

# How predictable is extinction?

Forecasting species survival at million-year timescales

Peter D Smits, Seth Finnegan

Department of Integrative Biology, University of California – Berkeley

# Foundational assertion of conservation paleobiology

By studying the **past**,  
we can better predict the **future**.

## What are we predicting?

Extinction is **hard** to predict, but is **important** to conservation decisions.

# Predicting extinction

- ▶ A taxon with a **greater than average** global geographic range is likely to survive for longer than a taxon with **less than average** global geographic range.

# Predicting extinction

- ▶ A taxon with a **greater than average** global geographic range is likely to survive for longer than a taxon with **less than average** global geographic range.
- ▶ A taxon's global geographic range can change over time.

# Predicting extinction

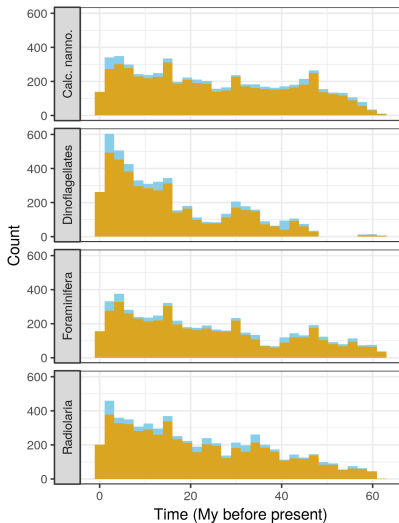
- ▶ A taxon with a **greater than average** global geographic range is likely to survive for longer than a taxon with **less than average** global geographic range.
- ▶ A taxon's global geographic range can change over time.
- ▶ What happens to extinction risk as a taxon changes geographic range? How is extinction risk impacted if that taxon's global geographic range has recently **increased** or **decreased**?

# Encoding the past

- ▶ Change in geographic range between current observation and previous observation.
- ▶ Average global temperature at time of previous observation (Mg/Ca isotope).
- ▶ Age in millions of years at time of observation.

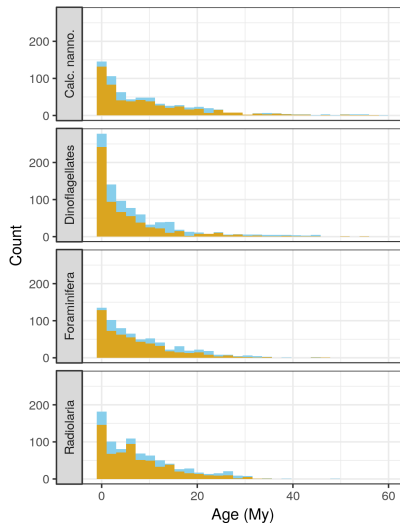
# Data being analyzed

## Occurrences



Occurrence type    Last    Standard

## Age distribution



State    Extant    Extinct



# How we're analyzing the data

- ▶ Predictors: geographic range, change in geographic range, global temperature, lag of global temperature.

# How we're analyzing the data

- ▶ Predictors: geographic range, change in geographic range, global temperature, lag of global temperature.
- ▶ Bayesian discrete-time survival model.
  - ▶ Bernoulli response distribution.
  - ▶ Time varying intercepts and slopes; varies by phylum.
  - ▶ Taxon age as non-nested varying intercept; varies by phylum.

# How we're analyzing the data

- ▶ Predictors: geographic range, change in geographic range, global temperature, lag of global temperature.
- ▶ Bayesian discrete-time survival model.
  - ▶ Bernoulli response distribution.
  - ▶ Time varying intercepts and slopes; varies by phylum.
  - ▶ Taxon age as non-nested varying intercept; varies by phylum.
- ▶ **Compare** models using WAIC/LOOIC.

# How we're analyzing the data

- ▶ Predictors: geographic range, change in geographic range, global temperature, lag of global temperature.
- ▶ Bayesian discrete-time survival model.
  - ▶ Bernoulli response distribution.
  - ▶ Time varying intercepts and slopes; varies by phylum.
  - ▶ Taxon age as non-nested varying intercept; varies by phylum.
- ▶ Compare models using WAIC/LOOIC.
- ▶ Explore model adequacy using posterior predictive distribution.

