# ECO 602 Analysis of Environmental Data

FALL 2019 - UNIVERSITY OF MASSACHUSETTS DR. MICHAEL NELSON

# Today's Agenda

More nonparametric (and parametric) OLS inference Resampling methods:

Bootstrapping

Monte Carlo sampling

ANOVA table partitioning variance

Wilcoxon signed rank test

**Predictions** 

# Today's Agenda

- Confidence interval visualization
- More nonparametric (and parametric) OLS inference
- Resampling
- T tests and Wilcoxon signed-rank tests
- Maximum Likelihood preview

# Visualizing confidence intervals

https://seeing-theory.brown.edu/frequentist-inference/index.html#section2

# Today's Agenda

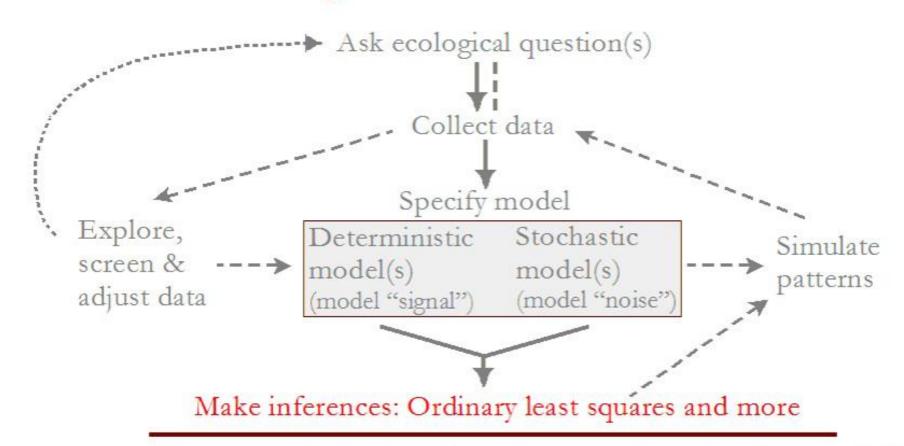
Confidence interval visualizations

Seeing theory

Model para m cCIs

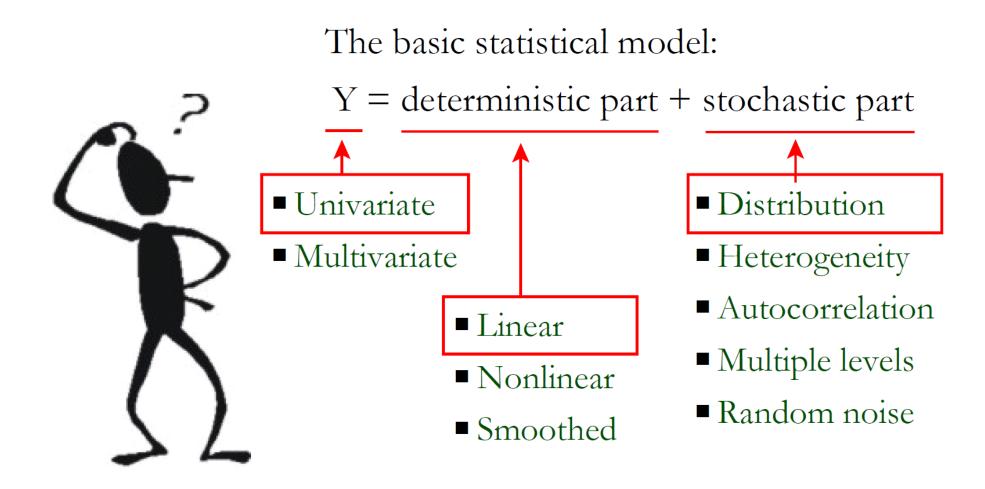
Hypotheses of slope vs intercept

- Much of the mathematical hardware is similar to parametric inference.
- Main difference: no attempt to guess a theoretical distribution for the population.
- Main consequence: weaker inference
- 'Nonparametric' refers to the lack of an explicit stochastic model for the population.
- We usually calculate statistics in nonparametric inference!



Nonparametric inference involves confronting the model
with data to estimate parameters, test hypotheses,
compare alternative models, or (with difficulty) make
predictions, without specifying a probability distribution

## Landscape of Statistical Methods...



#### What is the statistical model?

■ Do brown creepers increase in relative abundance with increasing extent of latesuccessional forest?

