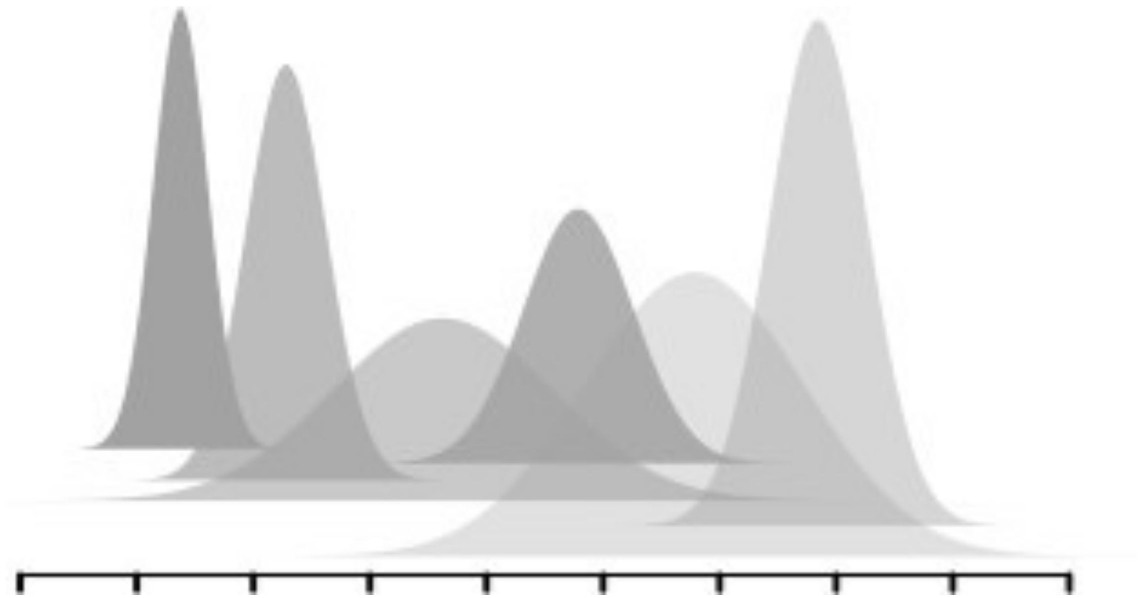
5.2 Fitting empirical data to models



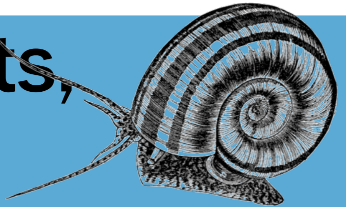
Jelena H. Pantel

Faculty of Biology

University of Duisburg-Essen

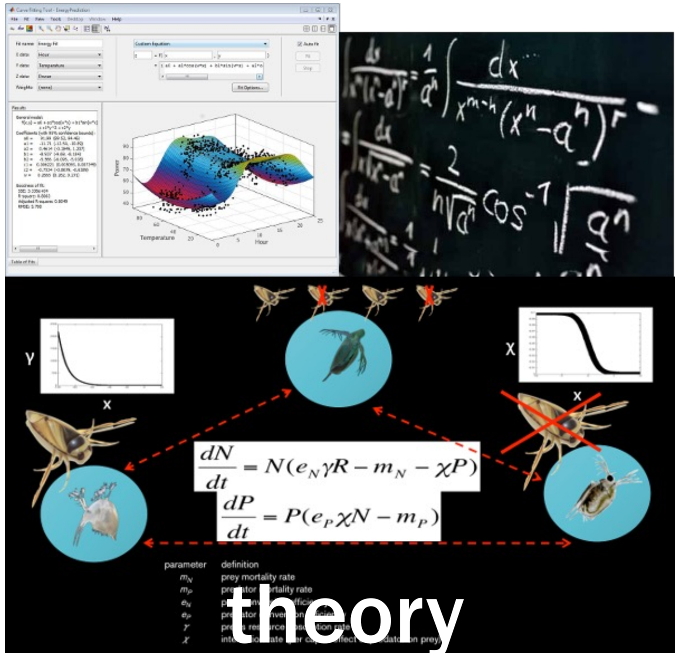
jelena.pantel@uni-due.de

Research approach – combine surveys, experiments, and models



Research goals

- Develop accurate models to explain and predict biodiversity
- Understand the consequences of evolution for communities, metacommunities, and ecosystems
- Determine how eco-evolutionary dynamics influence the response of biodiversity to environmental change



