



Mathematical and Statistical Modeling in Biology

**Competitive Exclusion, Coexistence,
Estimation, and Control**

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Principle of Competitive Exclusion

- When two or more species compete for the same basic resources, the “strongest” survives; the weaker species is driven to extinction.

- Biologist G. F. Gause (1932, 1934) illustrates various competitive outcomes when the competing species are yeasts, e.g., *Saccharomyces cerevisiae* and *Schizosaccharomyces kephir*.

Equilibrium Analysis

Recall for a differential equation of the form

$$x' = f(x), \text{ solutions } \bar{x} \text{ that satisfy } f(\bar{x}) = 0$$

are called equilibrium points or steady state solutions.

$$f'(\bar{x}) < 0 \quad \text{implies } \bar{x} \text{ is locally stable.}$$

$$f'(\bar{x}) > 0 \quad \text{implies } \bar{x} \text{ is unstable.}$$

Equilibrium Analysis of a System

Given a system $x' = f(x, y)$ and $y' = g(x, y)$

and an equilibrium (\bar{x}, \bar{y}) , the Jacobian

$$J(\bar{x}, \bar{y}) = \begin{bmatrix} f_x(\bar{x}, \bar{y}) & f_y(\bar{x}, \bar{y}) \\ g_x(\bar{x}, \bar{y}) & g_y(\bar{x}, \bar{y}) \end{bmatrix} \text{ is used to determine stability.}$$

If the eigenvalues satisfy $\text{Re } \lambda_1, \text{Re } \lambda_2 < 0$

Or alternatively, if $\text{Det}(J) > 0$ and

$\text{Tr}(J) < 0$, then (\bar{x}, \bar{y})

Then the equilibrium point is locally stable.

Review

- Recall the classical logistic model,

$$x' = rx \left(1 - \frac{x}{K} \right)$$

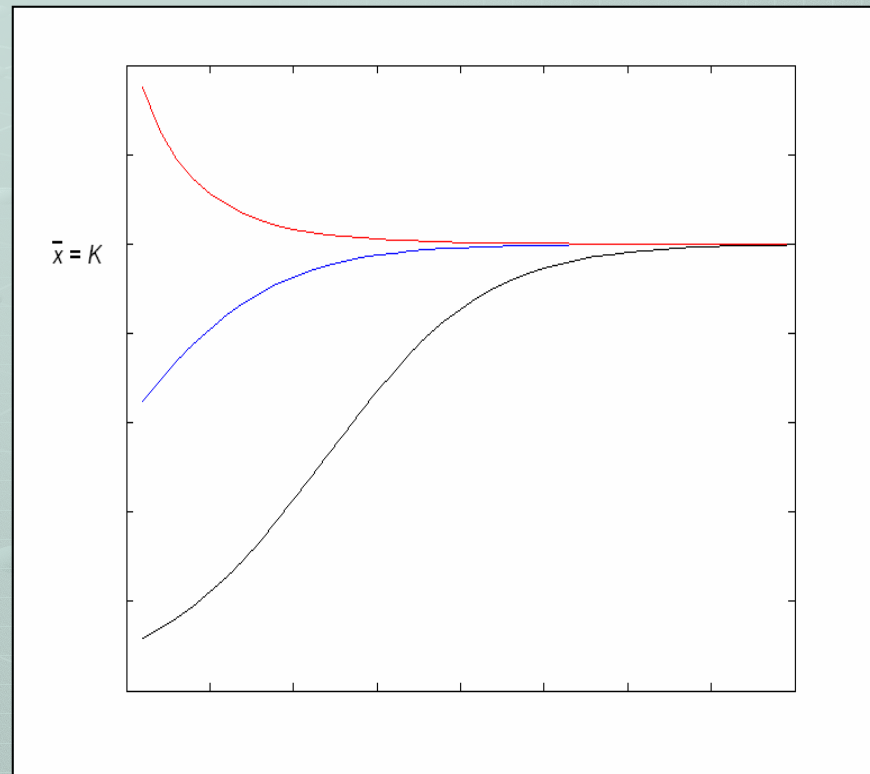
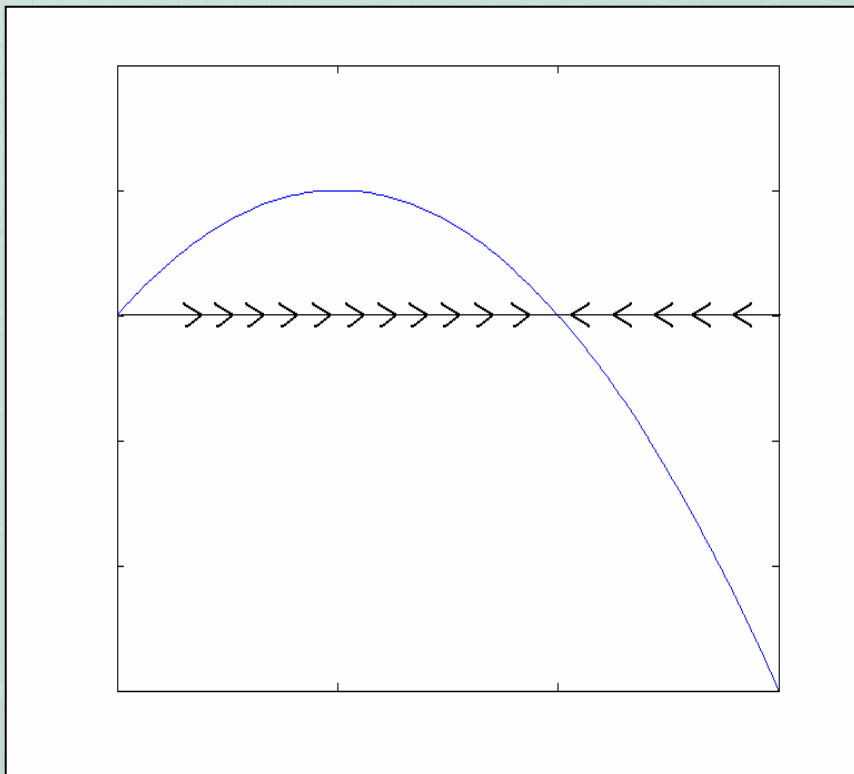
- Equilibria for this model are:

$$\bar{x} = 0 \quad \text{and} \quad \bar{x} = K$$

- Furthermore, stability analysis gives:

$$\bar{x} = 0 \quad \text{unstable}, \quad \bar{x} = K \quad \text{globally stable}$$

Logistic Continued



Lotka-Volterra Model for 2-Species: x_1 and x_2

$$\frac{dx_1}{dt} = r_1 x_1 \left(\frac{K_1 - x_1 - \beta_{12} x_2}{K_1} \right)$$

$$\frac{dx_2}{dt} = r_2 x_2 \left(\frac{K_2 - x_2 - \beta_{21} x_1}{K_2} \right)$$

where

Lotka-Volterra Model for 2-Species: x_1 and x_2

$$r_i, K_i, \beta_{ij} > 0$$

r_i is the intrinsic growth rate (births – deaths) of species i

K_i is the carrying capacity of species i

$\frac{\beta_{ij}}{K_i}$ is the competition coefficient of species i

Lotka-Volterra Model for 2-Species: x_1 and x_2

- The per capita growth rate

$$\frac{1}{x_i} \frac{dx_i}{dt} = f_i(x_1, x_2) \text{ is linear.}$$

- Also $\frac{\partial f_i}{\partial x_j} < 0$ for $i \neq j$ therefore this is a *competition* model.

