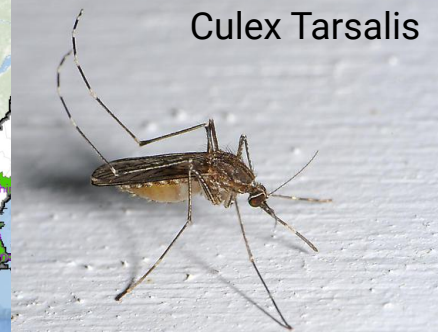
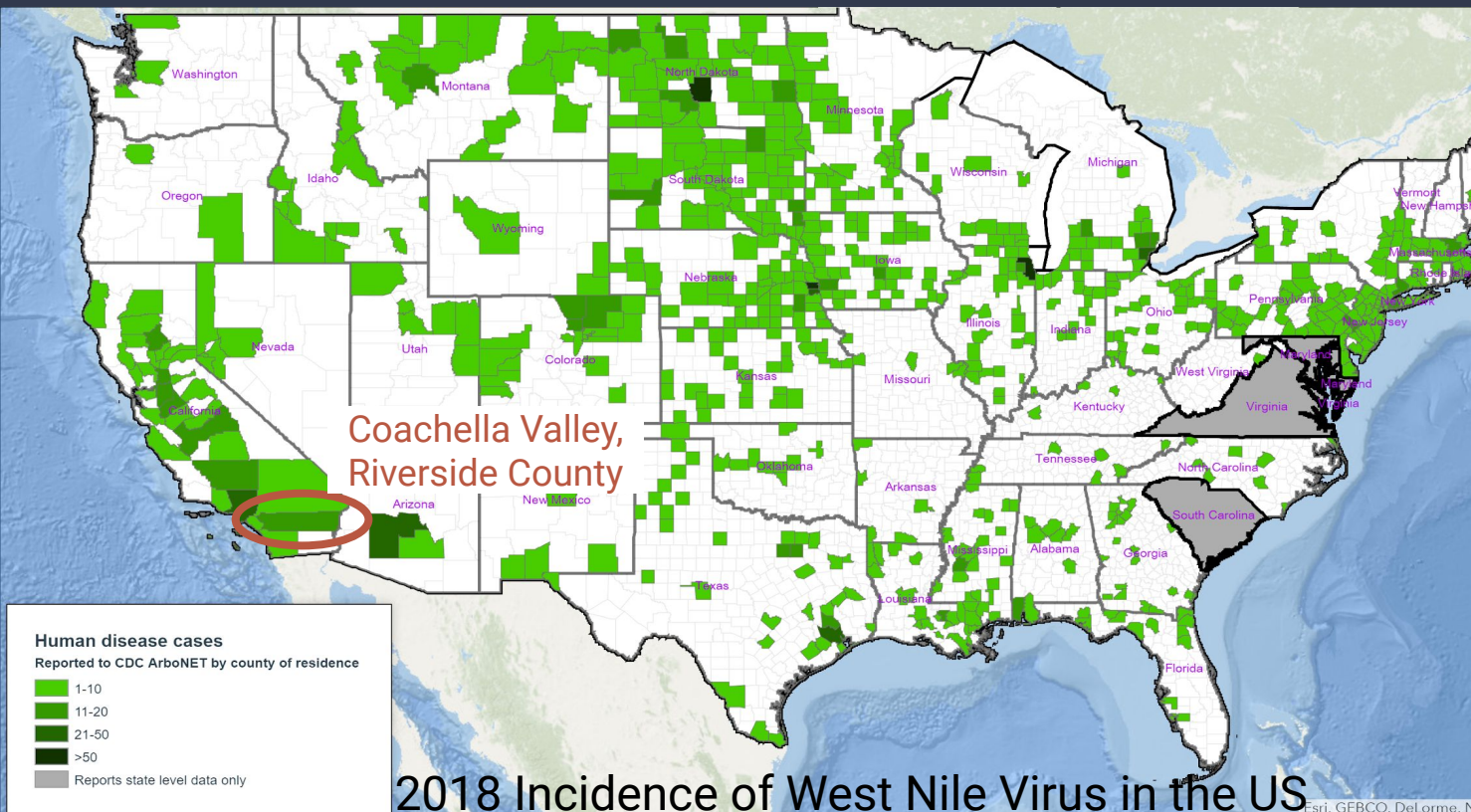