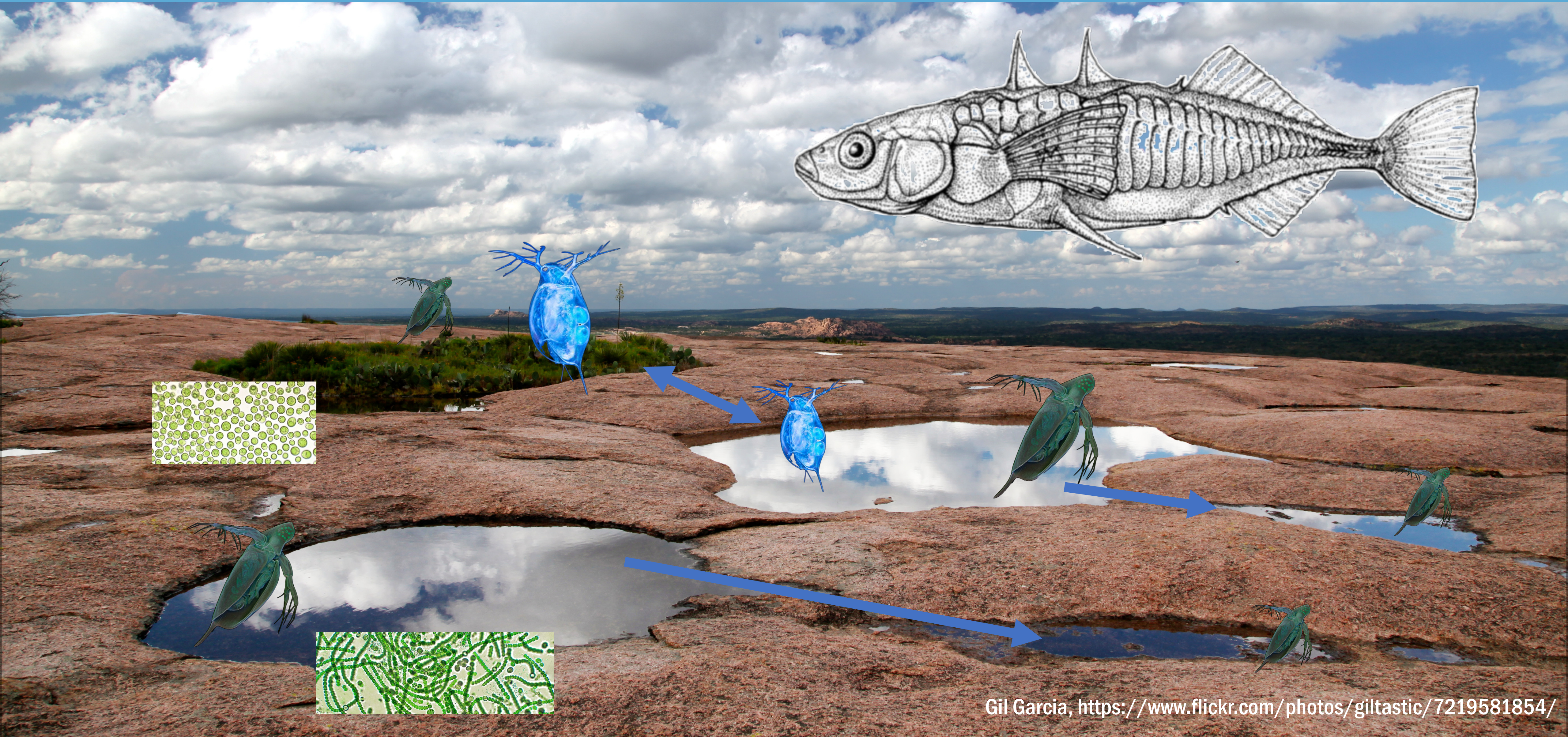
experiment

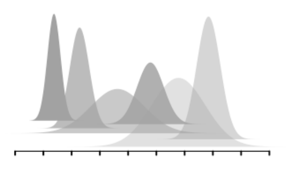
observation

Eco-evolutionary dynamics – overlapping ecological and evolutionary processes that are not independent of one another

Gil Garcia, https://www.flickr.com/photos/giltastic/7219581854/

Eco-evolutionary dynamics – overlapping ecological and evolutionary processes that are not independent of one another





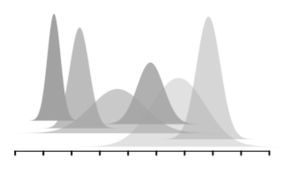
Research approach –eco-evolutionary hypothesis testing to fit data to models

Candidate model — 1. Identify candidate models for processes that structure observed data

Ecoevo H_0,H_A — 2. Generate alternative eco-evolutionary hypotheses

Simulations — 3. Simulate possible observed data under each hypothesis

Compare to observed data — 4. Compare observed data to alternative hypothesis simulations

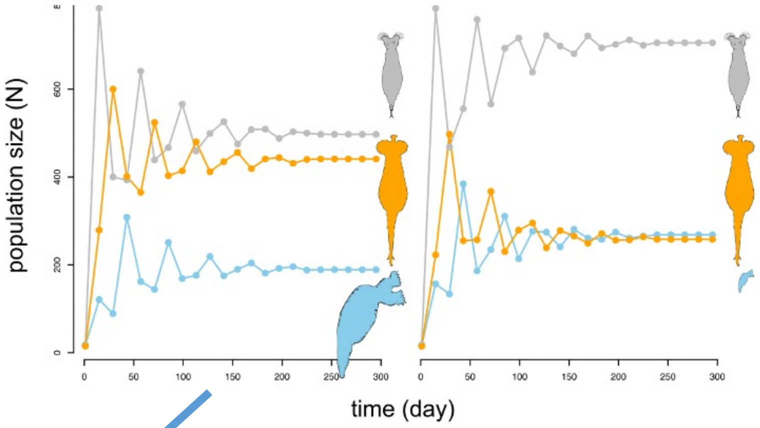


Research approach –eco-evolutionary hypothesis testing to fit data to models

Candidate model

1. Identify candidate models for processes that structure observed data

Ex 1) Coexistence / competition for a few species



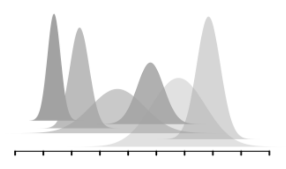
growth rate (as a function of a trait x)

$$\frac{N_{i,t+1}}{N_{i,t}} = \frac{\lambda_i(x)}{1 + \alpha_{ii} N_{i,t} + \alpha_{ij} N_{j,t}}$$

Intraspecific competition rate

Interspecific competition rate

Pantel & Becks (in review, Trends Ecology & Evolution)



Research approach –eco-evolutionary hypothesis testing to fit data to models

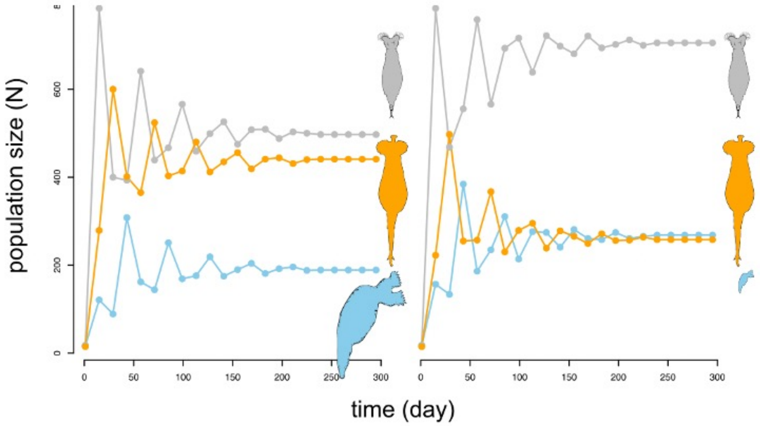
Ecoevo H_0,H_A

2. Generate alternative eco-evolutionary hypotheses

Simulations

3. Simulate possible observed data under each hypothesis

Ex 1) Coexistence / competition for a few species



H_{eco}

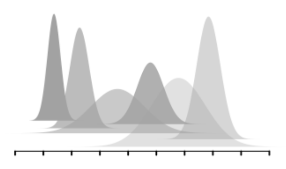
Trait x does not evolve

$H_{eco\text{-}evo}$

Trait x can evolve

$$\frac{N_{i,t+1}}{N_{i,t}} = \frac{\lambda_i(x)}{1 + \alpha_{ii}N_{i,t} + \alpha_{ij}N_{j,t}}$$