#### Statistical Model:

$$y_{i} = b_{0} + b_{1}x_{i} + e_{i}$$
Parameters Unspecified

# Brown creeper vs. Late-succesional forest Deterministic component Brown creeper abundance Stochasite component 100 Extent of late-successional forest

#### Estimate model parameters: OLS method

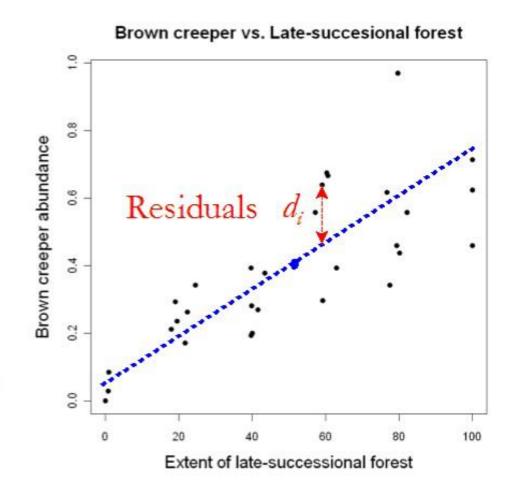
1. Define measure of (lack of) fit:

$$d_i = y_i - \hat{y}_i$$

$$\hat{y}_i = b_0 + b_1 x_i$$

$$d_i = y_i - b_0 - b_1 x_i$$

$$L(Y_i|b_0,b_1) = \sum_{i=1}^n d_i^2 = \sum_{i=1}^n (y_i - b_0 - b_1 x_i)^2$$



# How wo we minimize our lack-of-fit function?

We might require that the best fit line passes through the point at the mean of x and mean of y.

We could try to guess values of slope and intercept parameters that minimize lack-of-fit.

But...

If we do this, we've constrained our possibilities

# How wo we minimize our lack-of-fit function?

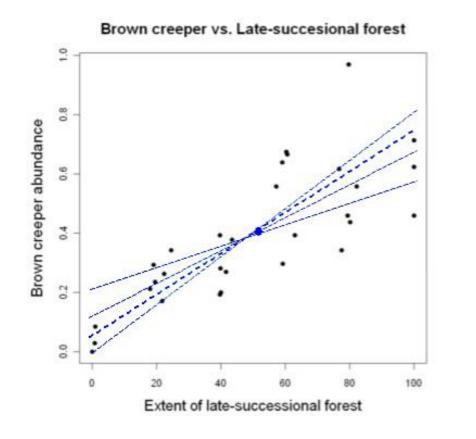
We might **require** that the best fit line passes through the point at the mean of x and mean of y.

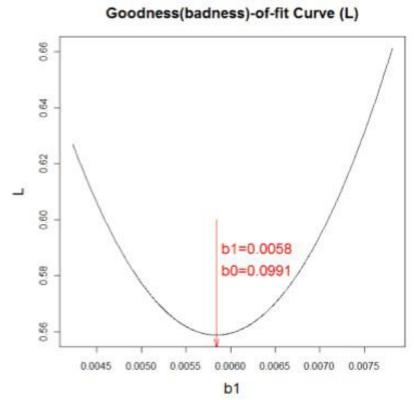
If we do this, we've constrained our possibilities!

How many parameters are actually free with this requirement?

### Estimate model parameters: OLS method

- 2. Find estimates that minimize  $L(Y_i | b_0, b_1)$ 
  - ▶ Numerical solution





# Seems reasonable, but what could go wrong?

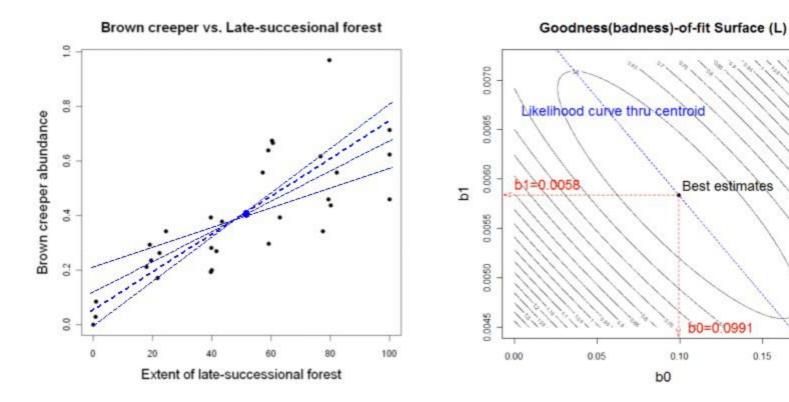
How certain are we about the mean values of the predictor and response?

