# BIOL 410 Population and Community Ecology 

## Age structured populations <br> Sampling population density

## Predicting Age Structure

| $x$ | i | $S(x)$ | $l(x)$ | $g(x)$ | $b(x)$ | $P_{i}$ | $F_{i}$ | $l(x) b(x)$ | $l(x) b(x) x$ | $e^{-r x} l(x) b(x)$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0 |  | 500 | 1.0 | 0.8 | 0 |  |  | 0.0 | 0.0 | 0.0 |
| 1 | 1 | 400 | 0.8 | 0.5 | 2 | 0.80 | 1.60 | 1.6 | 1.6 | 0.736 |
| 2 | 2 | 200 | 0.4 | 0.25 | 3 | 0.50 | 1.50 | 1.2 | 2.4 | 0.254 |
| 3 | 3 | 50 | 0.1 | 0 | 1 | 0.25 | 0.25 | 0.1 | 0.3 | 0.010 |
| 4 | 4 | 0 | 0 |  | 0 | 0 | 0 | 0.0 | 0.0 | 0.0 |

$$
\begin{aligned}
& n_{1}(t+1)=F_{1} n_{1}(t)+F_{2} n_{2}(t)+F_{3} n_{3}(t)+F_{4} n_{4}(t) \\
& n_{2}(t+1)=P_{1} n_{1}(t) \\
& n_{3}(t+1)=P_{2} n_{2}(t) \\
& n_{4}(t+1)=P_{3} n_{3}(t)
\end{aligned}
$$

## Leslie Matrix

## Representing Growth in matrix of $k x k$ age classes



Columns: age class at time $t$
$\left.\begin{array}{c}\text { Rows: age } \\ \text { Class at } \\ \text { time } \mathrm{t}+1\end{array}\right\} \mathbf{A}=\left[\begin{array}{cccc}\boldsymbol{F}_{\mathbf{1}} & \boldsymbol{F}_{\mathbf{2}} & \boldsymbol{F}_{\mathbf{3}} & \boldsymbol{F}_{\mathbf{4}} \\ \boldsymbol{P}_{\mathbf{1}} & 0 & 0 & 0 \\ 0 & \boldsymbol{P}_{\mathbf{2}} & 0 & 0 \\ 0 & 0 & \boldsymbol{P}_{\mathbf{3}} & 0\end{array}\right]_{\text {Survival probability }}$

## Leslie Matrix

| $x$ | i | $l(x)$ | $b(x)$ | $\boldsymbol{P}_{i}$ | $\boldsymbol{F}_{i}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 0 |  | 1.0 | 0 |  |  |
| 1 | 1 | 0.8 | 2 | 0.80 | 1.60 |
| 2 | 2 | 0.4 | 3 | 0.50 | 1.50 |
| 3 | 3 | 0.1 | 1 | 0.25 | 0.25 |
| 4 | 4 | 0 | 0 | 0 | 0 |

$$
\begin{aligned}
& \mathbf{A}=\left[\begin{array}{cccc}
\boldsymbol{F}_{\mathbf{1}} & \boldsymbol{F}_{\mathbf{2}} & \boldsymbol{F}_{3} & \boldsymbol{F}_{4} \\
\boldsymbol{P}_{\mathbf{1}} & 0 & 0 & 0 \\
0 & \boldsymbol{P}_{2} & 0 & 0 \\
0 & 0 & \boldsymbol{P}_{3} & 0
\end{array}\right] \\
& \mathbf{A}=\left[\begin{array}{cccc}
\mathbf{1 . 6} & \mathbf{1 . 5} & \mathbf{0 . 2 5} & \mathbf{0} \\
\mathbf{0 . 8 0} & 0 & 0 & 0 \\
0 & \mathbf{0 . 5 0} & 0 & 0 \\
0 & 0 & \mathbf{0 . 2 5} & 0
\end{array}\right]
\end{aligned}
$$

## Leslie Matrix

- Forecasting future age structure ( $n$ at time $t+1$ ) based current population structure ( $n$ at time $t$ ) using Fertility and Survival Probability from the Leslie Matrix.