Pantel & Becks (in review, Trends Ecology & Evolution)

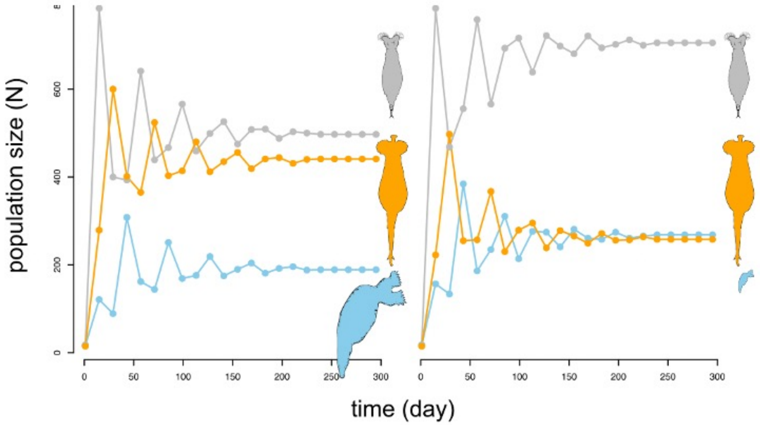


Research approach –eco-evolutionary hypothesis testing to fit data to models

Ecoevo H_0, H_A — 2. Generate alternative eco-evolutionary hypotheses

Simulations — 3. Simulate possible observed data under each hypothesis

Ex 1) Coexistence / competition for a few species



H_{eco}

Trait *x* does not evolve

$H_{eco\text{-}evo}$

Trait *x* can evolve

$$\frac{N_{i,t+1}}{N_{i,t}} = \frac{\lambda_i(x)}{1 + \alpha_{ii} N_{i,t} + \alpha_{ij} N_{j,t}}$$

Growth rate → fitness

$$\lambda_t = \overline{W}_t = \widehat{W} e^{\frac{-\left[\left(\frac{w+(1-h^2)P}{P+w}\right)(E-x_t)\right]^2}{2(P+w)}}$$

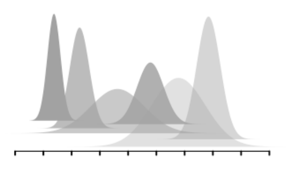
strength of selection

width of phenotypic distribution

heritability of trait *x*

Distance between trait *x* and optimum trait value E

Pantel & Becks (in review, Trends Ecology & Evolution)

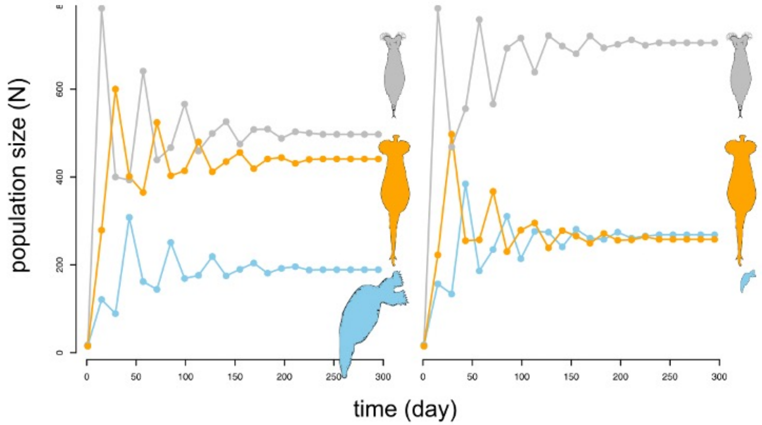


Research approach –eco-evolutionary hypothesis testing to fit data to models

Ecoevo H_0,H_A — 2. Generate alternative eco-evolutionary hypotheses

Simulations — 3. Simulate possible observed data under each hypothesis

Ex 1) Coexistence / competition for a few species



H_{eco}

Trait x does not evolve

$H_{eco\text{-}evo}$

Trait x can evolve

$$\frac{N_{i,t+1}}{N_{i,t}} = \frac{\lambda_i(x)}{1 + \alpha_{ii}N_{i,t} + \alpha_{ij}N_{j,t}}$$

Growth rate → fitness

strength of selection

width of phenotypic distribution

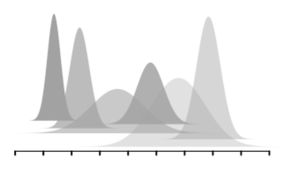
heritability of trait x

Distance between trait x and optimum trait value E

$$\lambda_t = \overline{W}_t = \widehat{W}e^{\frac{-\left[\left(\frac{w+(1-h^2)P}{P+w}\right)(E-x_t)\right]^2}{2(P+w)}}$$

$$N_{i,t+1} = \frac{\hat{W}e^{\frac{-[(\frac{w+(1-h^2)P}{P+w})(E-x_t)]^2}{2(P+w)}}N_{i,t}}{1+\alpha_{ii}N_{i,t}+\sum_j \alpha_{ij}N_{j,t}}$$

Pantel & Becks (in review, Trends Ecology & Evolution)