- Equilibria are:

$$(0,0) \quad (K_1,0) \quad (0, K_2) \quad \left(\frac{K_1 - \beta_{12}K_2}{1 - \beta_{12}\beta_{21}}, \frac{K_2 - \beta_{21}K_1}{1 - \beta_{12}\beta_{21}} \right)$$

Lotka-Volterra Model for 2-Species: x_1 and x_2

For species x_1 , isoclines are

$$x_1 = 0 \quad \text{and} \quad K_1 = x_1 + \beta_{12}x_2$$

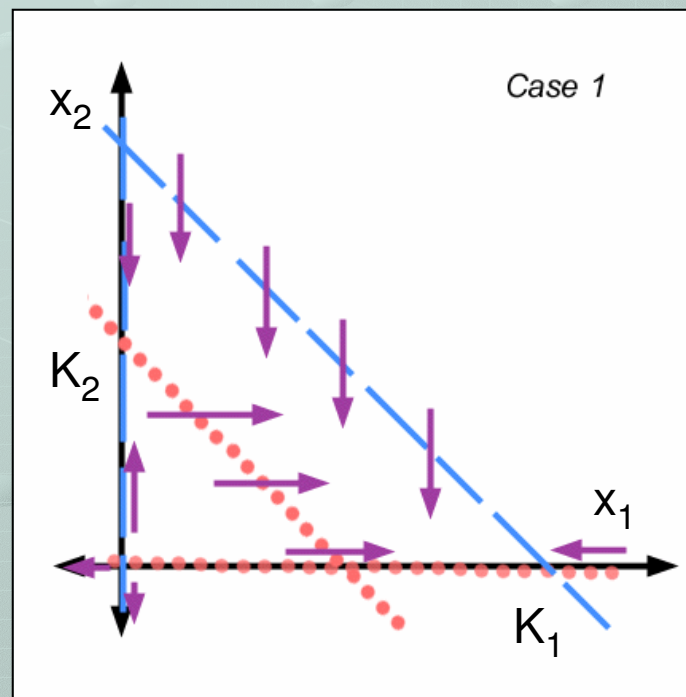
For species x_2 , isoclines are

$$x_2 = 0 \quad \text{and} \quad K_2 = x_2 + \beta_{21}x_1$$

There are four cases to consider depending on how isoclines intersect in the 1st quadrant ...

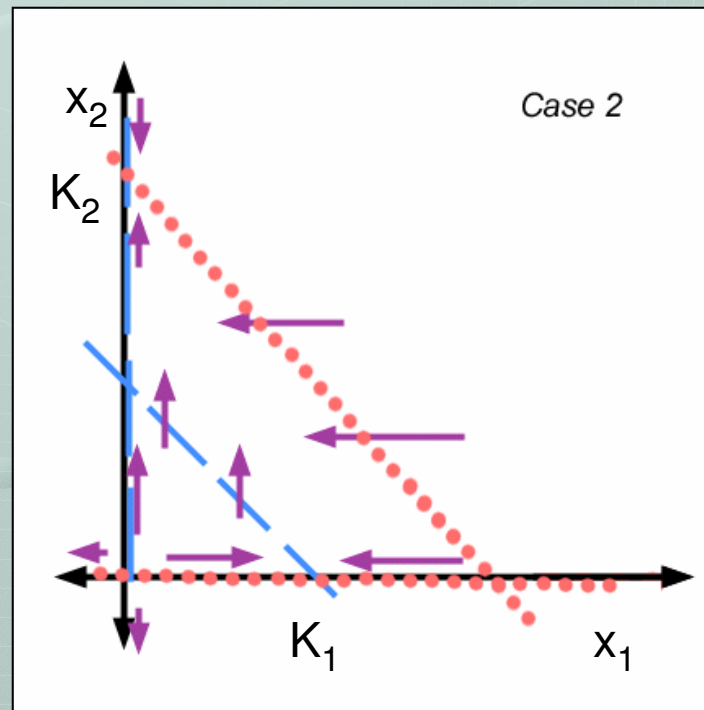
Lotka-Volterra Model for 2-Species: x_1 and x_2

Case 1 – Positive solutions approach equilibrium $(K_1, 0)$; species 1 always dominates (competitive exclusion).



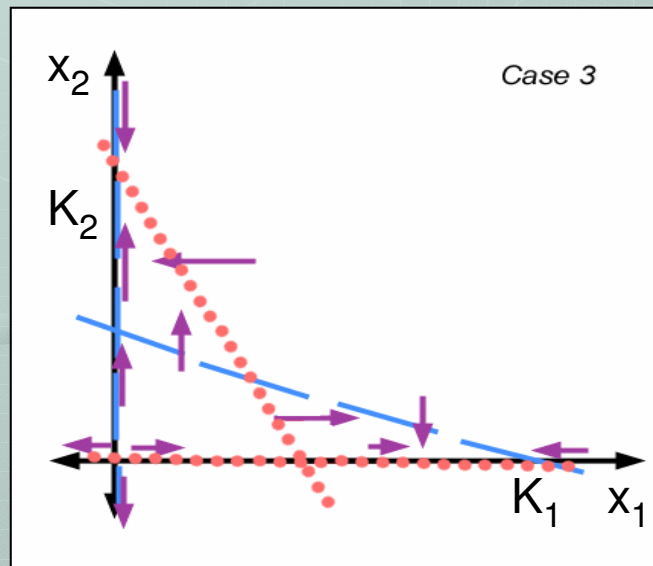
Lotka-Volterra Model for 2-Species: x_1 and x_2

Case 2 – Positive solutions approach equilibrium $(0, K_2)$; species 2 always dominates (competitive exclusion).



Lotka-Volterra Model for 2-Species: x_1 and x_2

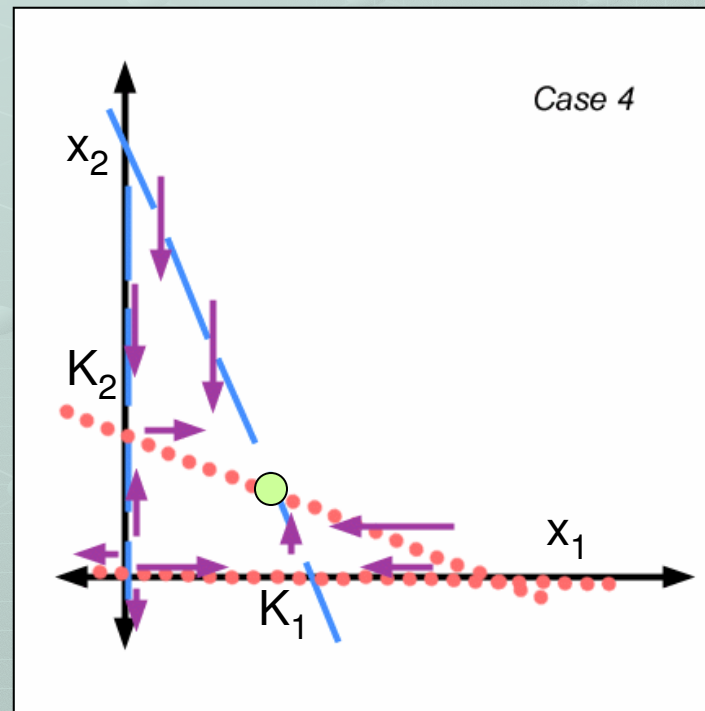
Case 3 – Positive solutions approach either equilibrium $(K_1, 0)$ or $(0, K_2)$. The outcome depends on initial conditions, referred to as the *Founder Effect*. The species first to establish itself (the founder) has an advantage and will be the superior competitor.



Lotka-Volterra Model for 2-Species: x_1 and x_2

Case 4 – Positive solutions approach the equilibrium

$$\left(\frac{K_1 - \beta_{12}K_2}{1 - \beta_{12}\beta_{21}}, \frac{K_2 - \beta_{21}K_1}{1 - \beta_{12}\beta_{21}} \right)$$





Lotka-Volterra Predator-Prey Models

Review of Classical Lotka-Volterra Predator-Prey Model

$$\frac{dX(t)}{dt} = X(t)[a - bY(t)] \quad \frac{dY(t)}{dt} = Y(t)[-c + dX(t)]$$
$$X(0) = X^0, \quad Y(0) = Y^0$$

$X(t)$ and **$Y(t)$** denote prey population size and predator population size, respectively at $t \geq 0$.

For **prey**: **a** and **b** are fixed growth and mortality rates, respectively.

For **predator**: **d** and **c** are fixed growth and mortality rates, respectively.

