Climactic Drivers of Mosquito Abundance

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Outline

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Introduction

- Mosquitoes are vectors of many human diseases
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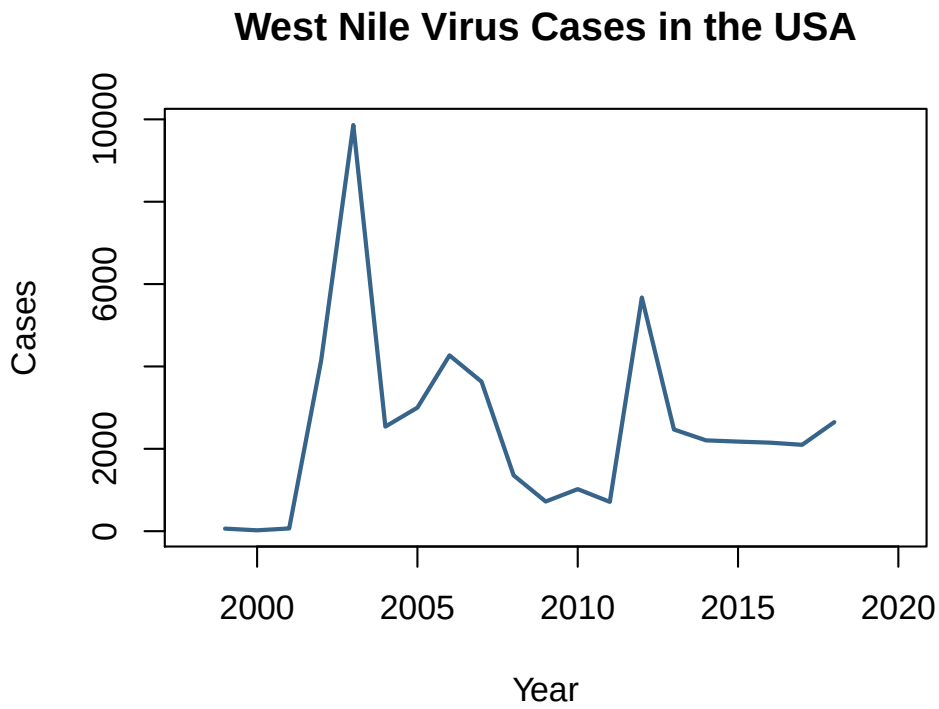

From www.cdc.gov

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Introduction

- Mosquitoes are vectors of many human diseases
- The ability to predict changes in abundance could help optimize control measures
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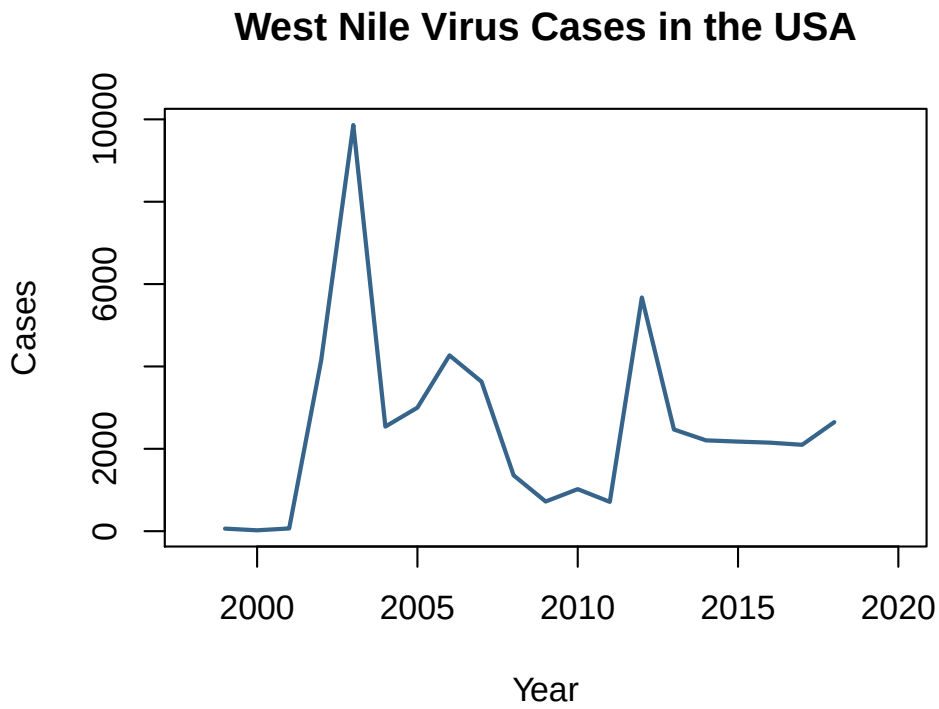