Research approach –eco-evolutionary hypothesis testing to fit data to models

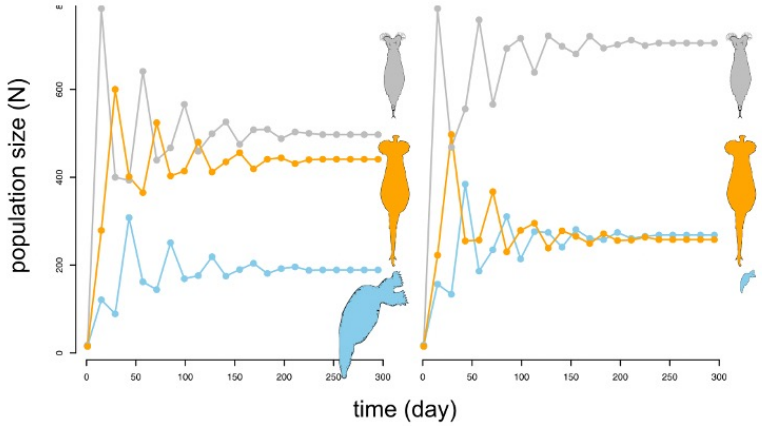
Ecoevo H_0,H_A

2. Generate alternative eco-evolutionary hypotheses

Simulations

3. Simulate possible observed data under each hypothesis

Ex 1) Coexistence / competition for a few species



H_{eco}

Trait x does not evolve

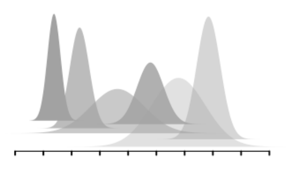
$$\frac{N_{i,t+1}}{N_{i,t}} = \frac{\lambda_i(x)}{1 + \alpha_{ii}N_{i,t} + \alpha_{ij}N_{j,t}}$$

$H_{eco\text{-}evo}$

Trait x can evolve

$$N_{i,t+1} = \frac{\hat{W} e^{\frac{-[(\frac{w+(1-h^2)P}{P+w})(E-x_t)]^2}{2(P+w)}} N_{i,t}}{1 + \alpha_{ii}N_{i,t} + \sum_j \alpha_{ij}N_{j,t}}$$

Pantel & Becks (in review, Trends Ecology & Evolution)



Research approach –eco-evolutionary hypothesis testing to fit data to models

Simulations

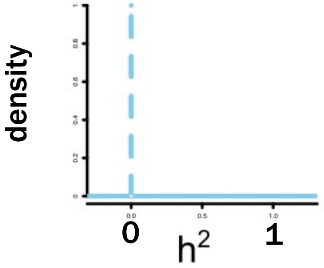
3. Simulate possible observed data under each hypothesis

Compare to observed data

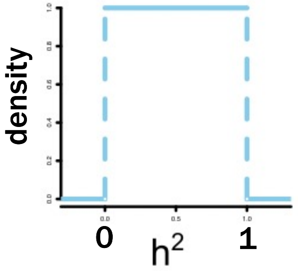
4. Compare observed data to alternative hypothesis simulations

sample a candidate parameter vector θ* from a proposed prior distribution, 100,000 simulations per model

H_1: No evolution (h^2=0)

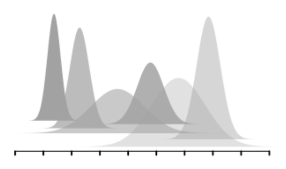


H_2: Evolution (h^2>0)



Approximate Bayesian Computing (eg Beaumont 2010)

Model parameters: h^2, α, w, $\widehat{W}$, P



Research approach –eco-evolutionary hypothesis testing to fit data to models

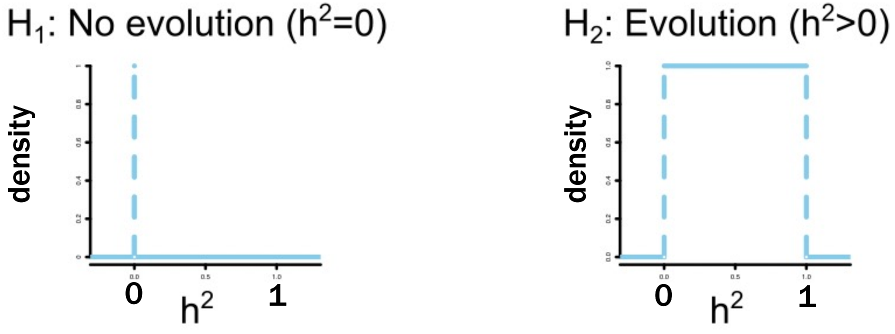
Simulations

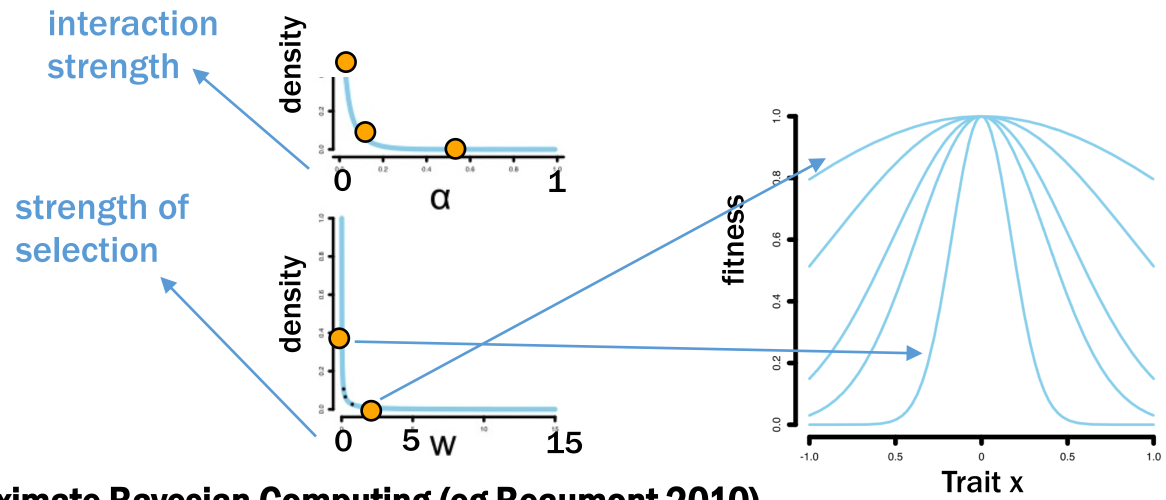
3. Simulate possible observed data under each hypothesis