Review of Classical Lotka-Volterra Predator-Prey Model

Equilibria: $(0,0)$, $\left(\frac{c}{d}, \frac{a}{b}\right)$

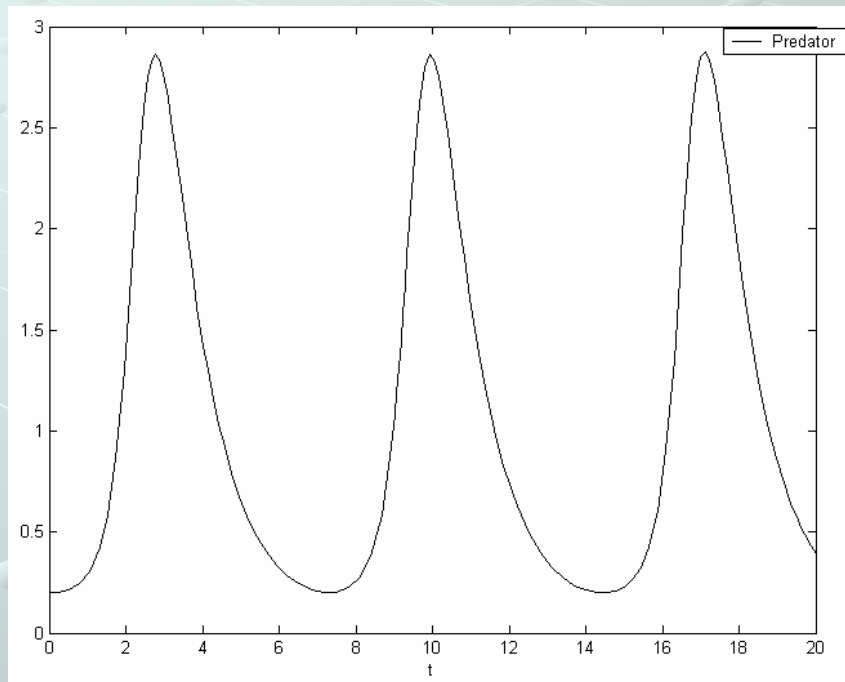
It is well known that the solution is a closed curve in $\text{int}R^2_+$

$$dX + bY - c \ln X - a \ln Y = k,$$

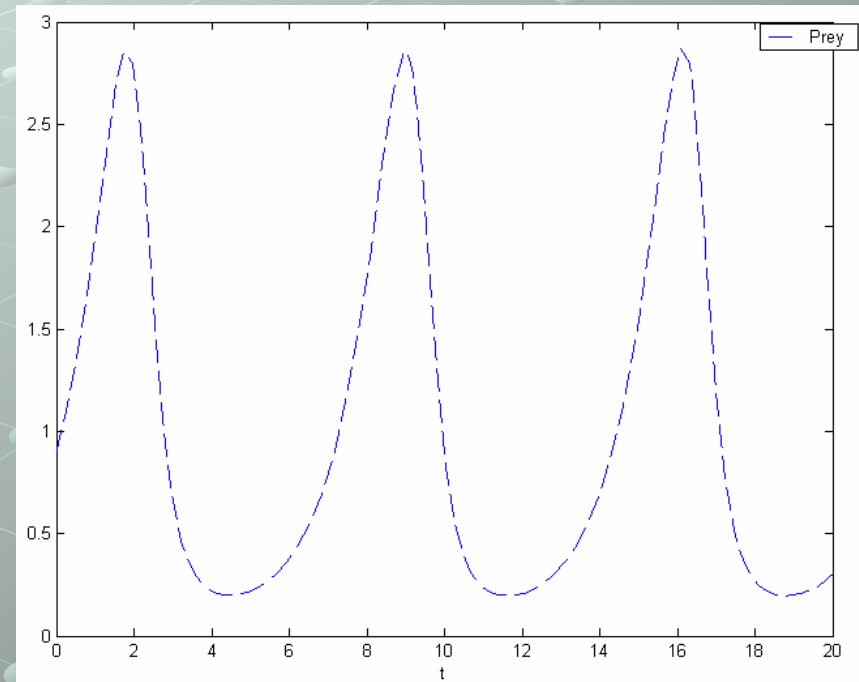
where k is a constant depending upon initial conditions and the point $\left(\frac{c}{d}, \frac{a}{b}\right)$ is interior to the curve.

Hint: Solve $\frac{dX}{dY} = \frac{X(a - bY)}{Y(-c + dX)}$

Review of Classical Lotka-Volterra Predator-Prey Model

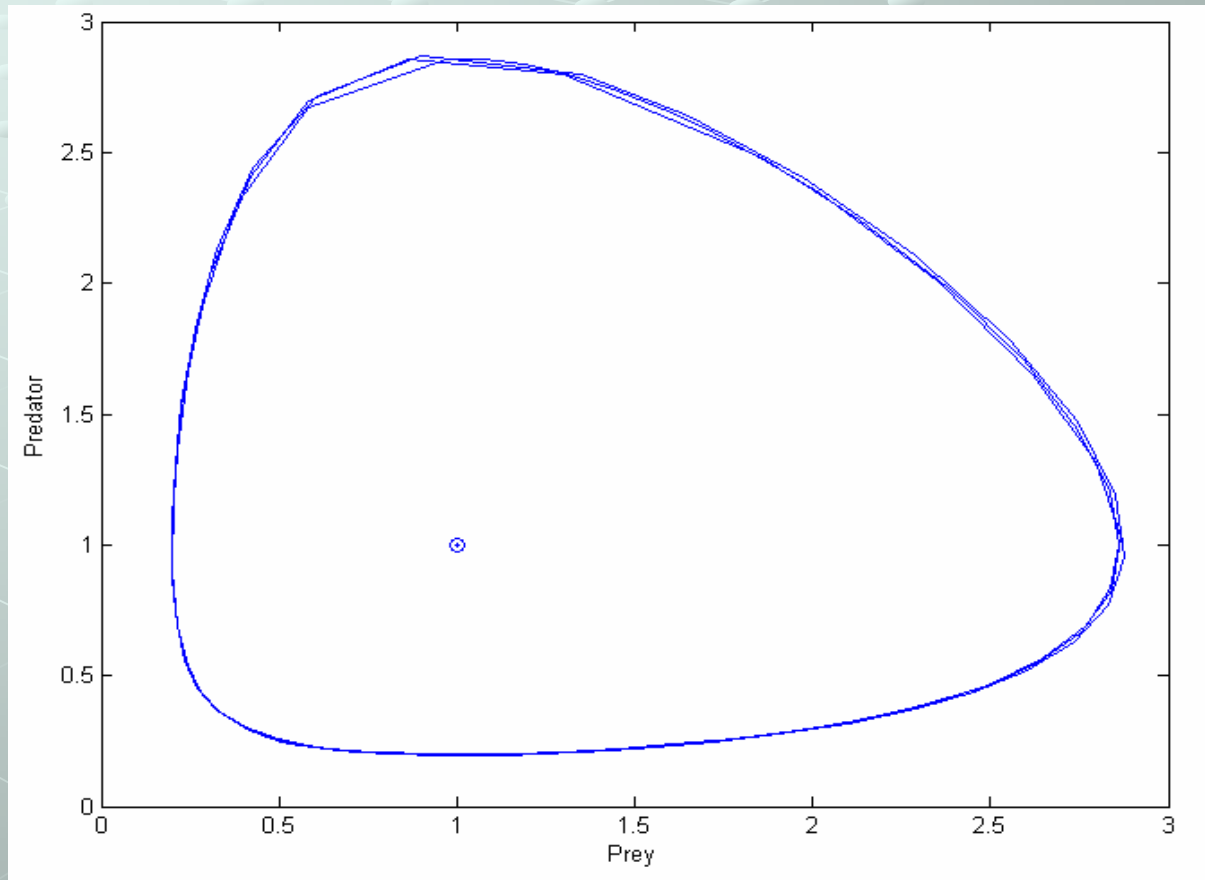


Predator $Y(t)$ vs Time



Prey $X(t)$ vs Time

Review of Classical Lotka-Volterra Predator-Prey Model



Predator $Y(t)$ vs Prey $X(t)$

Generalized Lotka-Volterra Predator-Prey Model

Assume: Prey and predator populations are divided into M and N subpopulations respectively.