$$
n(t+1)=A n(t)
$$

$$
n(t+1)=\left[\begin{array}{cccc}
\boldsymbol{F}_{\mathbf{1}} & \boldsymbol{F}_{\mathbf{2}} & \boldsymbol{F}_{\mathbf{3}} & \boldsymbol{F}_{\mathbf{4}} \\
\boldsymbol{P}_{\mathbf{1}} & 0 & 0 & 0 \\
0 & \boldsymbol{P}_{\mathbf{2}} & 0 & 0 \\
0 & 0 & \boldsymbol{P}_{\mathbf{3}} & 0
\end{array}\right] \boldsymbol{x}\left(\begin{array}{l}
n_{1} \\
n_{2} \\
n_{3} \\
n_{4}
\end{array}\right)
$$

## Matrix algebra

- Product of a square matrix and a column matrix (vector) is a column matrix
- Useful for solving linear equations


## Examples of Using Leslie Matrix

- Start with a cohort of 200 individuals in age-class 1 with the Fertility and Survival probabilities in our example:

$$
\begin{aligned}
& F_{1}=1.6 \quad \bar{F}_{2}=1.5 \quad F_{3}=0.25 \quad F_{4}=0 \\
& n(t+1)=\left[\begin{array}{cccc}
\boldsymbol{F}_{\mathbf{1}} & \boldsymbol{F}_{\mathbf{2}} & \boldsymbol{F}_{\mathbf{3}} & \boldsymbol{F}_{\mathbf{4}} \\
\boldsymbol{P}_{\mathbf{1}} & 0 & 0 & 0 \\
0 & \boldsymbol{P}_{\mathbf{2}} & 0 & 0 \\
0 & 0 & \boldsymbol{P}_{\mathbf{3}} & 0
\end{array}\right] \boldsymbol{x}\left(\begin{array}{l}
n_{1} \\
n_{2} \\
n_{3} \\
n_{4}
\end{array}\right)=\left[\begin{array}{cccc}
1.6 & 1.5 & 0.25 & 0 \\
0.8 & 0 & 0 & 0 \\
0 & 0.5 & 0 & 0 \\
0 & 0 & 0.25 & 0
\end{array}\right] \boldsymbol{x}\left(\begin{array}{c}
200 \\
0 \\
0 \\
0
\end{array}\right)
\end{aligned}
$$

## Examples of Using Leslie Matrix

$$
\begin{gathered}
n(t+1)=\left[\begin{array}{cccc}
\boldsymbol{F}_{\mathbf{1}} & \boldsymbol{F}_{\mathbf{2}} & \boldsymbol{F}_{\mathbf{3}} & \boldsymbol{F}_{\mathbf{4}} \\
\boldsymbol{P}_{\mathbf{1}} & 0 & 0 & 0 \\
0 & \boldsymbol{P}_{\mathbf{2}} & 0 & 0 \\
0 & 0 & \boldsymbol{P}_{\mathbf{3}} & 0
\end{array}\right] \boldsymbol{x}\left(\begin{array}{l}
n_{1} \\
n_{2} \\
n_{3} \\
n_{4}
\end{array}\right)=\left[\begin{array}{cccc}
1.6 & 1.5 & 0.25 & 0 \\
0.8 & 0 & 0 & 0 \\
0 & 0.5 & 0 & 0 \\
0 & 0 & 0.25 & 0
\end{array}\right] \boldsymbol{x}\left(\begin{array}{c}
200 \\
0 \\
0 \\
0
\end{array}\right) \\
n(t+1)=\left[\begin{array}{cccc}
1.6(200)+ & 1.5(0)+ & 0.25(0)+ & 0(0) \\
0.8(200)+ & 0(0)+ & 0(0)+ & 0(0) \\
0(200)+ & 0.5(0)+ & 0(0)+ & 0(0) \\
0(200)+ & 0(0)+ & 0.25(0)+ & 0(0)
\end{array}\right] \\
n(t+1)=\left[\begin{array}{c}
320 \\
160 \\
0 \\
0
\end{array}\right]
\end{gathered}
$$

