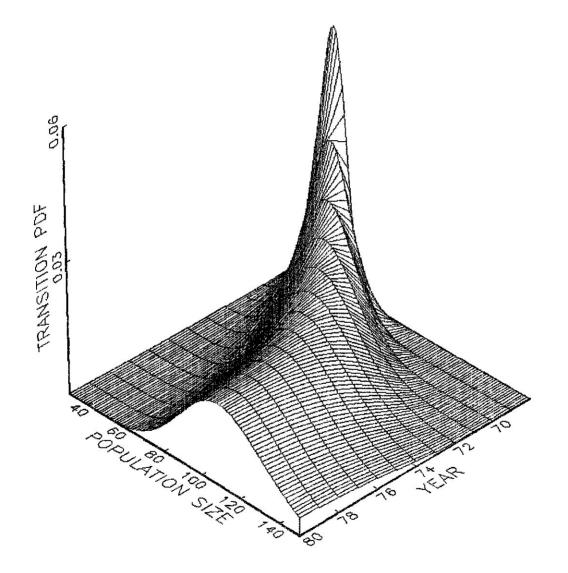
Residuals:

$$z_i = rac{\left(rac{\widehat{eta}_i n_i}{\widehat{lpha}_i}
ight)^{1/3} - \left(1 - rac{1}{9\widehat{lpha}_i}
ight)}{\sqrt{9\widehat{lpha}_i}}$$

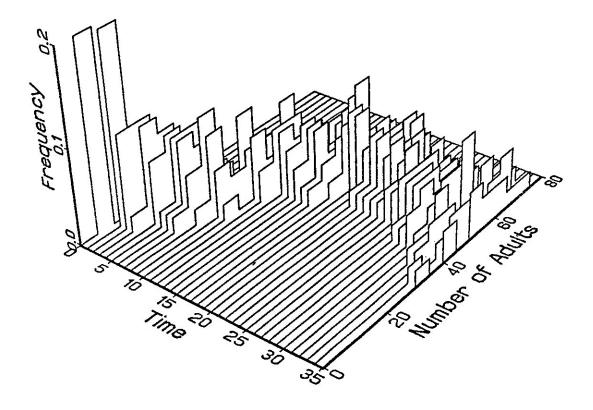
are approximately normal(0, 1) distributed, where

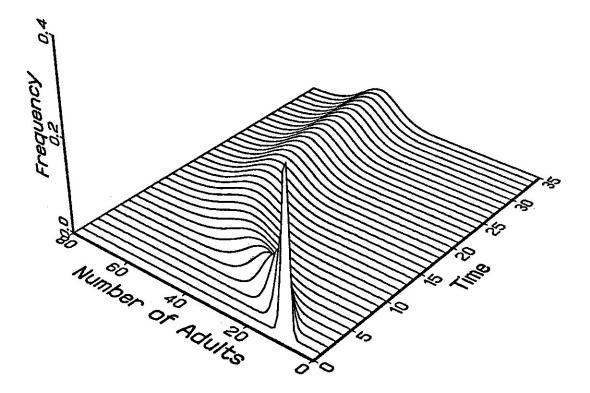
$$egin{aligned} \widehat{lpha}_i &= lpha_{ au_i} \Big(n_{i-1}, \widehat{r}, \widehat{k}, \widehat{\sigma}^2 \Big) \ \widehat{eta}_i &= eta_{ au_i} \Big(n_{i-1}, \widehat{r}, \widehat{k}, \widehat{\sigma}^2 \Big) \end{aligned}$$



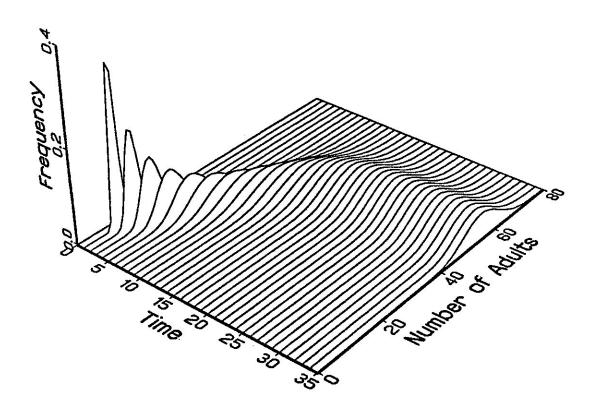


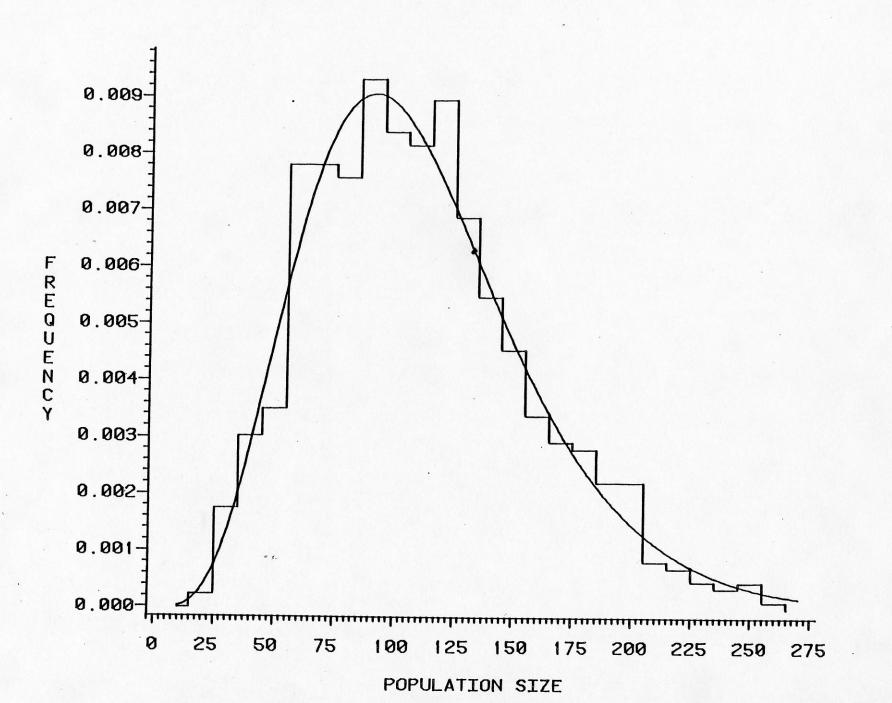






(b)







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References: Chapman 1928 Ecology, Dennis 1978 Mathematical Biosciences, Dennis 1989a Natural Resource Modeling, Dennis 1989b in MacDonald et al. eds. Estimation and analysis of insect populations, Dennis and Patil 1984 Mathematical Biosciences, Hutchinson 1978 An introduction to population ecology, Jones 2004 The American Statistician, Jones and Daly 1995 Communications in Statistics—Simulation and Computation, Leach 1981 JRSS A, Lotka 1925 Elements of physical biology, Pearl and Reed 1920 PNAS, Reed and Berkson 1929 J Physical Chemistry, Verhulst 1838 Correspondance Mathématique et Physique, Wieszak 1988 UI PhD Thesis, Williams 1972 in Deevey, ed. Growth by intussusception: ecological essays in honor of G. E. Hutchinson.