Mosquito Abundance Estimation in the Coachella Valley

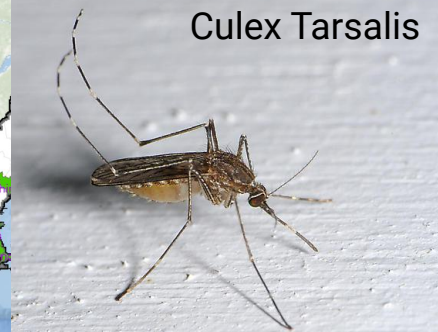
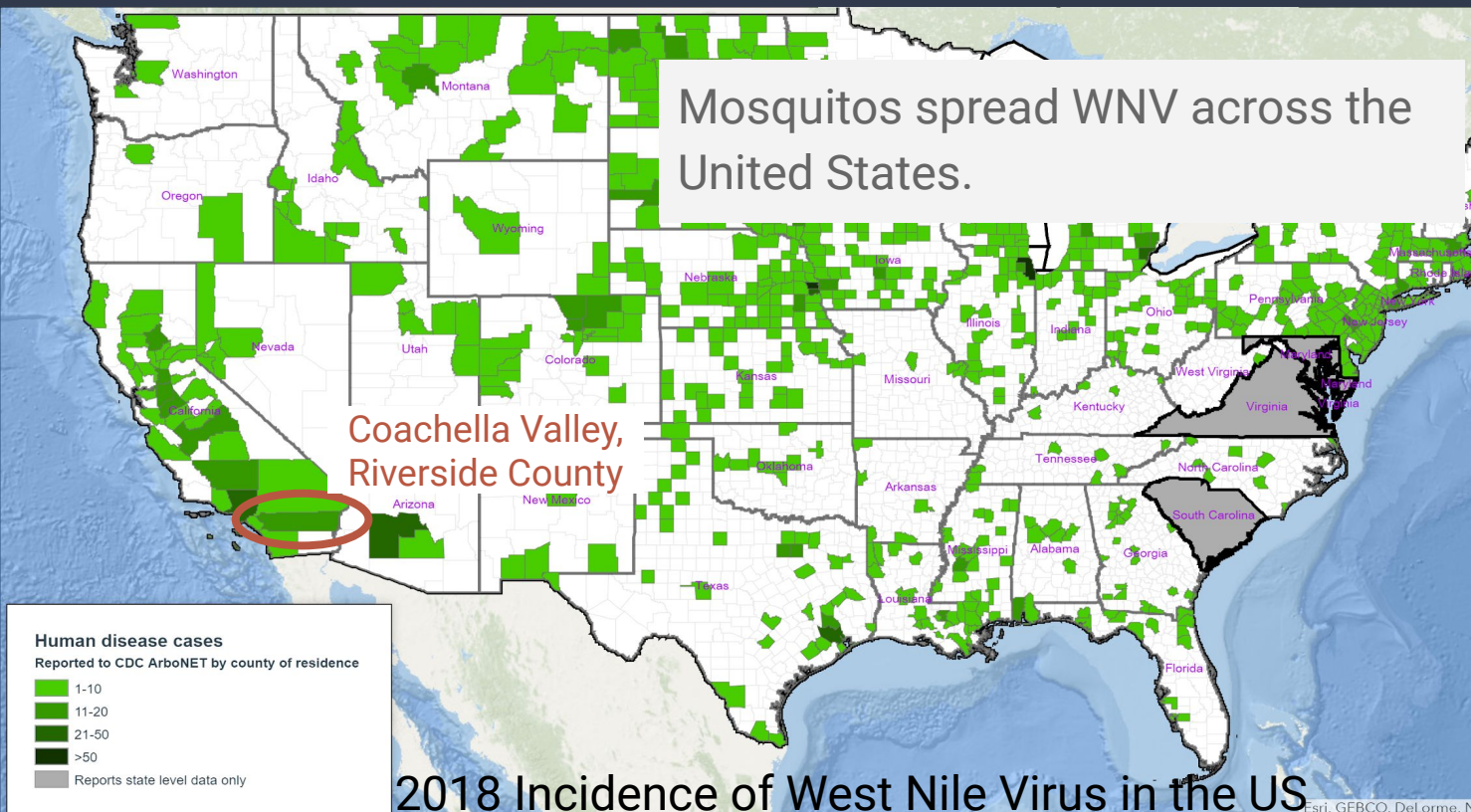
May 29, 2019