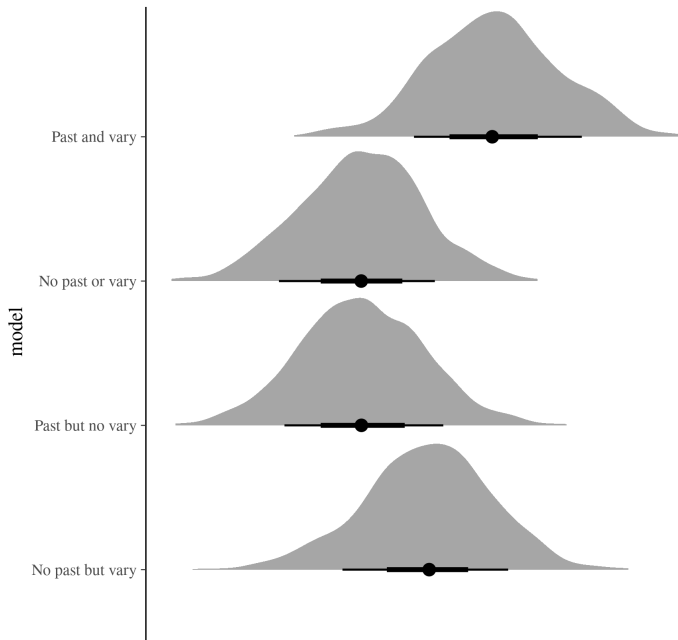
# How we're analyzing the data

- ▶ Predictors: geographic range, change in geographic range, global temperature, lag of global temperature.
- ▶ Bayesian discrete-time survival model.
  - ▶ Bernoulli response distribution.
  - ▶ Time varying intercepts and slopes; varies by phylum.
  - ▶ Taxon age as non-nested varying intercept; varies by phylum.
- ▶ **Compare** models using WAIC/LOOIC.
- ▶ Explore model **adequacy** using posterior predictive distribution.
- ▶ Estimate out-of-sample **predictive performance** using  $k$ -fold cross-validation.

# A conceptual model for predicting extinction

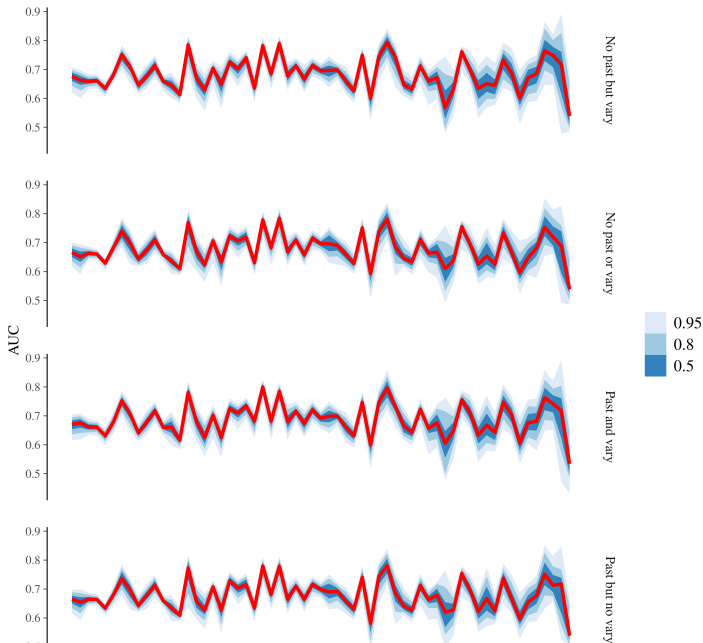
# A statistical model for predicting extinction