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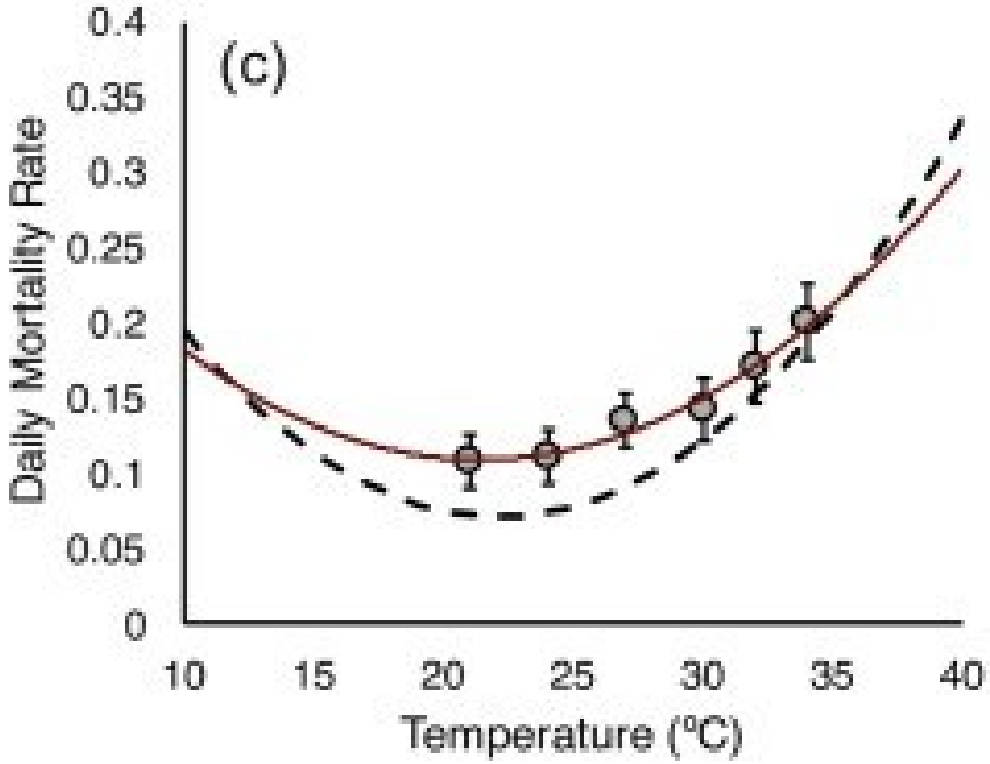
Introduction

- Mosquitoes are vectors of many human diseases
- The ability to predict changes in abundance could help optimize control measures
- Abundance dynamics are dependent on environmental factors that are likely to be affected by climate change



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Adapted from Shapiro et al. 2017

Questions

1. Which length of temporal lag of meteorological variables is most appropriate for estimating mosquito abundance dynamics?
2.
3.

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2. Which temporal scale of environmental drivers best predicts mosquito abundance changes?
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Questions

1. Which length of temporal lag of meteorological variables is most appropriate for estimating mosquito abundance dynamics?
2. Which temporal scale of environmental drivers best predicts mosquito abundance changes?
3. Can a model developed from these questions predict West Nile Virus risk?