Jacob Shultz
Joseph Cole

Problem and Objectives

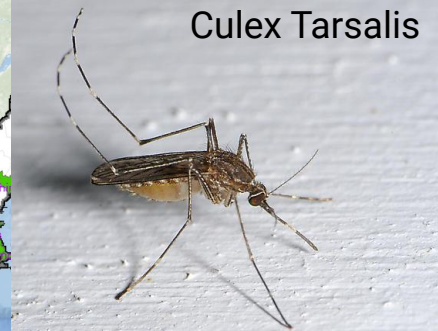
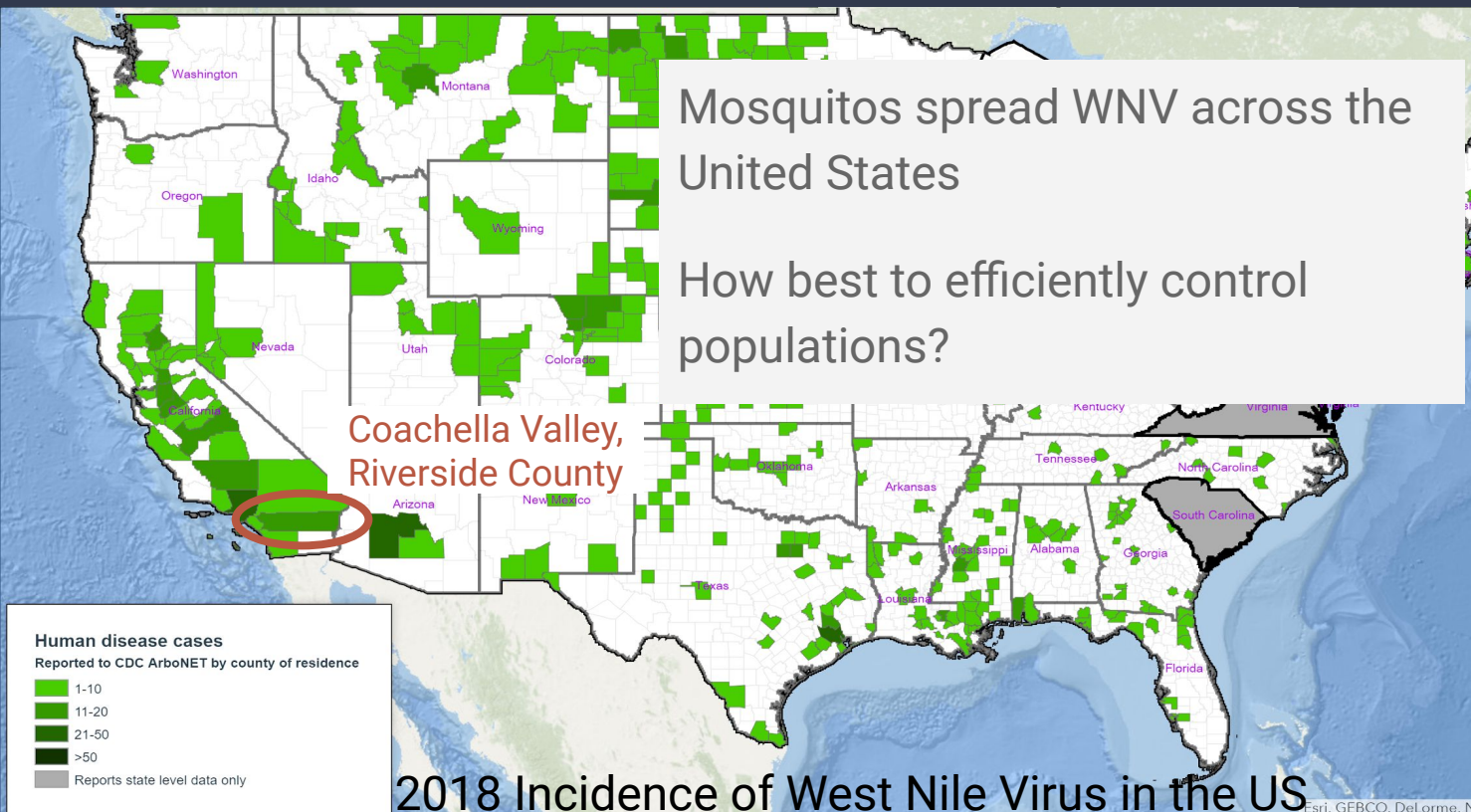