- ***Growth for prey*** is subpopulation specific, while ***mortality*** is driven by interaction with entire predator subpopulation.
- ***Growth for predator*** is driven by interaction with entire prey population; ***mortality*** is subpopulation specific.

Let $x_i(t)$ and $y_j(t)$ be the sizes of the i^{th} prey subpopulation and the j^{th} predator subpopulation at time $t \geq 0$, where $i = 1, \dots, M$ and $j = 1, \dots, N$.

Let $x(t) = (x_1(t), \dots, x_M(t))$ and $y(t) = (y_1(t), \dots, y_N(t))$.

Generalized Lotka-Volterra Predator-Prey Model

Let $X(t) = \sum_{i=1}^M x_i(t)$ be the total prey population size.

Let $Y(t) = \sum_{j=1}^N y_j(t)$ be the total predator population size.

$$\frac{dx_i(t)}{dt} = x_i(t)[a_i - b_i Y(t)], \quad i = 1, \dots, M; \quad x(0) = (x_1(0), \dots, x_M(0))$$

$$\frac{dy_j(t)}{dt} = y_j(t)[-c_j + d_j X(t)], \quad j = 1, \dots, N; \quad y(0) = (y_1(0), \dots, y_N(0))$$

Dominance and Extinction of Non-dominant Subpopulation

Suppose subpopulations are ordered such that:

$$\frac{a_1}{b_1} > \frac{a_k}{b_k} \quad , k = 2, \dots, M$$

$$\frac{d_1}{c_1} > \frac{d_k}{c_k} \quad , k = 2, \dots, N$$

x_1 and y_1 are ***dominant*** in the sense that they have the highest *growth to mortality ratios* within the prey and predator classes, respectively.

Dominance and Extinction of Non-dominant Subpopulation

$x_k(t) \rightarrow 0$ as $t \rightarrow \infty$ and $y_k(t) \rightarrow 0$ as $t \rightarrow \infty$

For $k \neq 1$

- x_1 and y_1 remain bounded and strictly positive.

This is why:

For any $t \geq 0$, define $H(t) = \Gamma(t) + \Lambda(t) + \Phi(t) + \Psi(t)$

where

$$\Gamma(t) = \frac{d_1}{b_1} \left(x_1(t) - \frac{c_1}{d_1} - \frac{c_1}{d_1} \ln \left(\frac{d_1 x_1(t)}{c_1} \right) \right)$$

$$\Lambda(t) = \frac{d_1}{b_1} \left(y_1(t) - \frac{a_1}{b_1} - \frac{a_1}{b_1} \ln \left(\frac{b_1 y_1(t)}{a_1} \right) \right)$$

$$\Phi(t) = \sum_{i=2}^M \frac{d_1}{b_i} x_i(t) \quad \Psi(t) = \sum_{j=2}^N \frac{c_1}{c_j} x_j(t)$$

and observe that $H \in C^1([0, \infty); \mathbb{R}_+)$.

Dominance and Extinction of Non-dominant Subpopulation

The total derivative of H along any solution of the system is negative. That is,

$$H'(t) = \frac{\partial H}{\partial x_1} \frac{dx_1}{dt} + \dots + \frac{\partial H}{\partial x_M} \frac{dx_M}{dt} + \frac{\partial H}{\partial y_1} \frac{dy_1}{dt} + \dots + \frac{\partial H}{\partial y_N} \frac{dy_N}{dt} < 0$$

for all $t \geq 0$. Hence, the auxiliary function H is bounded above on $[0, \infty)$.

Dominance and Extinction of Non-dominant Subpopulation

$$x_k(t) \rightarrow 0 \text{ as } t \rightarrow \infty \text{ and } y_k(t) \rightarrow 0 \text{ as } t \rightarrow \infty$$

We begin by considering the prey case. Use the ratio

$$r(t) = \frac{x_k^{b_k}(t)}{x_1^{b_1}(t)}$$

to establish a comparison between $x_1(t)$ and $x_k(t)$ and use the fact that $x_1(t)$ is bounded on $[0, \infty)$, along with the comparison result, to conclude that $x_k(t) \rightarrow 0$ as $t \rightarrow \infty$. If k is in $\{2, \dots, M\}$, then ...

Dominance and Extinction of Non-dominant Subpopulation

$$\frac{d}{dt} \begin{bmatrix} \frac{1}{x_k^{b_k}} \\ \frac{1}{x_1^{b_1}} \end{bmatrix} = \begin{bmatrix} \frac{1}{b_k} x_k^{\frac{1}{b_k}} (a_k - b_k Y) - \frac{1}{b_1} x_k^{\frac{1}{b_k}} (a_1 - b_1 Y) \\ \frac{1}{b_1} x_1^{\frac{1}{b_1}} (a_1 - b_1 Y) - \frac{1}{b_k} x_1^{\frac{1}{b_k}} (a_k - b_k Y) \end{bmatrix} \begin{bmatrix} \frac{1}{x_k^{b_k}} \\ \frac{1}{x_1^{b_1}} \end{bmatrix}$$
$$= \begin{bmatrix} \frac{1}{x_k^{b_k}} \\ \frac{1}{x_1^{b_1}} \end{bmatrix} \begin{bmatrix} \frac{a_k}{b_k} - \frac{a_1}{b_1} \\ \frac{a_1}{b_1} - \frac{a_k}{b_k} \end{bmatrix}$$

Dominance and Extinction of Non-dominant Subpopulation

By the dominance of x_1 , we have where λ_k is a positive constant. $\frac{a_k}{b_k} - \frac{a_1}{b_1} = -\lambda_k,$

So we have a first order differential equation of the form $r'(t) = -\lambda_k r(t),$ whose solution is $r(t) = r(0)e^{-\lambda_k t}.$ In terms of $x,$ we have

$$\frac{x_k^{b_k}(t)}{x_1^{b_1}(t)} = \left[\frac{x_k^{b_k}(0)}{x_1^{b_1}(0)} \right] e^{-\lambda_k t}.$$

Dominance and Extinction of Non-dominant Subpopulation

Solving for x_k , we obtain $x_k(t) = \left[\frac{x_k(0)}{x_1^{b_1}(0)} \right] e^{-\lambda_k b_k t} x_1^{b_k}(t)$.

Since $x_1(t)$ is bounded on $[0, \infty)$, there exists a positive constant A such that $x_k(t) \leq A e^{-\lambda_k b_k t}$, for $t \geq 0$. So $x_k(t) \rightarrow 0$ as $t \rightarrow \infty$, for $k \neq 1$.

An analogous argument for the predator case yields $y_k(t) \rightarrow 0$ as $t \rightarrow \infty$, for $k \neq 1$.

Dominance and Extinction of Non-dominant Subpopulation

NUMERICAL RESULTS

- Given ten predator and prey subpopulations:

For the **dominant** prey subpopulation,

$$a_1 = 1, b_1 = 0.8$$

For the **dominant** predator subpopulation,

$$c_1 = 0.6, d_1 = 1.2$$

- Each $x_i(0)$, $i = 1, \dots, M$ and $y_j(0)$, $j = 1, \dots, N$ is set equal to 0.18.