In the sample?

In the population?

#### Estimate model parameters: OLS method

- 2. Find estimates that minimize  $L(Y_i | b_0, b_1)$ 
  - ▶ Numerical solution



Best estimates

b0=0 0991

b0

0.15

# What if we didn't require passage through the centroid?

#### Estimate model parameters: OLS method

- 2. Find estimates that minimize  $L(Y_i | b_0, b_1)$ 
  - ► Analytical solution

$$\frac{dL(Y_i|b_0,b_1)}{db_1} = -2\sum_{i=1}^n x_i(y_i - b_0 - b_1x_i)$$

Set to zero and solve for  $b_1$ 

Sums of squares & products:

$$SSXY = \sum_{i=1}^{n} (x_i - \overline{x}_i)(y_i - \overline{y}_i)$$

$$SSX = \sum_{i=1}^{n} (x_i - \overline{x}_i)^2$$

$$SSY = \sum_{i=1}^{n} (y_i - \overline{y}_i)^2$$

$$b_1 = \frac{SSXY}{SSX}$$

$$b_0 = \overline{y} - b_1 \overline{x}$$

#### Example:

$$b_1 = 0.0058$$
  
 $b_0 = 0.0991$ 

Estimate model parameters: OLS method

Pros and Cons of OLS Estimation:



- No assumptions about the error required
- Squared deviations make analytical solutions easier
- If the errors are normally distributed, then the sums of squares is identical to other methods of estimation
- No a priori justification for using the squared measure of deviation, which has an accelerating penalty

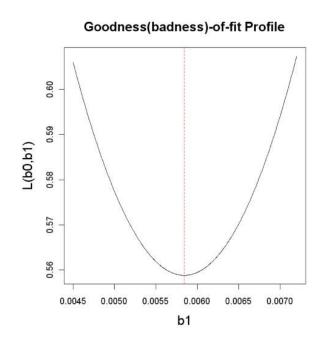
# Nonparametric confidence intervals

#### Nonparametric Inference...

Confidence intervals for model parameters

What is a confidence interval?

- *Interval* estimate of the uncertainty associated with each of the estimated parameters; in other words, the precision of our estimate
- "Were this procedure to be repeated on multiple samples, the calculated confidence interval (which would differ for each sample) would encompass the true population parameter say 95% of the time"



# What kind of confidence interval have we considered?

Remember: Standard Errors can be calculated for any statistic (parameter estimate).

What about a CI for a slope or intercept?

# Resampling Methods

Create new samples from our existing sample.

It sounds like cheating, but....

Remember our random sampling scheme?

 Nonparametric inference can't help us if we use a poor sampling design.

Bootstrapping and Monte Carlo methods

# What to resample?

What does resampling mean?

Should we use replacement?

# Nonparametric CI: Bootstrapping

#### Nonparametric Inference...

Confidence intervals for model parameters

Nonparametric bootstrap confidence interval:

 Repeatedly resample the data, with replacement, and recompute the parameter estimate each time

Obs Y	$\underline{\mathbf{X}}$	Ob	$\underline{s} Y$	$\underline{\mathbf{X}}$	
1 y <sub>1</sub>	x <sub>1</sub>	2	$y_2$	$\mathbf{x}_2$	ъ
2 y <sub>2</sub>	$x_2$	3	$y_3$	$\mathbf{x}_3$	Bootrap sample
3 y <sub>3</sub>	x <sub>3</sub>	2	$y_2$	$\mathbf{x}_2$	
4 y <sub>4</sub>	$X_4$	<b>1</b>	$y_1$	$\mathbf{x}_1$	
D		3	У3	$X_3$	2015
Repeat many times		3	<b>y</b> <sub>3</sub>	$X_3$	Bootrap
		1	$y_1$	$\mathbf{x}_1$	sample 2
		4	$y_4$	$X_4$	•

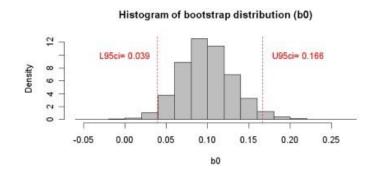
# (Re)sampling distributions of estimates

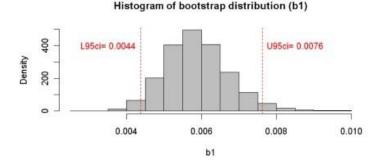
#### Nonparametric Inference...