Problem and Objectives

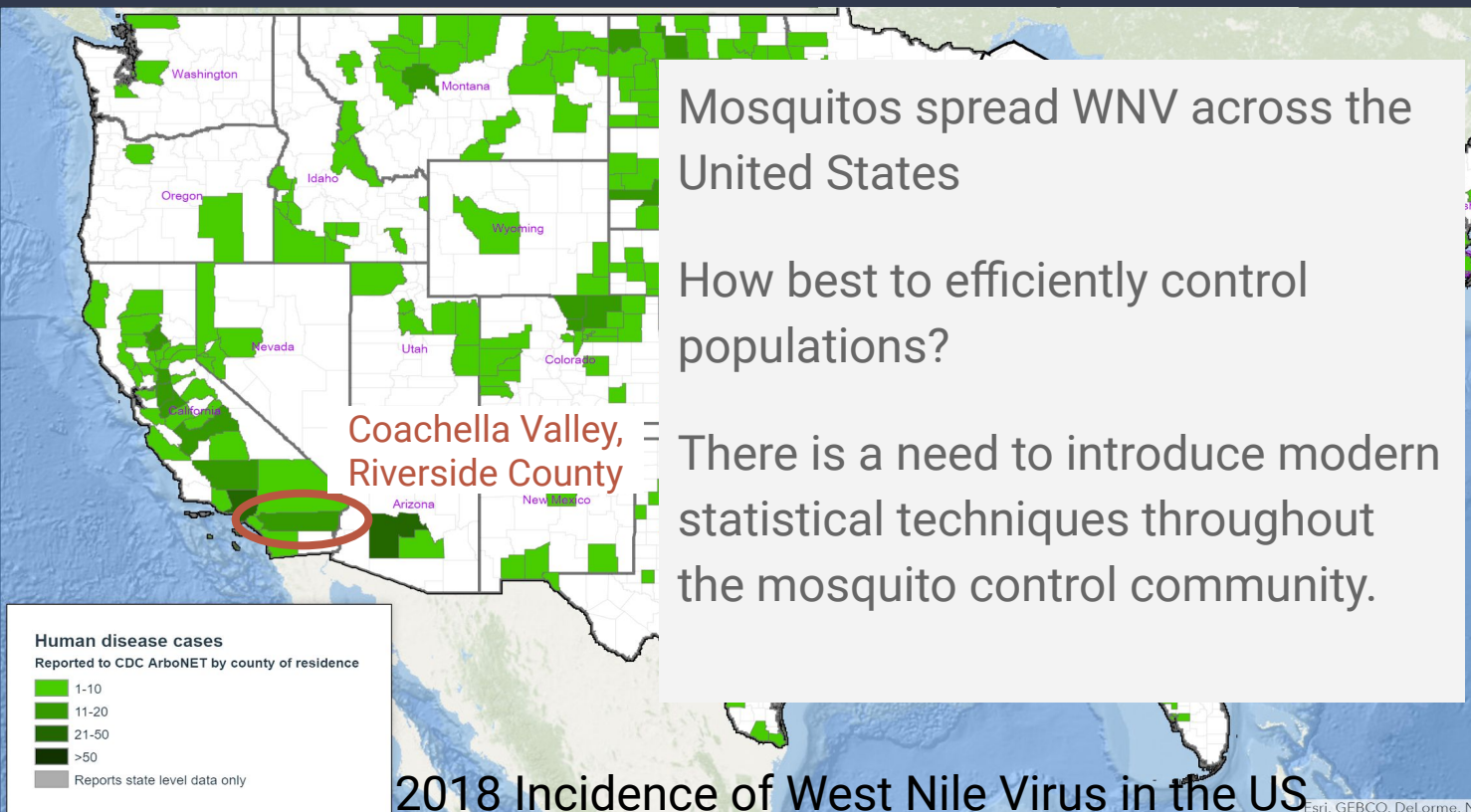


Pelecanus Occidentalis

Problem and Objectives



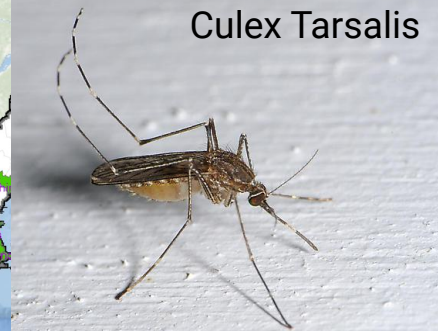
Problem and Objectives



Mosquitos spread WNV across the United States

How best to efficiently control populations?

There is a need to introduce modern statistical techniques throughout the mosquito control community.



Data Description



Data Summary

Primary Model Inputs

Trap Number: i

- Integer in [1, 64] describing which trap the data was collected from
- Trap 28 removed due to zero samples taken

Time: t

- Integer in [1, 42] describing when the sample was taken
- An increase in 1 corresponds to a change in two weeks
- Ranges from Apr 1994 to Nov 1995 (Gap from Oct 1994 to Feb 1995)

Count: $n_{i,t}$

- Integer in [0, 7936] describing the number of *Culex tarsalis* captured at trap i during time period t
- Treated as a continuous response

Predictor	Site/Obs Level	Data Type	Description
Latitude	Site	Continuous [33.44, 33.55]	Latitude of trap i
Longitude	Site	Continuous [-116.15, -115.89]	Longitude of trap i
Dist to sea	Site	Continuous [0.20, 9.78]	Distance from trap i to the Salton Sea
Max Temp (tenths of degrees C)	Obs	Continuous [261.9, 453.6]	Average of all daily highs within time period t
Observed Temp (tenths of degrees C)	Obs	Continuous [233.7, 433.9]	Average of all temps taken at 17:00 within time period t
Biomes (9 types)	Site	Continuous [0, 1]	Percent biome surrounding a trap