Dominance and Extinction of Non-dominant Subpopulation

- For **non-dominant** subpopulations ...

$$a_n = a_{n-1} - 0.020(n-1)$$

$$b_n = b_{n-1} + 0.016(n-1)$$

$$c_n = c_{n-1} + 0.012(n-1)$$

$$d_n = d_{n-1} - 0.024(n-1)$$

$$n = 2, \dots, 10$$

Dominance and Extinction of Non-dominant Subpopulation

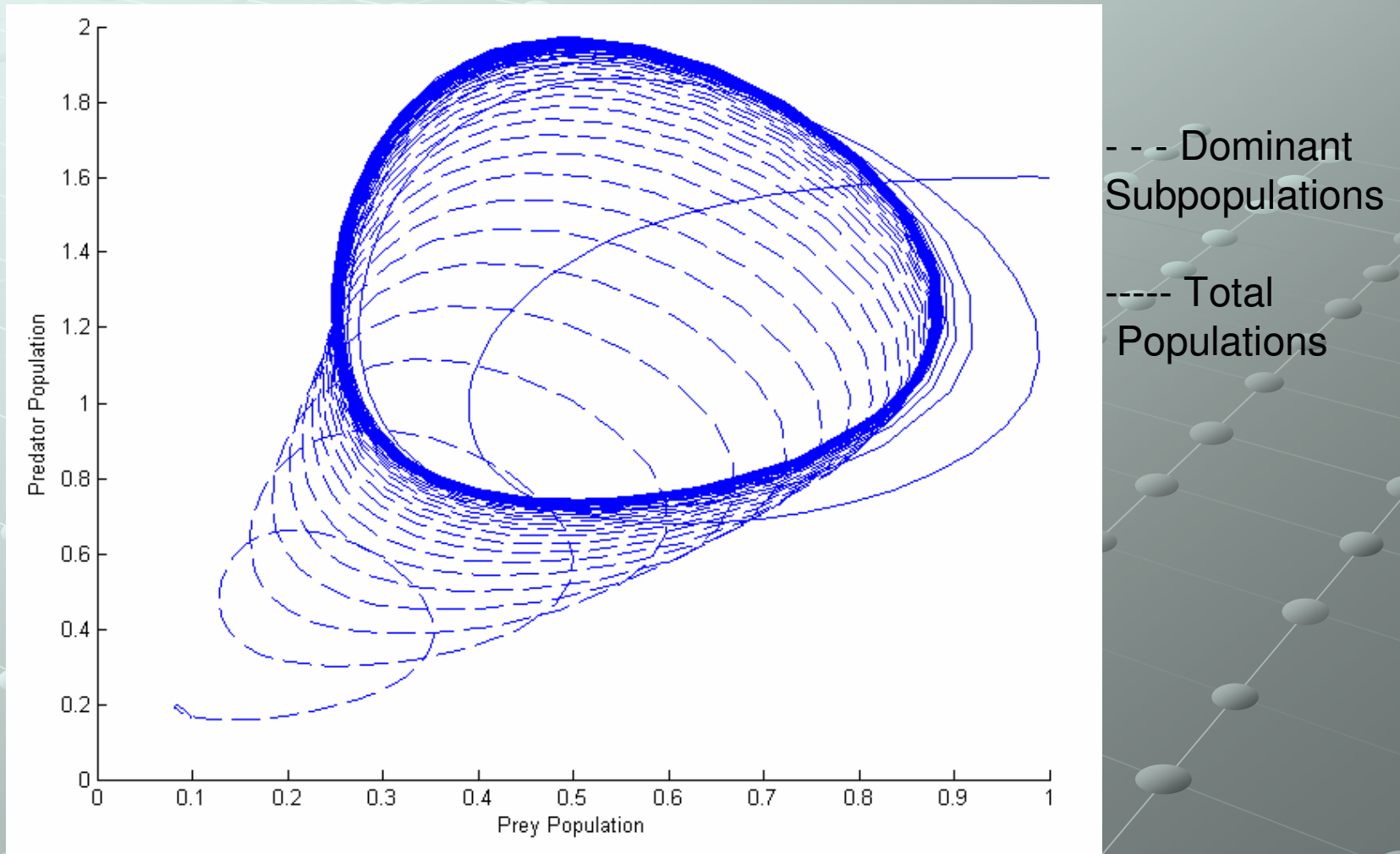


Figure 1: Total and dominant population trajectories for t in $[0,250]$

Dominance and Extinction of Non-dominant Subpopulation

Figure 1 presents the *predator population* vs. *prey population* for t in $[0,250]$.

- When $t = 0$, the total population trajectory starts at the point $(X(0), Y(0)) = (1, 1.6)$ and moves in a counterclockwise fashion.
- When $t = 0$, the dominant subpopulations trajectory starts at $(x_1(0), y_1(0)) = (0.1, 0.1)$ and moves in a counterclockwise fashion as it approaches total population trajectory.

Dominance and Extinction of Non-dominant Subpopulation

- Since every prey subpopulation other than the dominant one approaches zero as $t \rightarrow \infty$ the dominant prey subpopulation must approach the total prey population as $t \rightarrow \infty$
- The predatory case is strictly analogous. So, the trajectories must approach one another.

Dominance and Extinction of Non-dominant Subpopulation

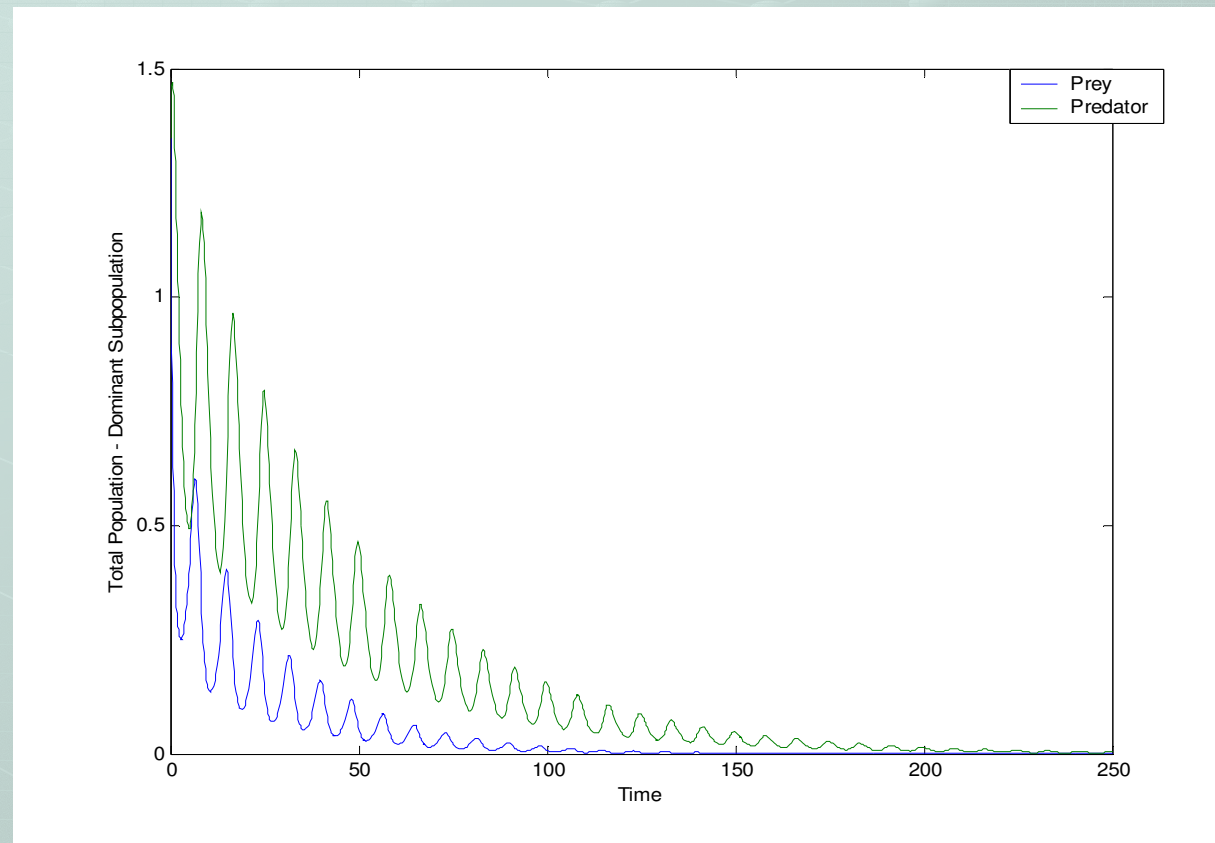


Figure 2: Population differences vs. time

Dominance and Extinction of Non-dominant Subpopulation

Let $a = a_1$, $b = b_1$, $c = c_1$, $d = d_1$ in the classical predator-prey system with initial conditions

$$(X(0), Y(0) = (x_1(250), y_1(250)))$$

After enough time has passed, the trajectory for the dominant predator-prey pair from the generalized system closely approximates the solution curve of a classical predator-prey system with this initial condition.