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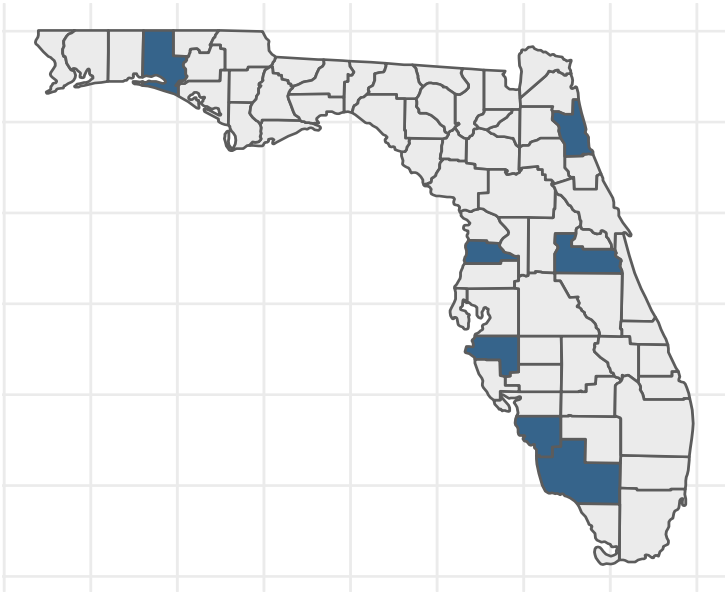
Data

- VectDyn: 206 datasets worldwide
- 7 Florida counties, 5 of which have high quality datasets
- Climate data from NOAA



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Methods

1. Extract Florida abundance datasets from large raw data file
2. Extract climate data from NOAA temperature and precipitation rasters and map to abundance data
3. Aggregate datasets to weekly, biweekly, and monthly scales to create time series
4.
5.
6.
7.

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Methods

1. Extract Florida abundance datasets from large raw data file
2. Extract climate data from NOAA temperature and precipitation rasters and map to abundance data
3. Aggregate datasets to weekly, biweekly, and monthly scales to create time series
4. Fit time series models with a range of temporal lags at different time scales
5. Conduct model selection
6. Use SIR models with abundance incorporated to transmission rate to estimate disease risk
7. Compare to disease surveillance data

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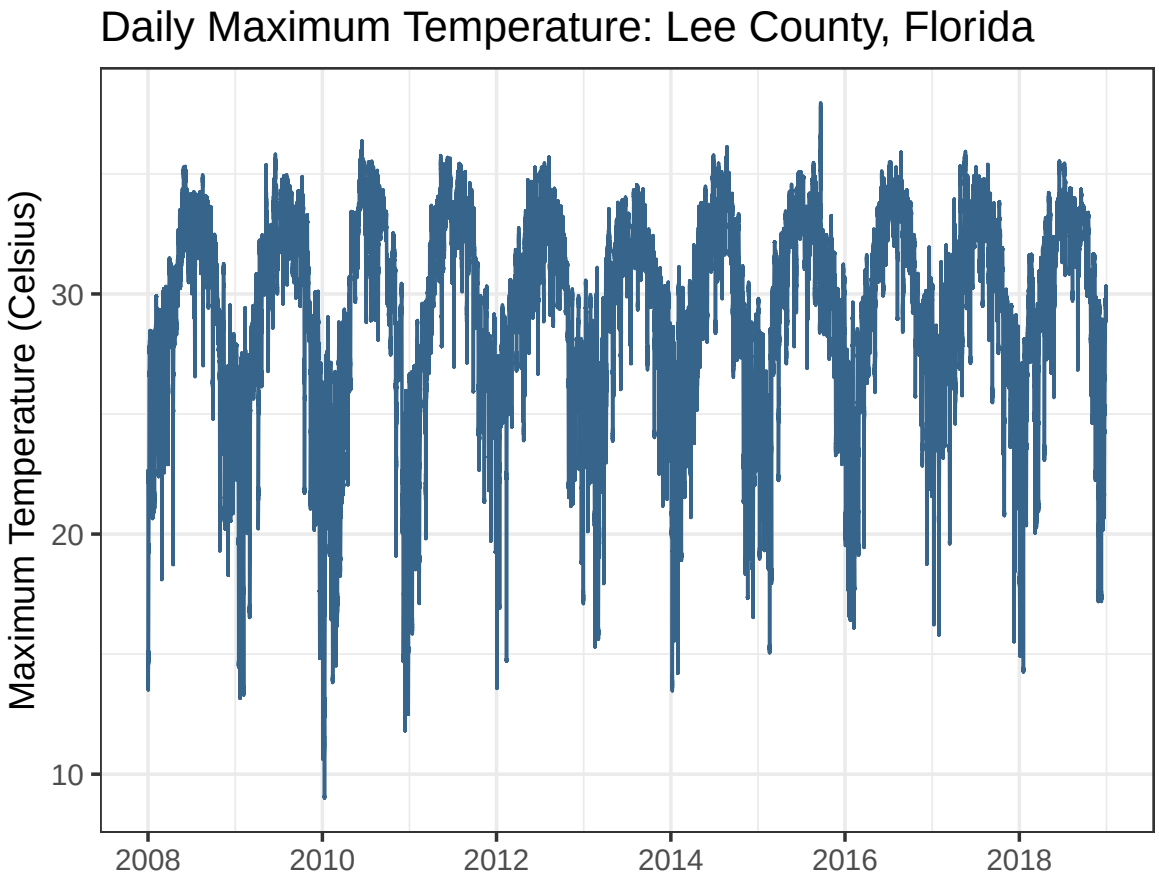
Extraction