## Leslie Matrix

\# Age structured growth - one time step
A <- matrix (c(1.6,1.5,0.25,0,0.8,0,0,0,0,0.5,0,0,0,0,0.25,0), nrow=4, byrow=TRUE)

|  | $[, 1]$ | $[, 2]$ | $[, 3]$ | $[, 4]$ |
| :--- | ---: | ---: | ---: | ---: |
| $[1]$, | 1.6 | 1.5 | 0.25 | 0 |
| $[2]$, | 0.8 | 0.0 | 0.00 | 0 |
| $[3]$, | 0.0 | 0.5 | 0.00 | 0 |
| $[4]$, | 0.0 | 0.0 | 0.25 | 0 |

N0 <- matrix(c(200, 0, 0, 0), ncol=1)

|  | $[, 1]$ |
| :--- | ---: |
| $[1]$, | 200 |
| $[2]$, | 0 |
| $[3]$, | 0 |
| $[4]$, | 0 |

N1 <- A \%*\% N0

|  | $[, 1]$ |
| :--- | ---: |
| $[1]$, | 320 |
| $[2]$, | 160 |
| $[3]$, | 0 |
| $[4]$, | 0 |

## Leslie Matrix

```
A <- matrix(c(1.6,1.5,0.25,0,0.8,0,0,0,0,0.5,0,0,0,0,0.25,0), nrow=4, byrow=TRUE)
N0 <- matrix(c(200,0,0,0),ncol=1)
years <- 6
N.projections <- matrix(0,nrow=nrow(A),ncol = years +1)
N.projections[,1]<- N0
for(year in 1:years){
    N.projections[,year+1]<- A %*% N.projections[,year]
}
```

|  |  | Year |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | [,1] | [,2] | [,3] | [,4] | [,5] | [,6] | [,7] |
| Age class | [1,] | 200 | 320 | 752 | 1607.2 | 3505.92 | 7613.312 | 16549.12 |
|  | [2,] | 0 | 160 | 256 | 601.6 | 1285.76 | 2804.736 | 6090.65 |
|  | [3,] | 0 | 0 | 80 | 128 | 300.8 | 642.88 | 1402.368 |
|  | [4,] | 0 | 0 | 0 | 20 | 32 | 75.2 | 160.72 |

## Leslie Matrix

A <- matrix $(c(1.6,1.5,0.25,0,0.8,0,0,0,0,0.5,0,0,0,0,0.25,0)$, nrow=4, byrow=TRUE) N0 <- matrix $(c(200,0,0,0), n c o l=1)$
years <- 6
N.projections <- matrix(0, nrow=nrow(A), ncol = years +1)
N.projections[,1]<- N0
for(year in 1:years)\{
N.projections[,year+1]<- A \%*\% N.projections[,year]
\}


## Leslie Matrix (different starting structure)

```
A <- matrix(c(1.6,1.5,0.25,0,0.8,0,0,0,0,0.5,0,0,0,0,0.25,0), nrow=4, byrow=TRUE)
N0 <- matrix(c(50,50,50,50),ncol=1)
years <- 6
N.projections1 <- matrix(0,nrow=nrow(A),ncol = years +1)
N.projections1[,1]<- N0
for(year in 1:years){
    N.projections1[,year+1]<- A %*% N.projections1[,year]
}
```



## Age distribution

$$
n(\mathbf{0})=\left[\begin{array}{c}
200 \\
0 \\
0 \\
0
\end{array}\right]=200
$$

$$
n(\mathbf{0})=\left[\begin{array}{l}
50 \\
50 \\
50 \\
50
\end{array}\right]=200
$$




- Dynamics initially strongly influenced by starting population age distribution
- However, populations quickly approach a stable and stationary age distribution


## Stable Age Distribution

- If Survival and Fertility schedules stay constant, the proportion of individuals in the population at each age will stay constant (Stable Age Structure) even as the population as a whole increases.
- The proportion of the population within each age $[\mathrm{c}(\mathrm{x})]$ is the number in that age divided by the total population size.
- $c(x)=\frac{e^{-r x} l(x)}{\sum_{x=0}^{k} e^{-r x} l(x)}$