Conclusion

- As seen from both theoretical and numerical results, all non-dominant subpopulations in the generalized predator-prey model are forced to extinction as $t \rightarrow \infty$ due to closed reproduction.

Closed reproduction/Selection - individuals with the highest growth to mortality ratio only produce more of themselves.

- This conclusion may change with an open reproduction.

Conclusion

- **Open reproduction/Mutation** - individuals in one subpopulation have a positive probability of producing individuals that belong to different subpopulations.

Hence, survival of the dominant species implies survival of some of the others. In this case, surviving subpopulations have an *oscillatory* behavior.



SELECTION MODELS

Selection Models

Consider a competition among N populations where the dynamics of each population is expressed in the following form:

$$x_i' = x_i(a_i - b_i X) \quad \text{where} \quad X = \sum_{i=1}^N x_i \quad \frac{a_1}{b_1} > \frac{a_i}{b_i}$$

$$\begin{aligned} X &= \sum x_i' = \sum x_i(a_i - b_i X) \\ &\leq \sum x_i(\bar{a} - \underline{b}X) \\ &= X(\bar{a} - \underline{b}X) \end{aligned}$$

X is bounded.

Selection Models

As the asymptotic behavior shows, the population with the parameter (a_1, b_1) is the *fittest population*. That is, this is the only population that persists and the rest go to extinction.

Consider the ratio $\frac{x_i^\xi}{x_1^\delta}$. Thus $\frac{d}{dt}(x_i^\xi x_1^{-\delta}) = \xi x_i^{\xi-1} x_i' x_1^{-\delta} - \delta x_i^\xi x_1^{-\delta-1} x_1'$

If we let $x_i^\xi x_1^{-\delta} = \lambda$ then we arrive at

$$\frac{d}{dt}(\lambda) = \lambda(\xi a_i + \xi b_i X - \delta a_1 - \delta b_1 X)$$

Selection Models

Letting $\xi = \frac{1}{b_i}$, and $\delta = \frac{1}{b_1}$,

$$\begin{aligned}\frac{d\lambda}{dt} &= \lambda \left(\frac{a_i}{b_i} + X - \frac{a_1}{b_1} - X \right) \\ &= \lambda \left(\frac{a_i}{b_i} - \frac{a_1}{b_1} \right) = c\lambda\end{aligned}$$

Since $\frac{a_1}{b_1} > \frac{a_i}{b_i}$, we have $c < 0$. Thus, $\frac{x_i^\xi}{x_1^\delta}$ approaches zero as

$t \rightarrow \infty$. Because the denominator is bounded, the numerator must tend to zero at infinity. Thus, all non-dominant subpopulations die.

Selection Models

Now we show that the dominant subpopulation x_1 survives:

Recall $x_1' = x_1(a_1 - b_1x_1 - b_1\hat{X})$ $\hat{X} = \sum_{j=2}^n x_j$

and consider $y' = y(a_1 - b_1y)$

- Notice $x_1' \leq x_1(a_1 - b_1x_1)$

Hence $x(t) \leq y(t)$ by comparison.

Selection Models

Next, consider
$$\frac{d}{dt} \ln\left(\frac{x_1}{y}\right) = \frac{x_1'}{x_1} - \frac{y_1'}{y} = (a_1 - b_1 x_1 - b_1 \hat{X}) - (a_1 - b_1 y)$$

Making the substitution $\xi = \frac{1}{b_i}$, and $\delta = \frac{1}{b_1}$ we arrive at

$$b_1(y - x_1) = b_1 \hat{X} + \frac{d}{dt} \ln\left(\frac{x_1}{y}\right)$$

Selection Models

Integrating the equation from t_0 to t we arrive at:

$$\int_{t_0}^t (y(\tau) - x_1(\tau)) d\tau = \int_{t_0}^t \hat{X}(\tau) d\tau + \int_{t_0}^t \left(\frac{1}{b_1} \frac{d}{d\tau} \ln \left(\frac{x_1}{y} \right) \right) d\tau$$

$$= \frac{1}{b_1} \ln \left(\frac{x_1}{y} \right) \Big|_{t_0}^t + \int_{t_0}^t \hat{X}(\tau) d\tau$$

$$\leq \frac{1}{b_1} \ln \left(\frac{x_1}{y} \right) + \gamma \int_{t_0}^t (e^{-c\tau} d\tau) = \hat{M}$$

Since $0 \leq \int_{t_0}^{\infty} (y - x_1) dt \leq \hat{M}$ and $(y' - x_1')$ are bounded,

we have $y - x_1 \rightarrow 0$ as $t \rightarrow \infty$. Since y approaches $\frac{a_1}{b_1}$

in the long term, so too does x_1



EPIDEMIC MODELS



Competitive Exclusion for an Epidemic Model

Competitive Exclusion for an epidemic model

The model considered is of the **SIR** type, in that the host population consists of susceptible, **S**, individuals infected with strains 1 through n , I_j , $j=1,2, \dots, n$ and immune or removed individuals, **R**. In addition, it is assumed that there is mass action horizontal transmission:

$$\dot{S}(t) = S \left(f(N) - \sum_{j=1}^n \beta_j I_j \right) + \sum_{j=1}^n b I_j + bR$$

$$\dot{I}_j(t) = I_j (f(N) - b + \beta_j S_j - \gamma_j - \mu_j), \quad j = 1, 2, \dots, n.$$

$$\dot{R}(t) = R (f(N) - b) + \sum_{j=1}^n \gamma_j I_j$$

$$N = S + R + \sum_{j=1}^n I_j$$

$$\dot{N}(t) = Nf(N) - \sum_{j=1}^n \mu_j I_j$$

b is a birth rate, **f(N)** is the per capita growth rate, and **b-f(N)** is the natural death rate. β_j denotes the transmission rate for the i^{th} strain and γ_j is the recovery rate from infection with strain j . All parameters are positive.

Competitive Exclusion for an epidemic model

Competitive Exclusion

Let $c_j = b_j + \gamma_j + \mu_j > f(0)$

Then the basic reproduction number for strain j is given by:

$$R_{0,j} = \frac{\beta_j}{c_j} K, \quad j = 1, 2, \dots, n$$

We define

$$B_{0,j} = \frac{\beta_j K}{c_j - f(0)}, \quad j = 1, 2, \dots, n$$

and assume for the rest of this section that for each $j=2, \dots, n$, one of the following conditions holds:

$$\text{or (3) } R_{0,1} > R_{0,j} \quad \text{and} \quad c_j > c_1$$

$$(4) \quad B_{0,1} > B_{0,j} \quad \text{and} \quad \beta_j > \beta_1$$

The following stronger conditions imply (3) or (4):

$$R_{0,1} > R_{0,j} \quad \text{and} \quad B_{0,1} > B_{0,j}$$

Competitive Exclusion for an epidemic model

$$S(t) \geq \underline{S} \text{ for } t \in [0, \infty)$$

We show that all the strains, except possibly one, die out.

- For $j = 2, \dots, n$;

$$\lim_{t \rightarrow \infty} I_j(t) = 0.$$

- First assume that the conditions in (3) hold for a fixed j and define

$$\Gamma(t) = \frac{I_j^{\frac{1}{c_j}}}{I_1^{\frac{1}{c_1}}}$$

$$\begin{aligned} \frac{d}{dt} \Gamma_1(t) &= \frac{\frac{1}{c_j} I_j^{\frac{1}{c_j}} (f(N) + \beta_j S - c_j) I_1^{\frac{1}{c_1}} - \frac{1}{c_1} I_1^{\frac{1}{c_1}} (f(N) + \beta_1 S - c_1) I_j^{\frac{1}{c_j}}}{I_1^{\frac{2}{c_1}}} \\ &= \frac{1}{c_j} \Gamma_1(t) (f(N) + \beta_j S - c_j) - \frac{1}{c_1} \Gamma_1(t) (f(N) + \beta_1 S - c_1) \end{aligned}$$

Competitive Exclusion for an epidemic model

$$\begin{aligned}\frac{d}{dt}\Gamma_1(t) &= \Gamma_1(t) \left(\frac{f(N)}{c_j} - \frac{f(N)}{c_1} + \left(\frac{\beta_j}{c_j} - \frac{\beta_1}{c_1} \right) S \right) \\ &\leq \frac{1}{2} \Gamma_1(t) \left(\frac{\beta_j}{c_j} - \frac{\beta_1}{c_1} \right) S\end{aligned}$$

Expressed in terms of logarithms,

$$\frac{d \ln \Gamma_1(t)}{dt} \leq \frac{1}{2} \left(\frac{\beta_j}{c_j} - \frac{\beta_1}{c_1} \right) S$$

Thus

$$\Gamma_1(t) \leq \Gamma_1(0) e^{\frac{1}{2} \left(\frac{\beta_j}{c_j} - \frac{\beta_1}{c_1} \right) S t}; \quad I_j^{c_j}(t) \leq I_1^{c_1}(t) \Gamma_1(0) e^{\frac{1}{2} \left(\frac{\beta_j}{c_j} - \frac{\beta_1}{c_1} \right) S t}$$

Since I_1 is bounded, and $\left(\frac{\beta_j}{c_j} - \frac{\beta_1}{c_1} \right) < 0$ we have $\lim_{t \rightarrow \infty} I_j(t) = 0$.