1. Extract Florida abundance datasets
2. Extract climate data
3. Aggregate to weekly, biweekly, and monthly scales



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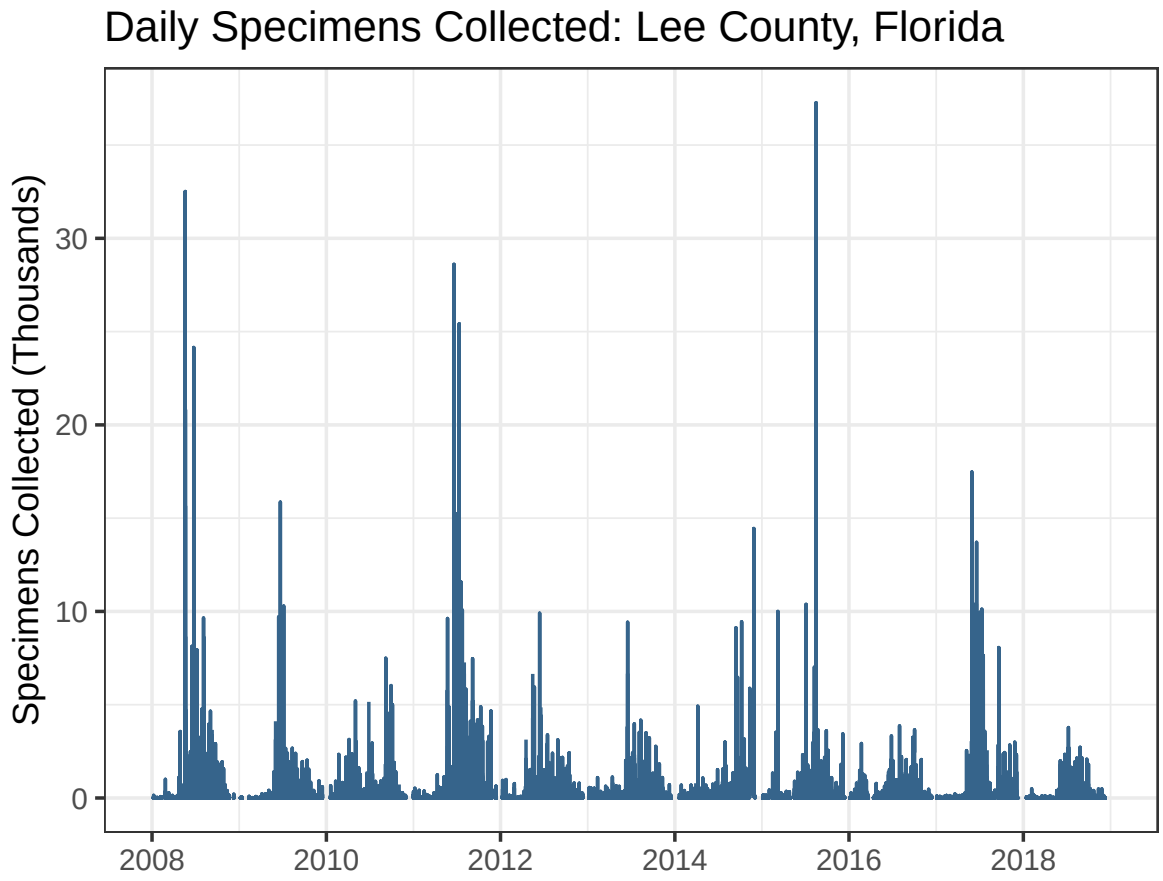