Compare to observed data

4. Compare observed data to alternative hypothesis simulations

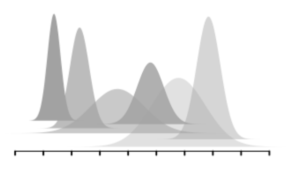
sample a candidate parameter vector θ* from a proposed prior distribution, 100,000 simulations per model





Approximate Bayesian Computing (eg Beaumont 2010)

Model parameters: h^2, α, w, $\widehat{W}$, P



Research approach – eco-evolutionary hypothesis testing to fit data to models

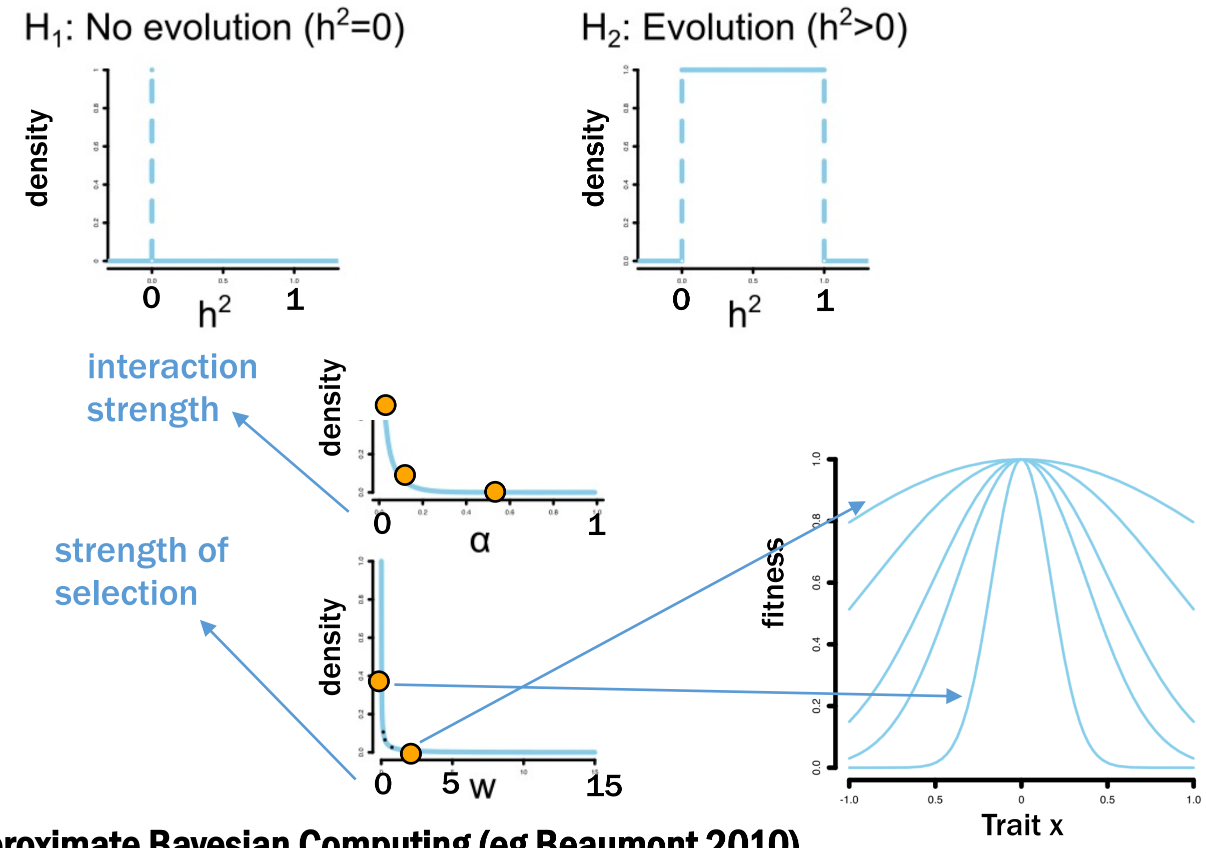
Simulations

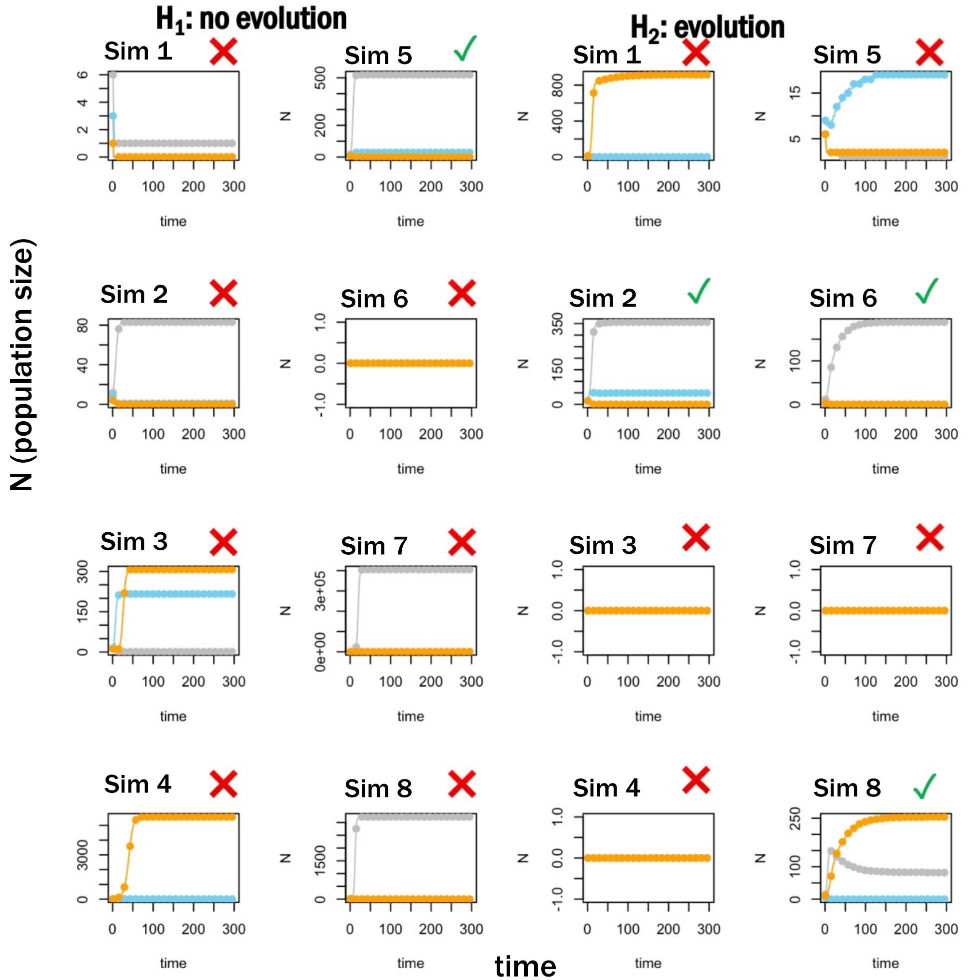
3. Simulate possible observed data under each hypothesis