Competitive Exclusion for an epidemic model

Now define $\Gamma(t) = \frac{I_j^{\frac{1}{\beta_j}}}{I_1^{\frac{1}{\beta_1}}}$

$$\begin{aligned} \frac{d}{dt} \Gamma_2(t) &= \Gamma_2(t) \left(\frac{f(N)}{\beta_j} - \frac{f(N)}{\beta_1} + \left(\frac{c_1}{\beta_1} - \frac{c_j}{\beta_j} \right) S \right) \\ &\leq \Gamma_2(t) \left(f(0) \left(\frac{1}{\beta_j} - \frac{1}{\beta_1} \right) + \left(\frac{c_1}{\beta_1} - \frac{c_j}{\beta_j} \right) \right) \\ &= \Gamma_2(t) \left(\frac{c_1 - f(0)}{\beta_1} - \frac{c_j - f(0)}{\beta_j} \right) \end{aligned}$$

Arguing as before we get $\lim_{t \rightarrow \infty} I_j(t) = 0$.

Competitive Exclusion for an Epidemic Model

Assume that

$$R_{0,1} > 1 \quad \text{then} \quad \liminf_{t \rightarrow \infty} I_1(t) > 0$$

Assume that $R_{0,1} < 1$

then

$$\lim_{t \rightarrow \infty} \left(S(t), \sum_{j=1}^n I_j(t), R(t) \right) = (K, 0, 0)$$

Competitive Exclusion for an Epidemic Model

Coexistence Case

Consider the following case with two strains ($n=2$). Let $f(N) = r\left(1 - \frac{N}{K}\right)$ where $K = 100$ and the intrinsic growth rate is $r = 4$.

Birth rate, $b_j = 6$ and the transmission rates and recovery rates for the two strains are:

$$\beta_1 = 2, \beta_2 = 1 \quad \text{and} \quad \gamma_1 = 1 = \gamma_2$$

Suppose strain 1 with the largest transmission rate also has the highest virulence, $\mu_1 = 10, \mu_2 = 3$. Clearly, in the case the reproduction number $R_{0,1} = 11.765 > 10 = R_{0,2}$. But, $C_1 = 17 > 10 = C_2$. However, $B_{0,1} = 15.385 < 16.667 = B_{0,2}$. But, $\beta_1 > \beta_2$ hence, neither condition (3) nor (4) are satisfied. Simple computations show that a positive steady state exists for this case and is given by

$$S = 7, I_1 = 4.929, I_2 = 8.571 \text{ and } R = 4.5$$

Competitive Exclusion for an Epidemic Model

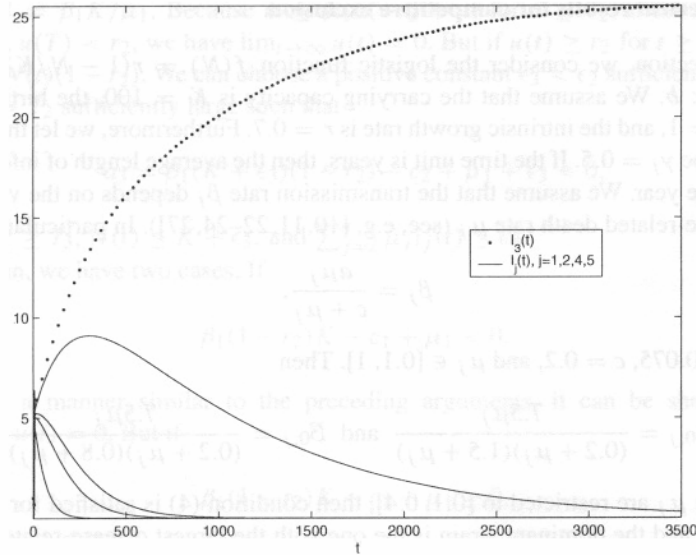


Fig. 1. Competitive exclusion when conditions (3) and (4) are not satisfied.

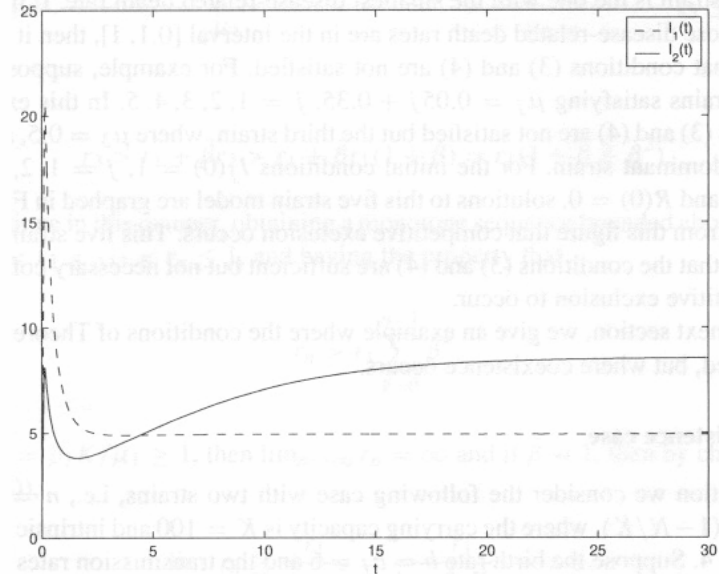



Fig. 2. Coexistence of the strains $I_1(t)$ and $I_2(t)$.

Local stability analysis proves that this positive steady state is locally asymptotically stable. In particular, the Jacobian matrix has eigen values given by

$$\lambda_1 = -8.657 + 6.833i, \lambda_2 = -8.657 - 6.833i, \lambda_3 = -1.899, \lambda_4 = -0.216$$

Our numerical results indicate that this equilibrium is indeed globally asymptotically stable.



**Competitive Exclusion and Coexistence
for a Quasilinear Size-Structured
Population Model**

Competitive Exclusion and Coexistence for a Quasilinear Size-Structured Population Model

Consider a species with n competing ecotypes.

For $i = 1, 2, \dots, n$, we describe the dynamics of the subpopulation consisting of individuals of the i^{th} ecotype with the following individual size-structured model of the McKendrick-von Foerster type.

$$(u_i)_t + g_i(P(t))(u_i)_x + m_i(P(t))u_i = 0 \quad 0 < x < \infty, \quad t > 0$$

$$g_i(P(t))u_i(0, t) = \sum_{j=1}^n \int_0^{\infty} \gamma_{ij} \beta_j(P(t))u_j(x, t) dx \quad t > 0$$

$$u_i(x, 0) = u_{i0}(x) \quad 0 \leq x < \infty$$

where $u_i(x, t)$ is the density of individuals of the i^{th} ecotype having size x at time t

Competitive Exclusion and Coexistence for a Quasilinear Size-Structured Population Model

$$P(t) = \sum_{i=1}^n \int_0^{\infty} u_i(x, t) dx \quad \text{is the total number of}$$

individuals in the population at time t . For an individual in the i^{th} subpopulation ...

g_i : is the i^{th} growth rate

m_i : is the i^{th} mortality rate

β_i : is the i^{th} reproduction rate

$0 \leq \gamma_{i,j} \leq 1$: probability that an individual of the j^{th} ecotype will reproduce an individual of the i^{th} ecotype.