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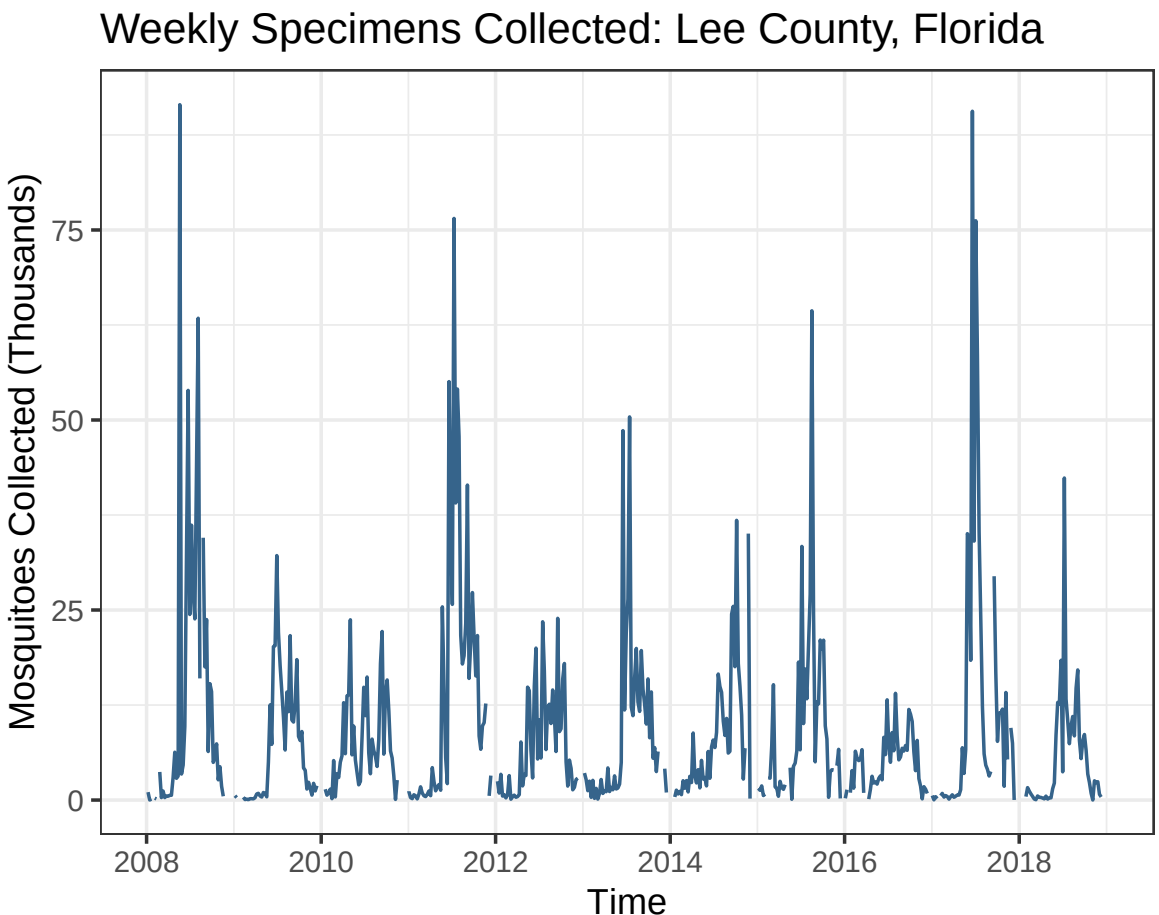