Compare to observed data

4. Compare observed data to alternative hypothesis simulations

sample a candidate parameter vector θ* from a proposed prior distribution, 100,000 simulations per model

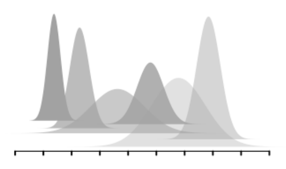




compare the simulated dataset x* to the observed data x_0, using a distance function d and a tolerance ε: if $d(x_0, x^*) \leq ε$, accept θ*

Approximate Bayesian Computing (eg Beaumont 2010)

Model parameters: h^2, α, w, $\widehat{W}$, P



Research approach –eco-evolutionary hypothesis testing to fit data to models

Compare to observed data

4. Compare observed data to alternative hypothesis simulations

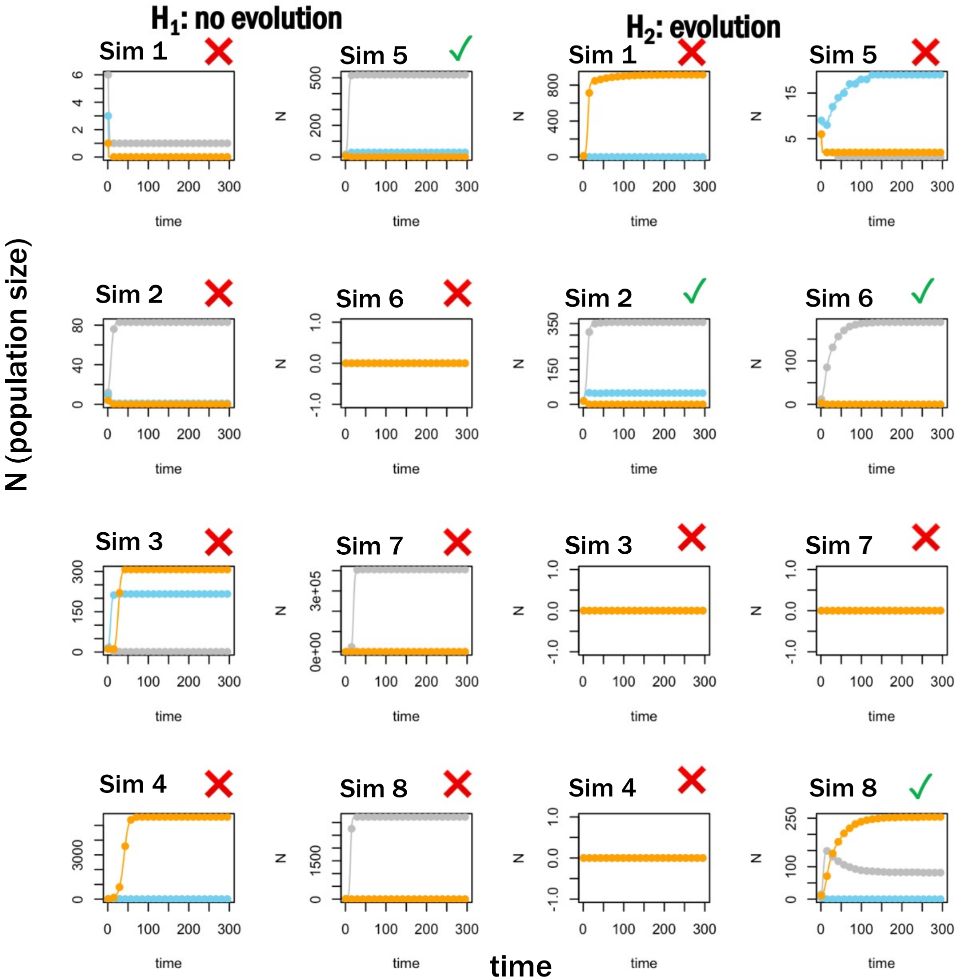
(i) Estimate posterior probability of alternative model hypotheses

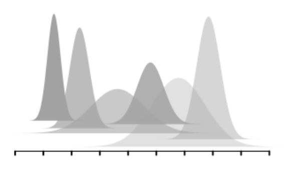
H_{eco}

$$\frac{n_{i,t+1}}{n_{i,t}} = \frac{\lambda_i}{1 + \alpha_{ii} N_{i,t} + \alpha_{ij} N_{j,t}}$$

$H_{eco\text{-}evo}$

$$N_{i,t+1} = \frac{\hat{W} e^{\frac{-[(\frac{w+(1-h^2)P}{P+w})(E-x_t)]^2}{2(P+w)}} N_{i,t}}{1 + \alpha_{ii} N_{i,t} + \sum_j \alpha_{ij} N_{j,t}}$$