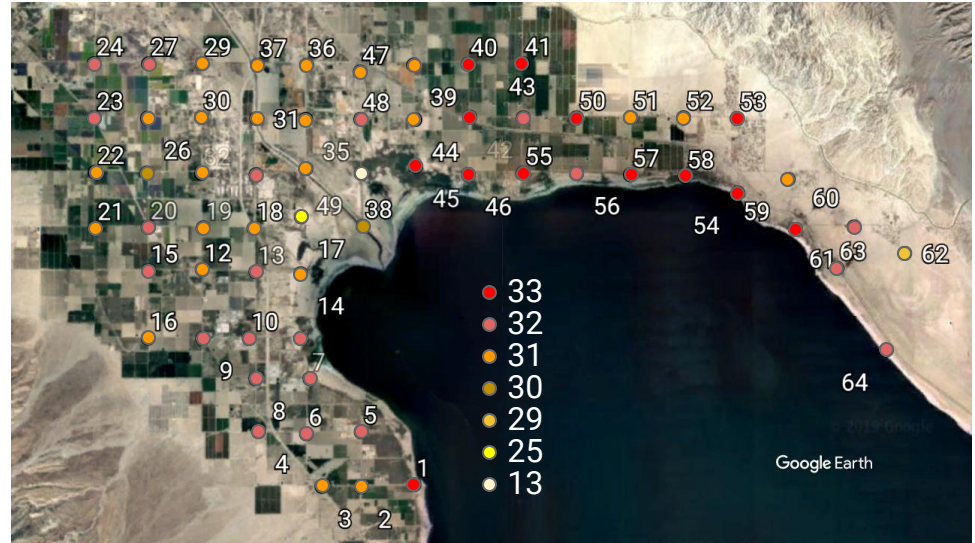
Exploratory Data Analysis

Mosquito Counts Over Time



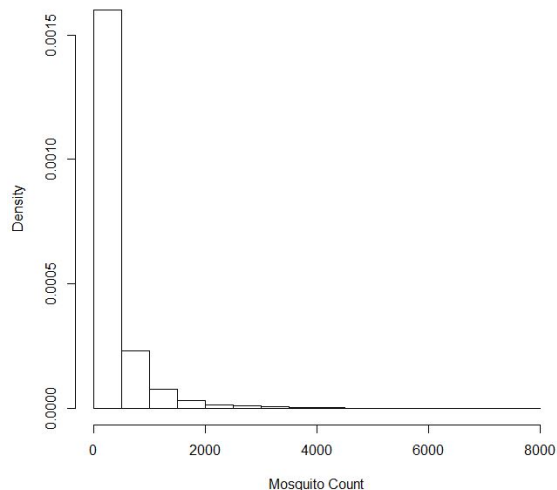
Google Earth

Number of Time Samples from Each Trap



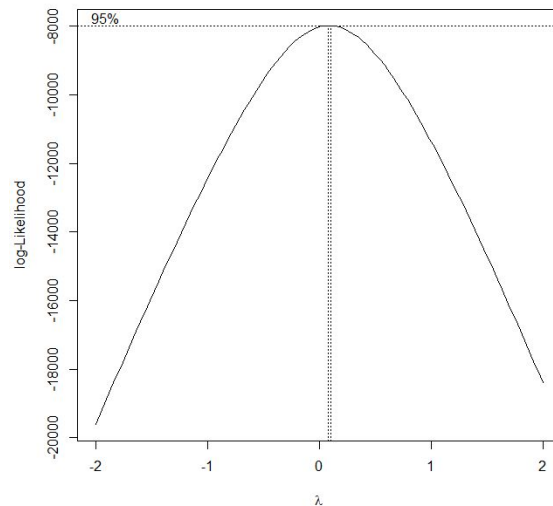
Exploratory Data Analysis

Distribution of Raw Count Data
(All traps, all time)



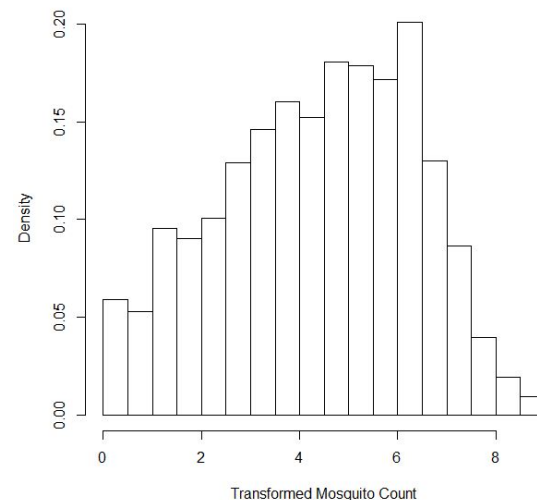
Skew: 5
Kurtosis: 38

Box-Cox Likelihood of
Transformation Power



Optimal data transform ($\lambda=0.1$) is close
to that used by Reisen ($\lambda=0$).