## Stable age distribution

$$
\begin{aligned}
&
\end{aligned}
$$

## Finite Rate of Change

- Use population Change from $n(t)$ to $n(t+1)$ to calculate the finite rate of change ( $\lambda$ )
- $\lambda=\frac{\mathrm{n}(\mathrm{t})}{\mathrm{n}(\mathrm{t}-1)}$
- $n(\mathbf{0})=\left[\begin{array}{c}200 \\ 0 \\ 0 \\ 0\end{array}\right]=200$

$$
\begin{aligned}
\lambda= & \frac{480}{200}=2.4 \\
& r=\ln \lambda=\ln 2.4=0.875
\end{aligned}
$$

- $n(\mathbf{1})=\left[\begin{array}{c}320 \\ 160 \\ 0 \\ 0\end{array}\right]=480$


## Stable age distribution

$$
\begin{aligned}
& \lambda=\frac{\mathrm{n}(\mathrm{t})}{\mathrm{n}(\mathrm{t}-1)} \\
& r=\ln \lambda
\end{aligned}
$$

## Assumptions

- Assumptions associated with Exponential Growth...
- Closed population
- No genetic structure
- No time lags
- Within Age-structured Populations
- Assume $I(x)$ and $b(x)$ schedules are constant
- no resource limitation


## Cohort vs Static Life Tables

- Cohort Life Tables - follow an entire cohort from birth to death to determine age-specific survivorship and fecundity schedules.
- Static Life Table - cross section of the population at a given time interval. Used to calculate short-term mortality rates by comparing number of individuals within each consecutive age class.
- Also assumes population has reached a stable age structure


## Changes in Age structure of populations over time

Changing age structure in Canadian Populations, and future projections



## State structured matrix model

Life Stage, rather than Age, Models (Lefkovitch Matrices)

- Fecundity and survivorship may be based more on life stage than absolute age
egg tadpole adult
$\underset{\text { tadpole }}{\text { egg }}$ adult $\left[\begin{array}{ccc}0 & 0 & F_{a-e} \\ P_{e-t} & \boldsymbol{P}_{t-t} & 0 \\ 0 & P_{t-a} & P_{a-a}\end{array}\right]$



## Stage structured model


\# Stage structured growth: frog 1
A <- matrix $(c(0,0,2.8,0.5,0.2,0,0,0.4,0.3)$, nrow=3, byrow=TRUE) N0 <- matrix(c(80,50,10), ncol=1)

$$
A=\begin{array}{rrrr} 
& {[, 1]} & {[, 2]} & {[, 3]} \\
{[1,]} & 0.0 & 0.0 & 2.8 \\
{[2,]} & 0.5 & 0.2 & 0.0 \\
{[3,]} & 0.0 & 0.4 & 0.3
\end{array}
$$

## Stage structured model

\# Stage structured growth: frog 1
A <- matrix $(c(0,0,2.8,0.5,0.2,0,0,0.4,0.3)$, nrow=3, byrow=TRUE)
N0 <- matrix(c(80,50,10),ncol=1)
years <- 30
N.projections1 <- matrix(0,nrow=nrow(A),ncol = years +1)
N.projections1[,1]<- N0
for(year in 1:years)\{
N.projections1[,year+1]<- A \%*\% N.projections1[,year] \}


Dynamic link between stage classes

## Stage structured model

\# Stage structured growth: frog 1
A <- matrix $(c(0,0,2.8,0.5,0.2,0,0,0.4,0.3)$, nrow=3, byrow=TRUE)
N0 <- matrix $(c(80,50,10), n c o l=1)$
years <- 30
N.projections1 <- matrix(0,nrow=nrow(A),ncol = years +1)
N.projections1[,1]<- N0
for(year in 1:years)\{
N.projections1[,year+1]<- A \%*\% N.projections1[,year] \}


What does this suggest about $r$ ?
What does this suggest about perturbation at $t=0$ ?