Research approach –eco-evolutionary hypothesis testing to fit data to models

Compare to observed data

4. Compare observed data to alternative hypothesis simulations

(i) Estimate posterior probability of alternative model hypotheses

H_{eco}

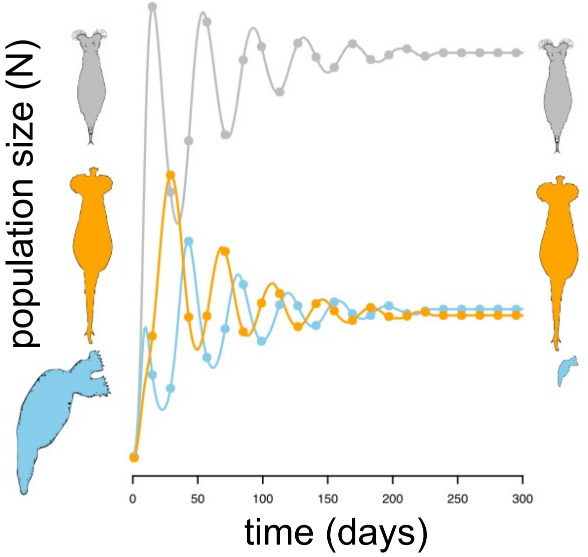
$$\frac{n_{i,t+1}}{n_{i,t}} = \frac{\lambda_i}{1+\alpha_{ii}N_{i,t}+\alpha_{ij}N_{j,t}}$$

$H_{eco\text{-}evo}$

$$N_{i,t+1} = \frac{\hat{W} e^{\frac{-[(\frac{w+(1-h^2)P}{P+w})(E-x_t)]^2}{2(P+w)}} N_{i,t}}{1+\alpha_{ii}N_{i,t}+\sum_j \alpha_{ij}N_{j,t}}$$

Case 1. With simulated model + data

With x_0 and x_{300} trait values



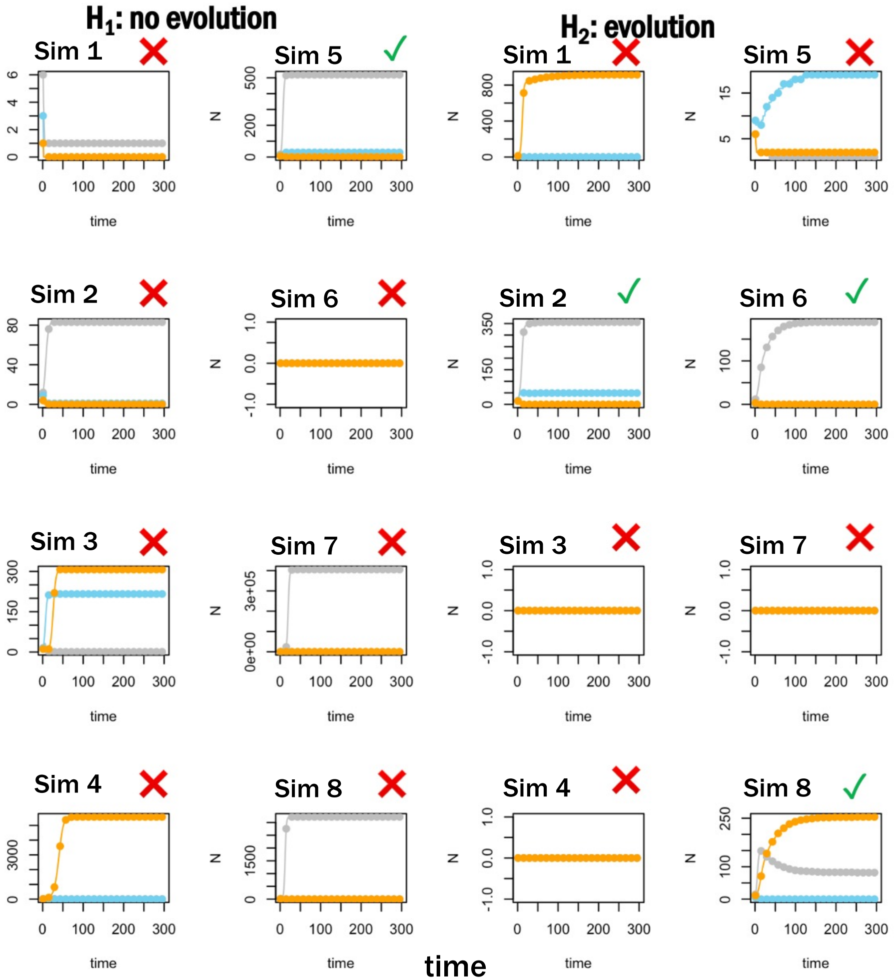
Posterior model probabilities for Observed Data

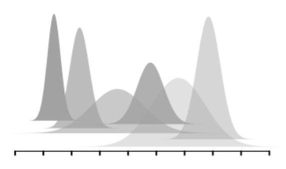
H_{eco} = 0.0001

$H_{eco\text{-}evo}$ = 0.9999

Based on % Accepted vs. Rejected per H_A model

Approximate Bayesian Computing + Neural network (for model classification) → trained on 100,000 simulations per model





Research approach –eco-evolutionary hypothesis testing to fit data to models

Compare to observed data

4. Compare observed data to alternative hypothesis simulations

(i) Estimate posterior probability of alternative model hypotheses

H_{eco}

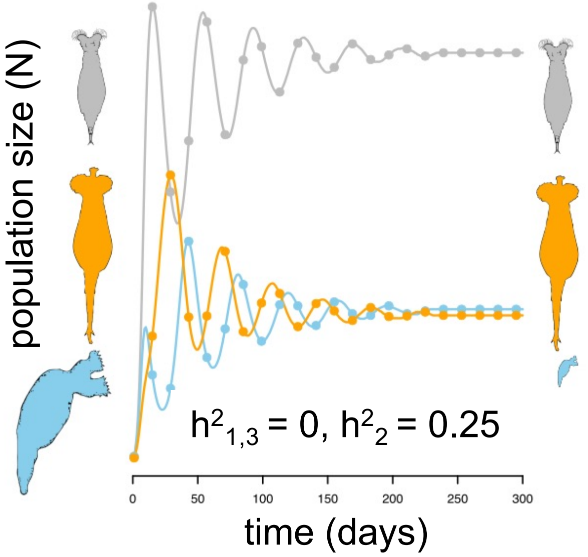
$$\frac{n_{i,t+1}}{n_{i,t}} = \frac{\lambda_i}{1 + \alpha_{ii} N_{i,t} + \alpha_{ij} N_{j,t}}$$