Confidence intervals for model parameters

Nonparametric bootstrap confidence interval:

- Repeated sampling of the data, with replacement, to empirically generate the sampling distribution of the estimate
- Quantiles of the bootstrap distribution give the specified confidence interval





# Parametric slope/intercept CIs

If we use parametric inference, we can often\* find a closed-form solution for parameter estimates and standard errors/confidence intervals!

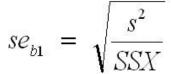
But we often cannot find analytical solutions for the models we actually want to use!

### Confidence intervals for model parameters

#### Parametric confidence interval:

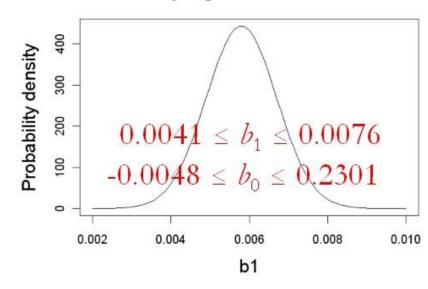
■ Calculate the *standard error* of the parameter estimate and multiply it by the appropriate value of Student's t and then subtract this interval from, and add it to, the parameter estimate to get the corresponding confidence interval

$$s^2 =$$
Error variance



$$se_{b0} = \sqrt{\frac{s^2 \sum x^2}{n \cdot SSX}}$$

#### Sampling distribution of b1



$$95\%CI = b_1 \pm t_{0.025,n-2} se_{b1}$$

$$se_{b0} = \sqrt{\frac{s^2 \sum x^2}{n \cdot SSY}}$$
 95%CI =  $b_0 \pm t_{0.025, n-2} se_{b0}$ 

#### Hypothesis testing

#### Null hypothesis:

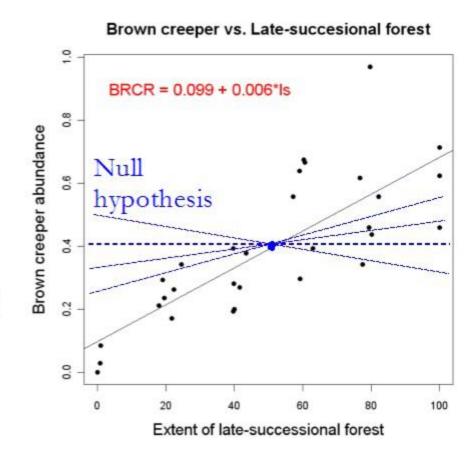
■ The slope of the regression line is zero; i.e., no dependence of y on x

#### *p*-value:

■ The probability of observing the observed slope or something more extreme (an even steeper slope) (under hypothetical repeated sampling) if the null hypothesis were true

#### Decision rule:

■ If p<0.05 (Type I error rate), reject null hypothesis



# Resampling x and y

Monte Carlo resampling

Sample predictor/response variables separately.

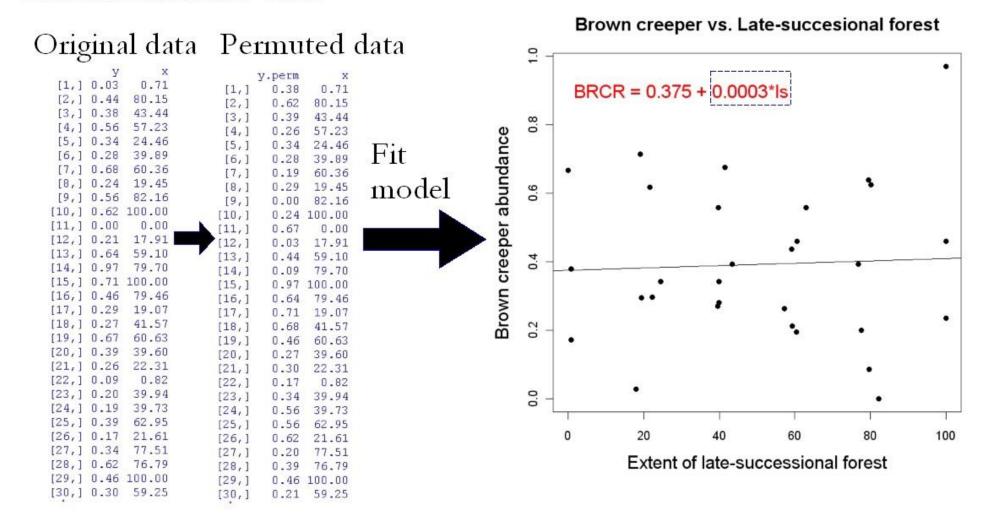
Readings say "remove structure"