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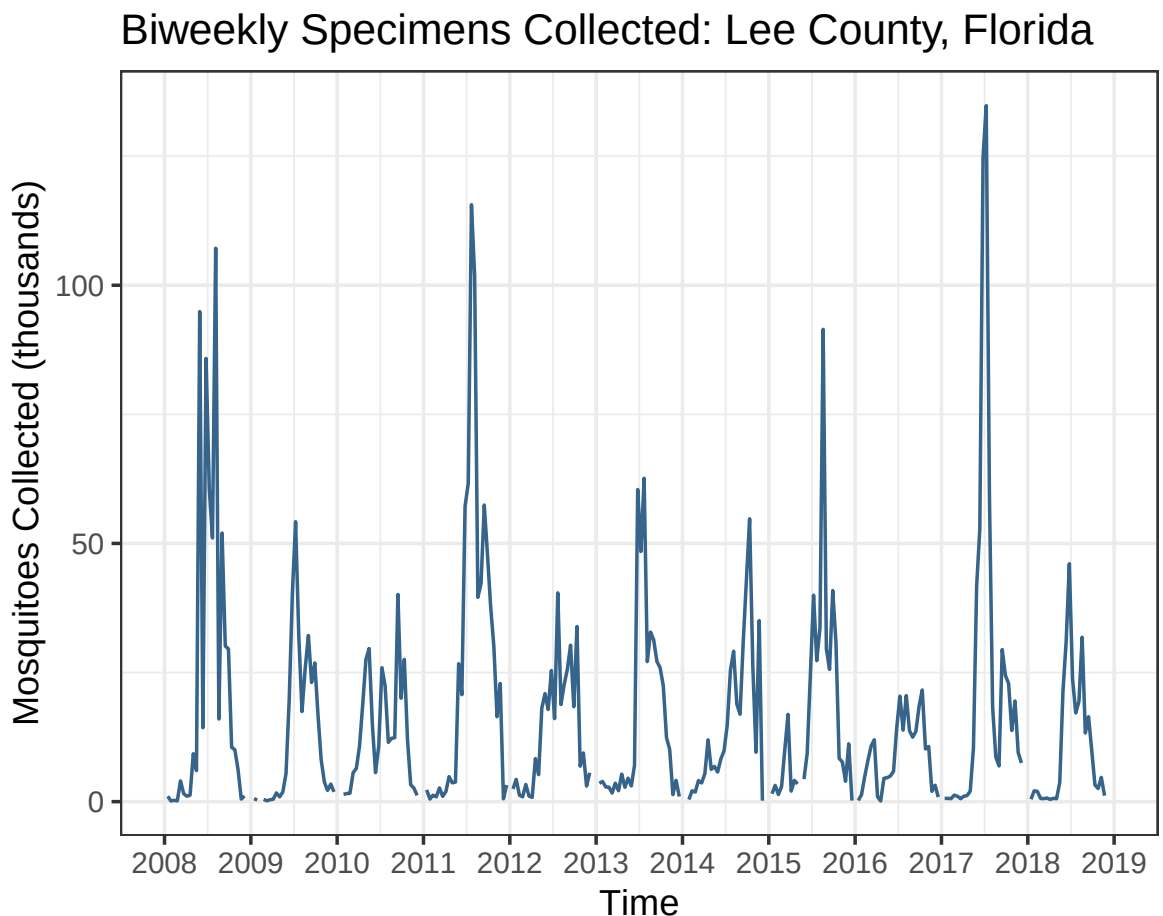