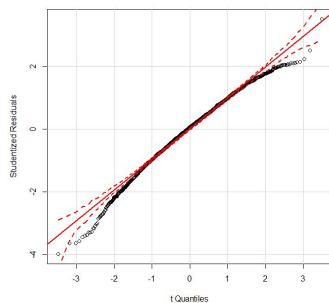
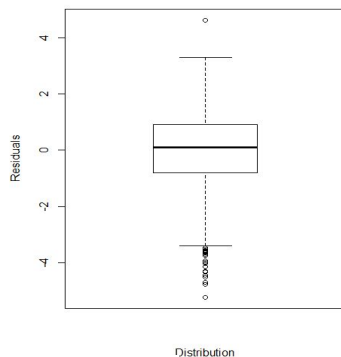
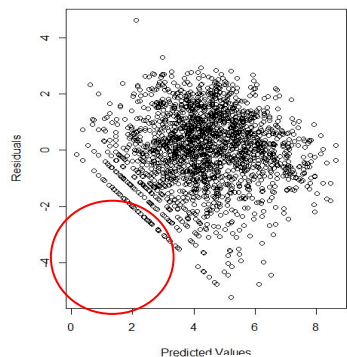
Distribution of Transformed
Count Data



Skew: -0.3
Kurtosis: 2.3

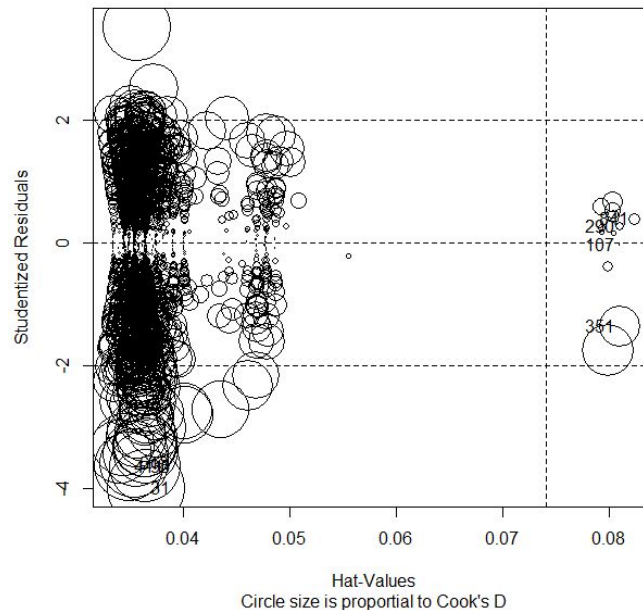
Exploratory Data Analysis

Linear Model Residual Diagnostics



Residuals form a left skewed distribution that has a heavier than expected tail on the left and a lighter than expected tail on the right. This is consistent with the failure of the response transformation to fully normalize the data.

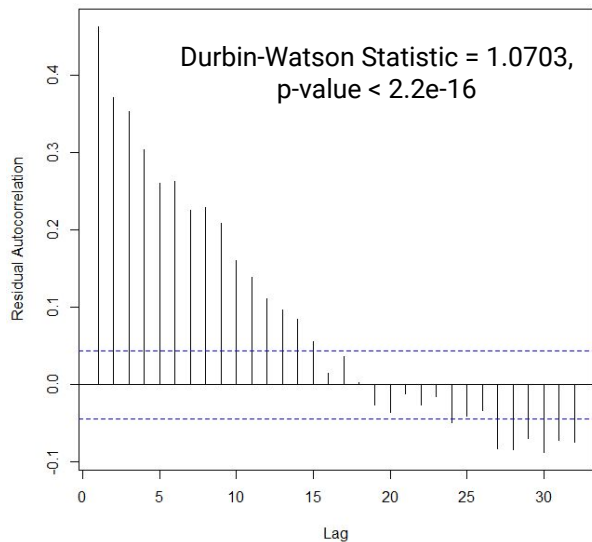
Identification of High Influence Data



Exploratory Data Analysis

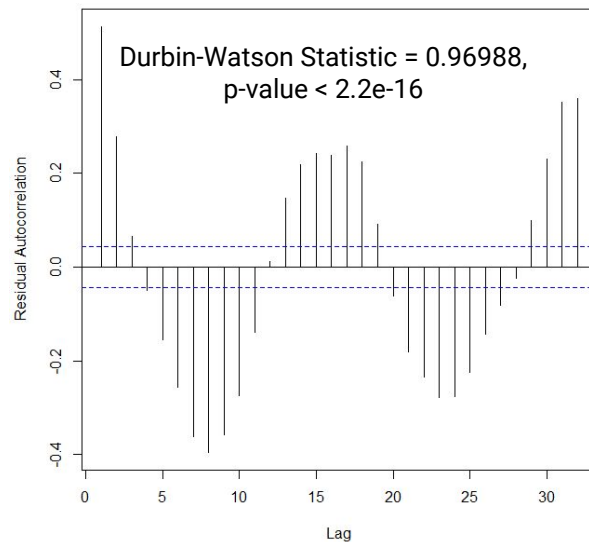
Evidence for the Need to Model Population Dynamics

Data ordered:
First by time period
Then by trap number



Correlation between nearby traps could indicate a need to model spatial dynamics.