Null hypothesis: MC resampling

Alternative hypothesis: Bootstrapping

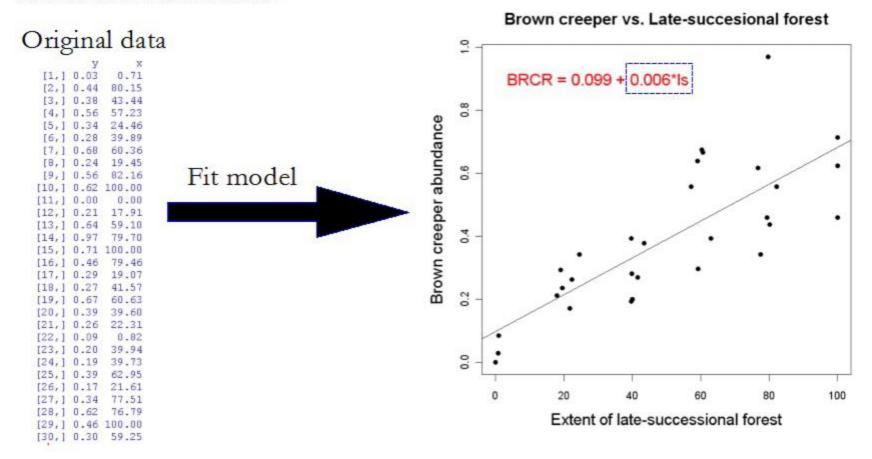
### Hypothesis testing

#### Randomization test:



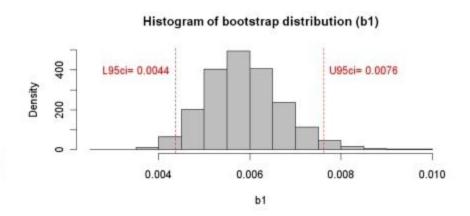
#### Hypothesis testing

#### Randomization test:

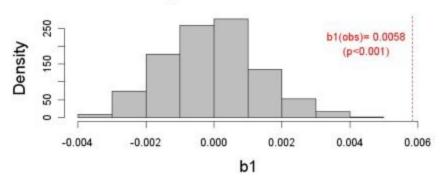


#### Bootstrap versus randomization procedures

- Bootstrap... repeated resampling of the original data with replacement to generate the sampling distribution of the test statistic under the alternative hypothesis, used for interval estimation!
- Randomization... repeated resampling of the original data after removing real structure via randomization to generate the sampling distribution under the <u>null</u> hypothesis, used for hypothesis testing!







# Bootstrap visualization

https://seeing-theory.brown.edu/frequentist-inference/index.html#section2

# Prediction is harder for nonparametric!

Parametric is easy.

Nonparametric requires resampling or simulation methods.

#### Predictions

#### Parametric predictions:

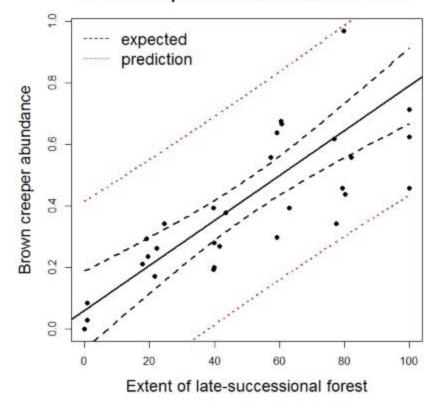
- Point estimates... apply the fitted deterministic model to new values of x
- Interval estimates... Calculate the standard error for a <u>predicted</u> value and construct as before