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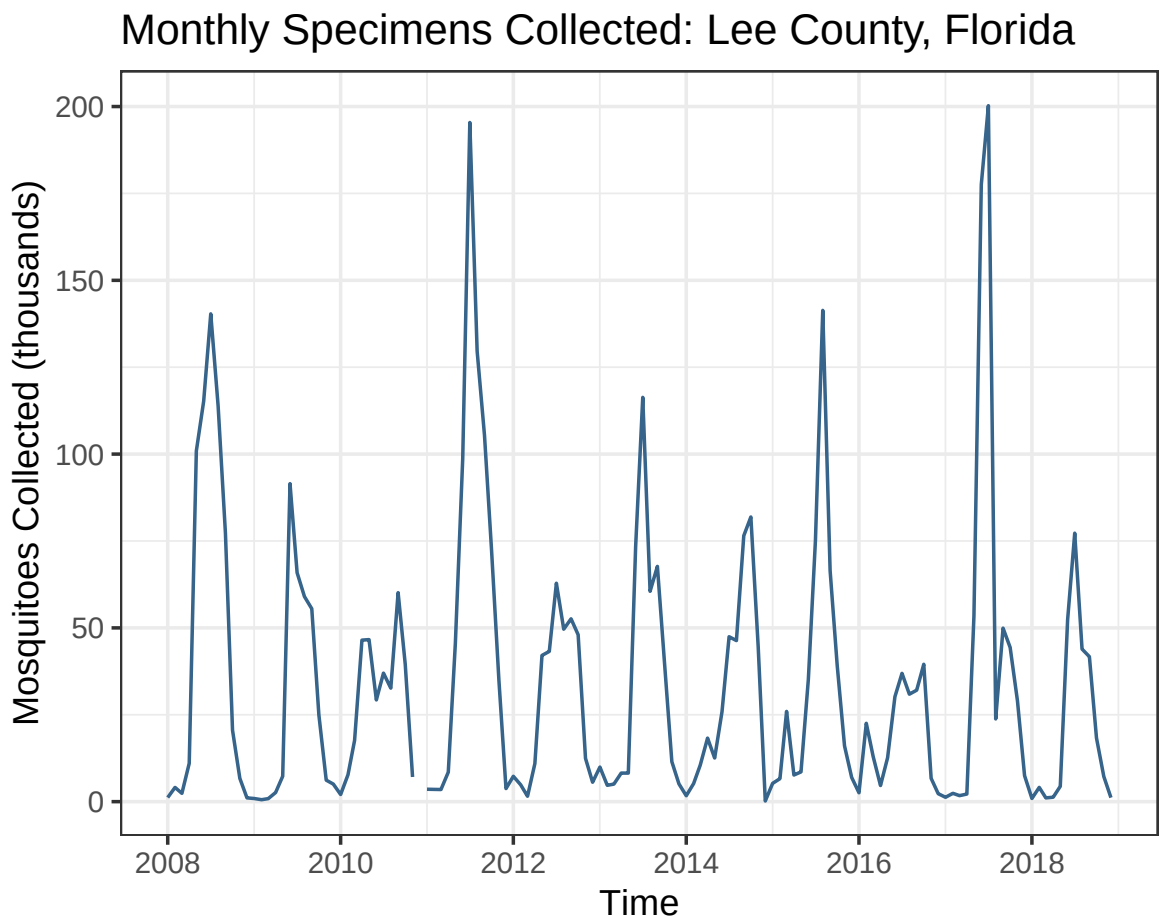

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Model Fit and Selection

4. Fit time series models: vary time scales and temporal lags using GLM, GAM, or ZIGAM
5. Model selection: AIC/BIC/Likelihood Ratio Test

General Model Format:

$$Abundance_t = Temperature_{t-lag} + Precipitation_{t-lag}$$

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Model Fit and Selection

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General Model Format:

$$Abundance_t = Temperature_{t-lag} + Precipitation_{t-lag}$$

Generalized Linear Model:

$$M_t = a_1 T_{t-lag}^2 + a_2 T_{t-lag} + b_1 P_{t-lag}^2 + b_2 P_{t-lag} + c$$

Wang et al 2011

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Tentative Next Steps

6. Use SIR models with abundance incorporated to transmission rate to estimate disease risk
7. Compare to disease surveillance data

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Questions?

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References

Shapiro, L., Whitehead, S. A., & Thomas, M. B. (2017). Quantifying the effects of temperature on mosquito and parasite traits that determine the transmission potential of human malaria. PLoS biology, 15(10), e2003489.

Wang, J. Ogden, N.H., & Zhu, H. (2011). The Impact of Weather Conditions on Culex pipiens and Culex restuans (Diptera: Culicidae) Abundance: A Case Study in Peel Region. Journal of Medical Entomology, 48(2), pages 468-475

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