Data ordered:
First by trap number
Then by time period



Correlation through time could indicate inadequate modelling of seasonal fluctuations.

Exploratory Data Analysis

Considerations for Model Selection

Covariate alternatives explored:

- | | | |
|----|-----------------------------|--------------------------------|
| 1) | Latitude/Longitude | vs. Distance to Salton Sea |
| 2) | Trap Number (as a factor) | vs. Habitat ratios and Lat/Lon |
| 3) | Year and Month (as factors) | vs. Time ID |
| 4) | Month (as a factor) | vs. Temperature |
- (selected options)

- Variance Inflation Factors used to find incompatible groups of covariates
- R^2_{adj} used as a rough model selection metric

Methodology: N-Mixture Model for Closed Populations

Goal: Estimate these primary model parameters

$p = P(\text{trapping an individual} \mid \text{individual in the sphere of influence of trap})$

$\lambda = \text{Abundance at a single site}$

Both parameters can be estimated with a simple intercept model or using vectors of covariates β_p and β_λ .

Open/Closed Populations:

- Closed populations have a constant site-level populations over time
- Open populations can have “additions or deletions” in site-level populations (Dail and Madson, 2011)
 - Require modeling of population dynamics...

Methodology: N-Mixture Model for Open Populations

Goal: Estimate all of these (Note abundance is now *initial* abundance)

Primary model parameters:

p = P(trapping an individual | individual in the sphere of influence of trap)

λ = Abundance at a single site at the first time step

Population dynamics:

γ = Arrival rate

ω = Survival percentage between time steps

Again, parameters can be estimated with a simple intercept model or using vectors of covariates β_p , β_λ , β_γ , and β_ω .

Fits a markov chain describing abundance through time

Testing For Closure

Key Concept:

Setting $\{\gamma = 0 \text{ and } \omega = 1\}$ in the open model implies a closed model assumption. Therefore, these models are nested and we can use LRT to test for closure

$$\begin{aligned} LR &= -2 \ln \left(\frac{\sup(L \text{ under closed assumption})}{\sup(L \text{ under open assumption})} \right) \\ &= -2 \ln \left(\frac{\sup(L(p, \lambda, |\gamma = 0, \omega = 1, \{n_{it}\}))}{\sup(L(p, \lambda, \gamma, \omega | \{n_{it}\}))} \right) \end{aligned}$$

LR is distributed as a mixture of $\chi^2_{(0)}$, $\chi^2_{(1)}$, and $\chi^2_{(2)}$ since γ and ω are on the edges of Θ .

Results:

For intercept-only models $LR = 2765.518$, providing strong evidence against closure

Intercept Model Parameter Estimates

All estimates were fit under intercept models (no covariates) using the `unmarked` package

	AIC	$\hat{\lambda}$	\hat{p}	$\hat{\gamma}$	$\hat{\omega}$
Open Population	12974.97	952.541	0.6439376	2.0719353	0.6509723
Closed Population	15736.49	7069.499	0.05684929	N/A	N/A

Open population assumption seems more reasonable

- Fitted abundance is more consistent with count summary statistics
- Smaller AIC in open population model