# In-sample predictive performance, full dataset





# In-sample predictive performance, by time



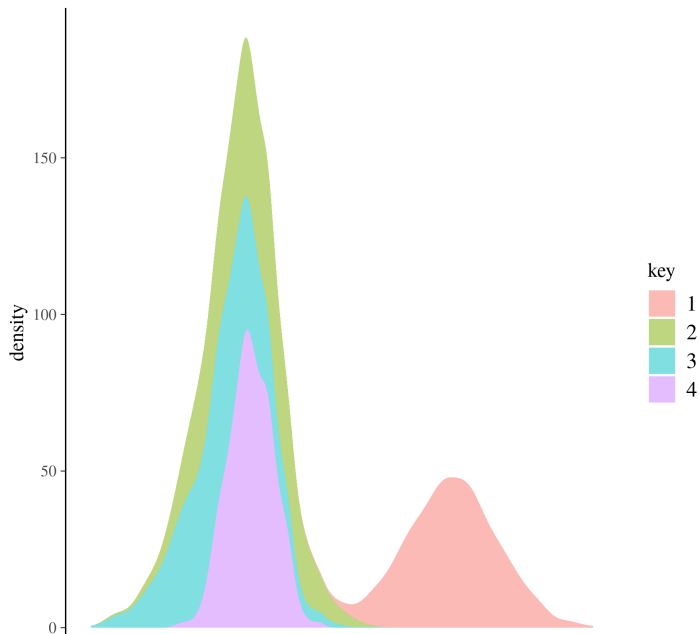
## Comparing our models

Model	LOOIC	SE LOOIC	WAIC	SE WAIC
Past and vary	12790.39	178.83	12786.06	178.77
No past but vary	12818.43	178.76	12815.40	178.71
Past but no vary	12850.45	179.42	12848.12	179.38
No past or vary	12850.87	179.46	12848.50	179.42

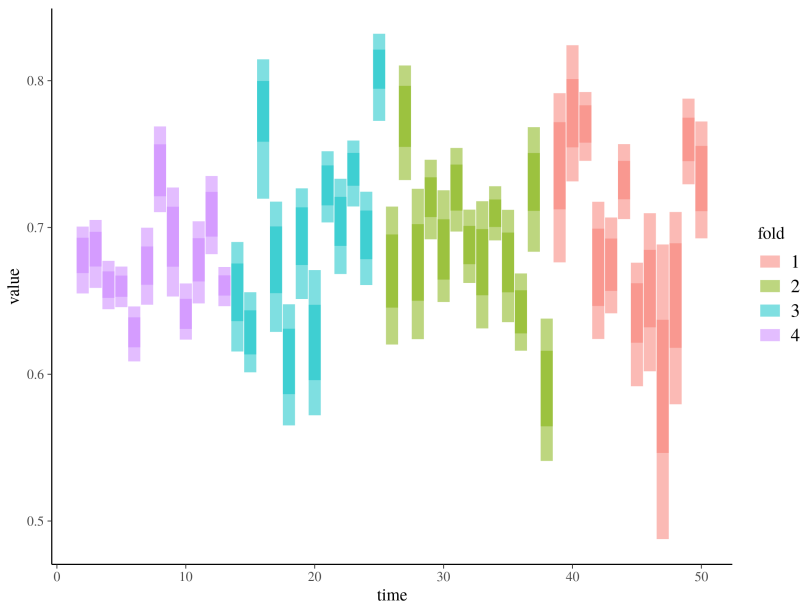
## Comparing our models

Model	LOOIC	SE LOOIC	WAIC	SE WAIC
Past and vary	12790.39	178.83	12786.06	178.77
No past but vary	12818.43	178.76	12815.40	178.71
Past but no vary	12850.45	179.42	12848.12	179.38
No past or vary	12850.87	179.46	12848.50	179.42

# Cross-validation results, full dataset



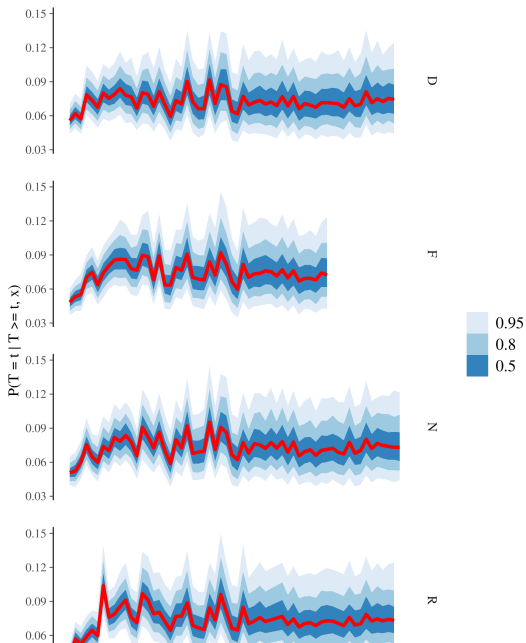
# Cross-validation results, by time



## Overall covariate effects

# Covariate effects over time

# Effects of age on extinction risk, by phylum





# Summary

- ▶ extinction is very random and our estimates aren't near perfect
- ▶ historical covariates and varying effects seem important
- ▶ increasing model complexity has only

# Conclusions

- ▶ consider non-linear effects of historical covariates – thresholds
- ▶ at MILLION YEAR timescales past kind of matters, but very marginally
- ▶ extinction is hard to predict at million year timescales – rarity

# Acknowledgements