## Stage structured model

```
A <- matrix(c(0,0,2.5,0.5,0.2,0,0,0.4,0.3), nrow=3, byrow=TRUE)
N0 <- matrix(c(80,50,45), ncol=1)
years <- 30
N.projections1 <- matrix(0,nrow=nrow(A),ncol = years +1)
N.projections1[,1]<- N0
for(year in 1:years){
    N.projections1[,year+1]<- A %*% N.projections1[,year]
}
```



## Life history complexity


$A=\left(\begin{array}{r}0 \\ 0.966 \\ 0.013 \\ 0.007 \\ 0.001 \\ 0\end{array}\right.$

wild teasel
H Caswell.

Matrix Population Models: Construction, Analysis, and Interpretation.
Sinauer Associates, Sunderland, MA, 2nd edition, 2001.

## Population sampling

$$
N_{t}=N_{0} e^{r t}
$$

$$
\frac{d N}{d t}=r N\left(1-\frac{N_{t-\tau}}{K}\right)
$$

$$
K
$$

$$
N_{t}=\overline{1+\left[\left(K-N_{0}\right) / N_{0}\right] e^{-r t}}
$$

$$
n(t+1)=A n(t)
$$

## Population sampling

## Estimating N



## N is always estimated (sampled)

- Distribution not a point estimate
- Measure of central tendency (mean)
- Measure of variation (standard deviation)
- Accuracy
- The distance of the measured value from the "true" value
- Precisions
- The degree of aggregation of the measured values
- Confidence intervals
- Bias
- A consistent directional disparity between the measured value and the true value.


## Normal vs. Poisson






\# Poisson distribution
$\mathrm{x}<-\mathrm{c}(0: 12)$
lamda <- 8 \# 0.1, 0.5, 1,2,3,8
p <-dpois(x,lamda)
barplot $(p$, axes $=$ TRUE, names.arg $=x$,
$y \lim =c(0, \max (p)+0.1)$,
ylab $=$ " $P(X)$ "
)
mtext(paste("lamda = ",lamda),side=3, outer=FALSE,line=-3,cex=1.5)

## Population sampling strategies

- Random sampling

- Stratified random sampling
- Stratified sampling
- Systematic sampling
- Objective: high accuracy, least bias, greatest precision, lowest cost



## Population sampling strategies

- Random sampling


Number
Density

- Minimizes the amount our estimate of $N$ is confounded by unknown or unmeasured variables
- Minimize bias (unknown, accessibility, judgement)
- Unknown (unknowable) environmental heterogeneity



## Population sampling strategies

- Stratified random sampling


Number
Density

- Assumed underlying ecological structure (grouping, subpopulations)
- Aggregate sampling by strata
- Random sampling within strata
- Unknown structure within strata



## Population sampling strategies



Number
Density

- Stratified sampling
- Assumed underlying ecological structure (grouping)
- Aggregate sampling by strata
- Systematic sampling within strata



## Population sampling strategies



- Systematic sampling
- Known or unknown ecological structure

Number
Density



## Population density sampling

- Quadrat counts
- Line transects
- Distance metrics


## Quadrat counts

- Count plants/ animals in a known area
- Simplest technique fore density estimation
- Counts can be taken from units using any number of sample designs: random, stratified random, systematic..

- Assumptions
- All individuals in the quadrate are observed
- Quadrat samples are representative of the study area as a whole
- Individuals don't move between quadrats during a sampling session



## Quadrat counts

- Statistical extrapolation
- Relate distribution of counts to a statistical distribution
- Use count distribution not a continuous distribution
- Devise a statistical model that estimates population size



## Line transects

- Used to calculate density of animals in rectangular "quadrats"



## Line transects

- Used to calculate density of animals in rectangular "quadrats"
- If detectability $100 \%$ simple count
- If detectability $<100 \%$ then develop detection function to estimate density

$$
\widehat{D}=\frac{n}{2 L a}
$$

$\widehat{D}=$ density of animals per unit area
$\mathrm{n}=$ number of animals seen on transect
$\mathrm{L}=$ length of transect
$\mathrm{a}=$ detection constant (detection probability vs distance)

## Distance methods

- Distance to individual from random point
- Distance to nearest neighbor

REDWOOD SEEDLINGS


$$
\widehat{N_{2}}=\frac{N}{\pi \sum\left(r_{i}^{2}\right)}=\text { trees } / \mathrm{m}^{2}
$$