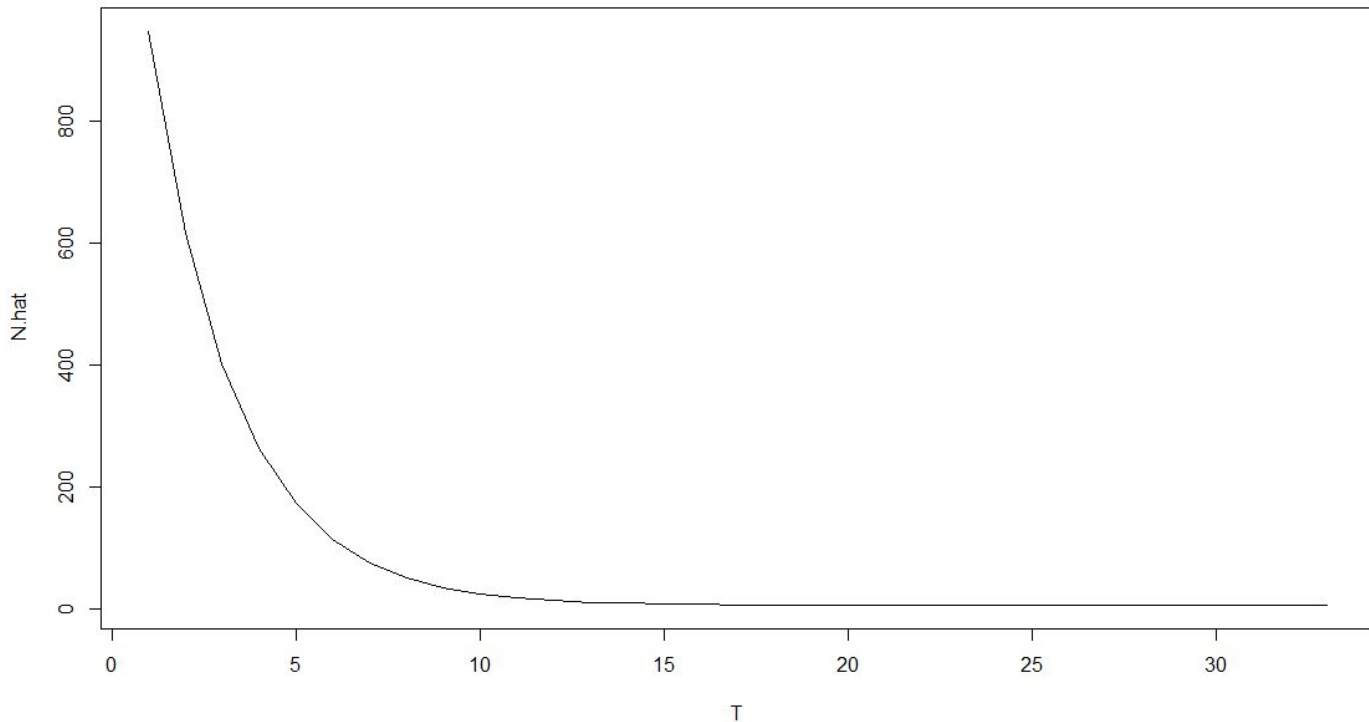
Intercept Model Parameter Estimates

We can step through the fitted Markov chain to estimate abundance over time

Intercept model is clearly underspecified

- No temporal effects
- No spatial effects

Estimated Average Single-Site Abundance: Open Intercept Model



Computational Challenges

1) R package `unmarked` doesn't allow for temporal modeling of population dynamics (only detection probability)

- Big concern: We observe counts cycling through time → dynamics are time-dependent
- Any model fit using `unmarked` will be underspecified

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- Closed intercept: < 30 Seconds
- Open intercept: ~10-30 Minutes
- Best model so far (next slide): ~12.5 Hours
 - Not an especially complex model

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3) Some combinations of predictors lead to identifiability issues (e.g. predicting detection probability using temperature)

Best Model So Far by AIC

Takeaways:

- Very high significance for all covariates
- Improved AIC compared to intercept models
- Model likely underspecified → Coefficients could be unreliable

Abundance (log-scale):

	Estimate	SE	z	P(> z)
(Intercept)	3.370	0.0885	38.1	0.00e+00
d.to.sea	-0.396	0.0311	-12.8	2.69e-37

Recruitment (log-scale):

	Estimate	SE	z	P(> z)
(Intercept)	1.696	0.0711	23.87	6.91e-126
d.to.sea	-0.128	0.0225	-5.69	1.25e-08

Apparent Survival (logit-scale):

	Estimate	SE	z	P(> z)
(Intercept)	0.6647	0.1419	4.68	2.81e-06
d.to.sea	0.0371	0.0326	1.14	2.55e-01

Detection (logit-scale):

	Estimate	SE	z	P(> z)
(Intercept)	-1.065	0.1055	-10.10	5.70e-24
seasonspring	1.154	0.0690	16.72	8.81e-63
seasonsummer	-0.311	0.0526	-5.92	3.28e-09

AIC: 12048.1

Conclusions

Contrasting Methods

Reisen (1999)

- Best response transformation for a linear regression model (judging by R^2_{adj})
- Still violates residual independence, normality, and constant variance assumptions
- Can't model population dynamics or imperfect detection

Conclusions

Contrasting Methods

Reisen (1999)

- Best response transformation and set of covariates for a linear regression model (judging by R^2_{adj})
- Still violates residual independence, normality, and constant variance assumptions
- Can't model population dynamics or imperfect detection

Dail, Madson (2011)

- Flexible models that account for imperfect detection and population dynamics
- Computation time and current R functions limit usability
- Lack of temporal modeling of population dynamics + high significance on included covariates → Current best model is almost certainly underspecified

Recommendations for Future Work

Two Paths

- 1) Likelihood methods
 - Continue finding MLE's using Dail, Madson model
 - Requires custom optimization code to work around limitations in `unmarked`

Recommendations for Future Work

Two Paths

- 1) Likelihood methods
 - Continue finding MLE's using Dail, Madson model
 - Requires custom optimization code to work around limitations in `unmarked`
- 2) Bayesian Methods (Our Recommendation)
 - Requires the likelihood + priors for all parameters
 - Likelihood given by Dail, Madson \square
 - Priors can be intentionally vague or based on outside sources
 - e.g. Prior on p could be based on existing studies of CO₂ trap effectiveness
 - Fit model by sampling from posterior (MCMC) \rightarrow obtain posterior densities for all parameters

Questions?