Clearly,
$$\sum_{j=1}^n \gamma_{i,j} = \sum_{i=1}^n \gamma_{i,j} = 1, \quad 1 \leq i, \quad j \leq n$$

Competitive Exclusion and Coexistence for a Quasilinear Size-Structured Population Model

We focus on the asymptotic behavior of the population in two cases:

1. ***Closed reproduction***: offspring always belong to same ecotype as the parent.

$$\gamma_{i,i} \quad \text{and} \quad \gamma_{i,j} = 0 \quad \text{for} \quad i \neq j$$

2. ***Open reproduction***: individuals of ecotype i may reproduce individuals of ecotype j .

By integration of the PDE from 0 to infinity with respect to t and by making the following substitutions,

$$P(t) = \sum_{i=1}^n \int_0^{\infty} u_i(x,t) dx \quad \text{and} \quad P(t) = \int_0^{\infty} u_i(x,t) dx$$

we arrive at a system of n ODEs ...

Competitive Exclusion and Coexistence for a Quasilinear Size-Structured Population Model

$$P_i'(t) = \sum_{j=1}^n (\gamma_{i,j} \beta_j(P) P_j) - m_i(P) P_i, \quad P_i(0) > 0, \quad i = 1, 2, \dots, n.$$

Asymptotic Behavior

In order to study the asymptotic behavior of the population, we consider the above system of coupled ordinary differential equations.

Assumptions for $0 \leq P < \infty$

$\beta_i(P)$ is non-increasing

$m_i(P)$ is increasing

There exists P_i^* such that $\beta_i(P_i^*) = m_i(P_i^*)$, $i = 1, 2, \dots, n$.

Competitive Exclusion and Coexistence for a Quasilinear Size-Structured Population Model

We first show that population $\mathbf{P}(t)$ is uniformly bounded.

Let $\bar{P} = \max_{1 \leq i \leq n} P_i^*$ and $\underline{P} = \min_{1 \leq i \leq n} P_i^*$.

For any $0 < \varepsilon < 1$, define $I_\varepsilon = [\underline{P}(1 - \varepsilon), \bar{P}(1 + \varepsilon)]$.

Then there exists a finite time t_ε^* such that $P \in I_\varepsilon$ for $t \geq t_\varepsilon^*$.

Closed Reproduction Case

Recall that in the closed reproduction case,
 $\gamma_{i,i}$ and $\gamma_{i,j} = 0$ for $i \neq j$

Therefore the system of ODEs reduces to the following,

$$P_i' = (\beta_i(P) - m_i(P))P_i \quad P_i(0) > 0, \quad i = 1, 2, \dots, n.$$

Competitive Exclusion and Coexistence for a Quasilinear Size-Structured Population Model

Under the assumption,

$$\frac{\beta_1(P)}{m_1(P)} > \frac{\beta_i(P)}{m_i(P)}, \quad i = 2, \dots, n; \text{ for any } P \in I_0 = [\underline{P}, \bar{P}]$$

Then the solution of $P_i' = (\beta_i(P) - m_i(P))P_i$ $P_i(0) > 0$, $i = 1, 2, \dots, n$.

satisfies that for each $i = 2, \dots, n$; $P_i(t) \rightarrow 0$ as $t \rightarrow \infty$

To show this, it suffices to show that for $i = 2, \dots, n$,

$$\frac{P_i^{\sigma_i}}{P_1} \rightarrow 0 \text{ as } t \rightarrow \infty \text{ for some positive constant } \sigma_i$$

Competitive Exclusion and Coexistence for a Quasilinear Size-Structured Population Model

What's left is to show that $P_1(t) \rightarrow P_1^*$ as $t \rightarrow \infty$

This can be shown by considering the following initial value problem:

$$\begin{cases} y' = (\beta_1(y) - m_1(y))y, & t_\varepsilon^* < t < \infty, \\ y(t_\varepsilon^*) = P_1(t_\varepsilon^*) \end{cases}$$

Clearly, $y(t) \rightarrow P_1^*$ as $t \rightarrow \infty$. Furthermore, since

$$P_1' \leq (\beta_1(P_1) - m_1(P_1))P_1 \quad \text{by comparison} \quad y(t) \geq P_1(t)$$

for all $t \geq t_\varepsilon^*$. On the other hand we have:

$$\frac{d}{dt} \ln\left(\frac{P_1}{y}\right) = \frac{P_1'}{P_1} - \frac{y'}{y} = (\beta_1(P) - m_1(P)) - (\beta_1(y) - m_1(y))$$

$$= (\beta_1(\hat{\xi}) - m_1(\hat{\xi}))(P_1 - y) + (\beta_1(\xi) - m_1(\xi)) \sum_{j=2}^n P_j$$

Where $\hat{\xi}$ is between P and P_1 and ξ is between P_1 and y

Competitive Exclusion and Coexistence for a Quasilinear Size-Structured Population Model

Rearranging the terms, we arrive at

$$y - P_1 \leq \frac{1}{c} \left(\frac{d}{dt} \ln\left(\frac{P_1}{y}\right) + (m_1'(\hat{\xi}) - \beta_1'(\hat{\xi})) \sum_{j=2}^n P_j \right)$$

Integrating from space to t , we get

$$\int_{t_\varepsilon^*}^t (y(\eta) - P_1(\eta)) d\eta \leq \frac{1}{c} \left(\ln\left(\frac{P_1(t)}{y(t)}\right) + \sum_{j=2}^n \int_{t_\varepsilon^*}^t ([m_1'(\xi) - \beta_1'(\xi)] P_j(\eta)) d\eta \right) \leq M < \infty$$

where M is independent of t .

Competitive Exclusion and Coexistence for a Quasilinear Size-Structured Population Model

Open Reproduction Case

In this case, we assume that reproduction is open under subpopulations, that is, individuals in the i^{th} subpopulation may also reproduce individuals in the j^{th} population. If the graph associated with the matrix $[\gamma_{i,j}]$ is strongly connected (the matrix is irreducible), then all ecotypes of the population coexist. For convenience, we assume the following:

Hypothesis 1:

$$\gamma_{1,2} > 0, \quad \gamma_{2,3} > 0, \dots \quad \gamma_{n-1,n} > 0 \text{ and } \gamma_{n,1} > 0. \quad \textit{otherwise}$$

$$\gamma_{i,j} > 0, \quad 1 \leq i, j \leq n$$

If Hypothesis 1 holds, then there exists a positive constant c such that

$$\liminf_{t \rightarrow \infty} P_i(t) \geq c \quad \textit{for } i = 1, 2, \dots, n$$

Competitive Exclusion and Coexistence for a Quasilinear Size-Structured Population Model

NUMERICAL RESULTS

In the **closed reproduction** case, it is clear that subpopulations with smaller ratios $\frac{\beta_i(P)}{m_i(P)}$ will go to extinction.

This leads to the question:

What happens if two subpopulations have the same largest ratio?

Competitive Exclusion and Coexistence for a Quasilinear Size-Structured Population Model

We focus on the following subsystem consisting of two subpopulations with the largest ratio $\frac{\beta_1(P)}{m_1(P)} = \frac{\beta_2(P)}{m_2(P)}$

$$P_i' = (\beta_i(P) - m_i(P))P_i, \quad P_i(0) > 0, \quad i = 1, 2.$$

In this case, both subpopulations should survive. However, the asymptotic behavior of this two-ecotype system depends on the initial conditions $P_i(0)$, $i = 1, 2$

Competitive Exclusion and Coexistence for a Quasilinear Size-Structured Population Model

In the **open reproduction** case, if the k^{th} ($1 \leq k \leq n$) node in the graph associated with the matrix $[\gamma_{i,j}]$ is not connected to any other node, i.e.,

$$\gamma_{k,k} = 1 \text{ and } \gamma_{k,j} = 1 \text{ for } j = 1, \dots, k-1, k+1, \dots, n,$$

then the k^{th} subpopulation may become extinct.