$$s^2 =$$
Error variance

$$se_{\hat{y}} = \sqrt{s^2 \left[ 1 + \frac{1}{n} + \frac{\left(x - \overline{x}\right)^2}{SSX} \right]}$$

$$95\%PI = \hat{y} \pm t_{0.025, n-2} se_{\hat{y}}$$

#### Brown creeper vs. Late-succesional forest

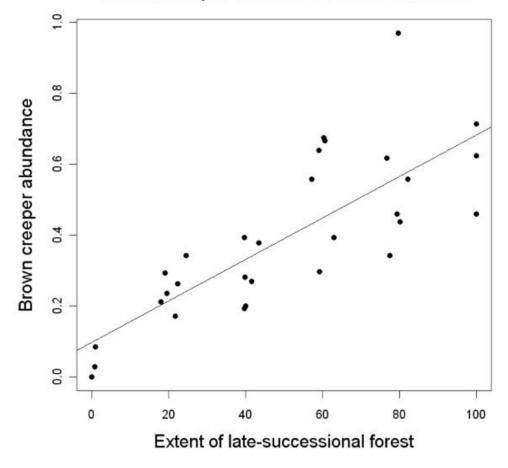


#### **Predictions**

#### Nonparametric predictions:

- Point estimates... apply the fitted deterministic model to new values of x
- Interval estimates... much more difficult to do; requires complex bootstrap procedure?

#### Brown creeper vs. Late-succesional forest



# Simpler nonparametric test: Wilcoxon signed rank-sum test

Kind of like a nonparametric analogue of a paired 2-sample ttest

Test two populations, often repeated measurements, for significant difference.

Useful when assumptions of independence, normality, etc are invalid.

#### Common examples:

- Grades for same students in 3<sup>rd</sup> and 4<sup>th</sup> graders.
- Drug efficacy, measured before and after

## Wilcoxon rank-sum

For each paired observation:

-1 if 2<sup>nd</sup> observation smaller, otherwise 1

What would we expect if there was no difference?

## Wilcoxon rank-sum

Null hypothesis is that sums are the same in the before and after populations.

## Likelihood

Shared element between frequentist and Boolean paradigms.

## Likelihood: Likelihood function

What combination of parameters make our observed data most likely?

#### Frequentist Parametric Inference...

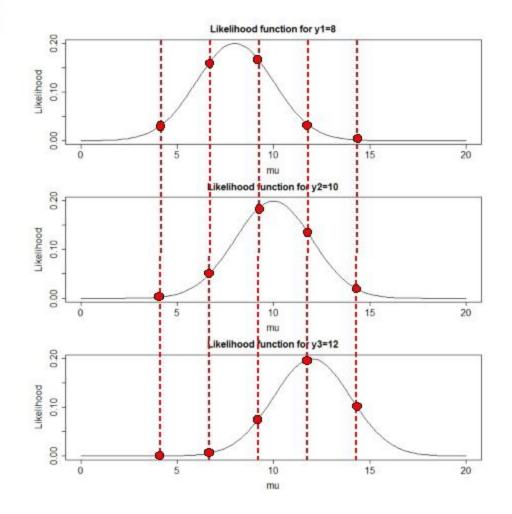
#### Estimate model parameters: MLE method

1. Define measure of (lack of) fit: *Likelihood* 

$$L\left\{Y_{i} = 8 | \mu_{\mathbf{m}}, \sigma_{m}\right\} = \frac{1}{\sigma \sqrt{2\pi}} \exp\left(-\frac{\left(y_{i} - \mu\right)^{2}}{2\sigma^{2}}\right)$$

$$L\{Y_i = 10 | \mu_{\mathbf{m}}, \sigma_{\mathbf{m}}\} = \frac{1}{\sigma \sqrt{2\pi}} \exp\left(-\frac{(y_i - \mu)^2}{2\sigma^2}\right) \qquad \stackrel{\text{op}}{=} \frac{2}{\sigma}$$

$$L\{Y_i = 12 | \mu_m, \sigma_m\} = \frac{1}{\sigma \sqrt{2\pi}} \exp\left(-\frac{(y_i - \mu)^2}{2\sigma^2}\right)$$



## Likelihood: Likelihood function

OLS likelihood function is pretty easy.

Most likelihood functions are not!

## For next time:

Finish Likelihood chapter (McGarigal ch. 9) Start Bayesian (McGarigal ch. 10)