$H_{eco\text{-}evo}$

$$N_{i,t+1} = \frac{\hat{W} e^{\frac{-[(\frac{w+(1-h^2)P}{P+w})(E-x_t)]^2}{2(P+w)}} N_{i,t}}{1 + \alpha_{ii} N_{i,t} + \sum_j \alpha_{ij} N_{j,t}}$$

Case 1. With simulated model + data

With x_0 and x_{300} trait values



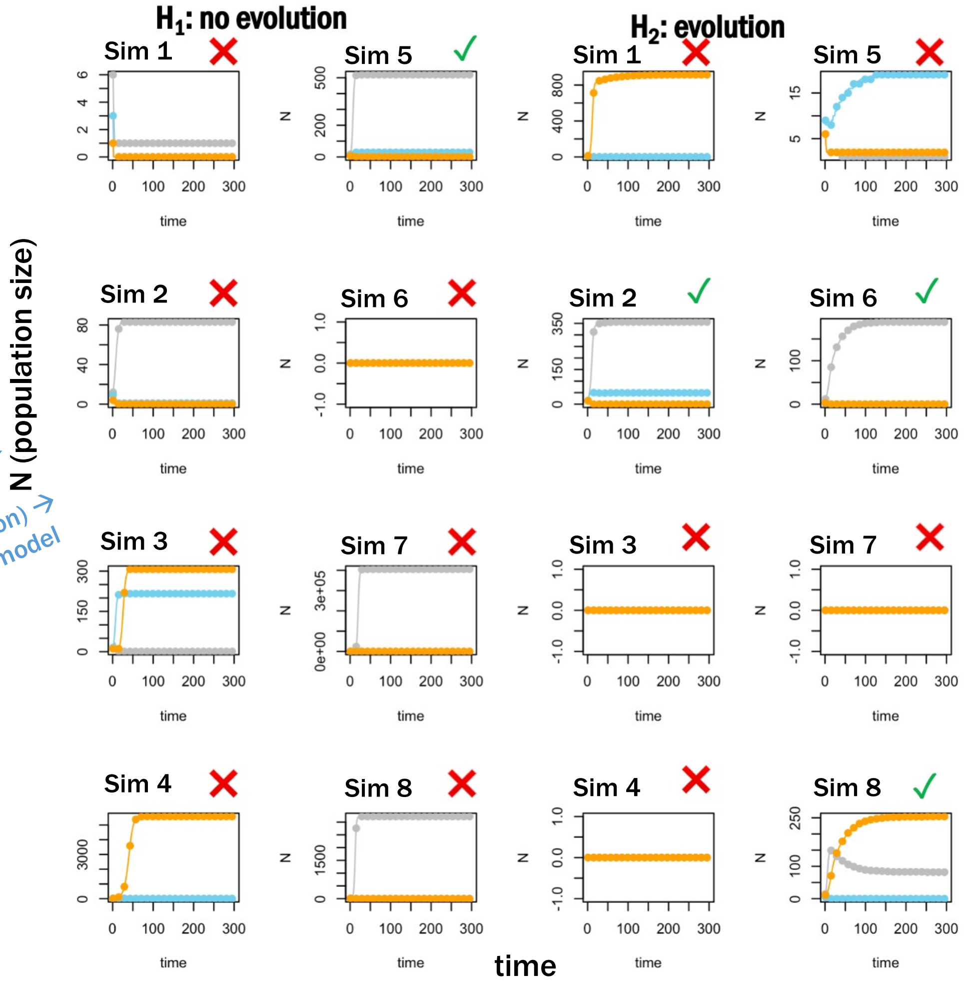
Posterior model probabilities for Observed Data

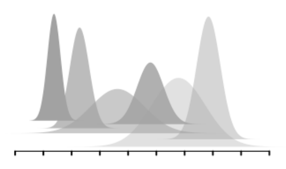
H_{eco} = 0.0001 ✗

$H_{eco\text{-}evo}$ = 0.9999 ✓

Based on % Accepted vs. Rejected per H_A model

Approximate Bayesian Computing + Neural network (for model classification) → trained on 100,000 simulations per model





Research approach –eco-evolutionary hypothesis testing to fit data to models

Compare to observed data

4. Compare observed data to alternative hypothesis simulations

(i) Estimate posterior probability of alternative model hypotheses

H_{eco}

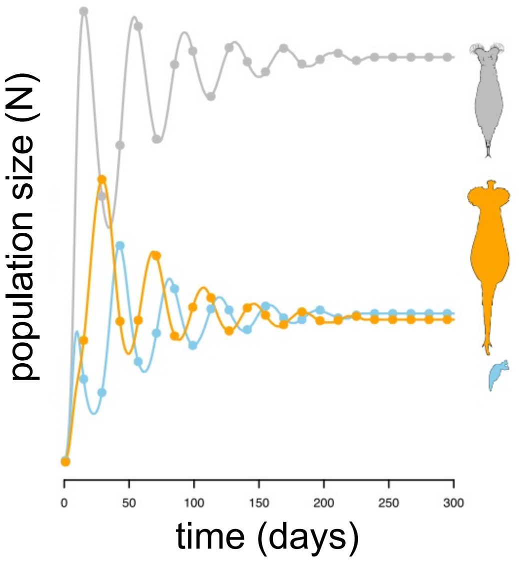
$$\frac{n_{i,t+1}}{n_{i,t}} = \frac{\lambda_i}{1+\alpha_{ii}N_{i,t}+\alpha_{ij}N_{j,t}}$$

$H_{eco\text{-}evo}$

$$N_{i,t+1} = \frac{\hat{W} e^{\frac{-[(\frac{w+(1-h^2)P}{P+w})(E-x_t)]^2}{2(P+w)}} N_{i,t}}{1+\alpha_{ii}N_{i,t}+\sum_j \alpha_{ij}N_{j,t}}$$

Case 2. With simulated model + data

With x_{300} trait values only (!!)

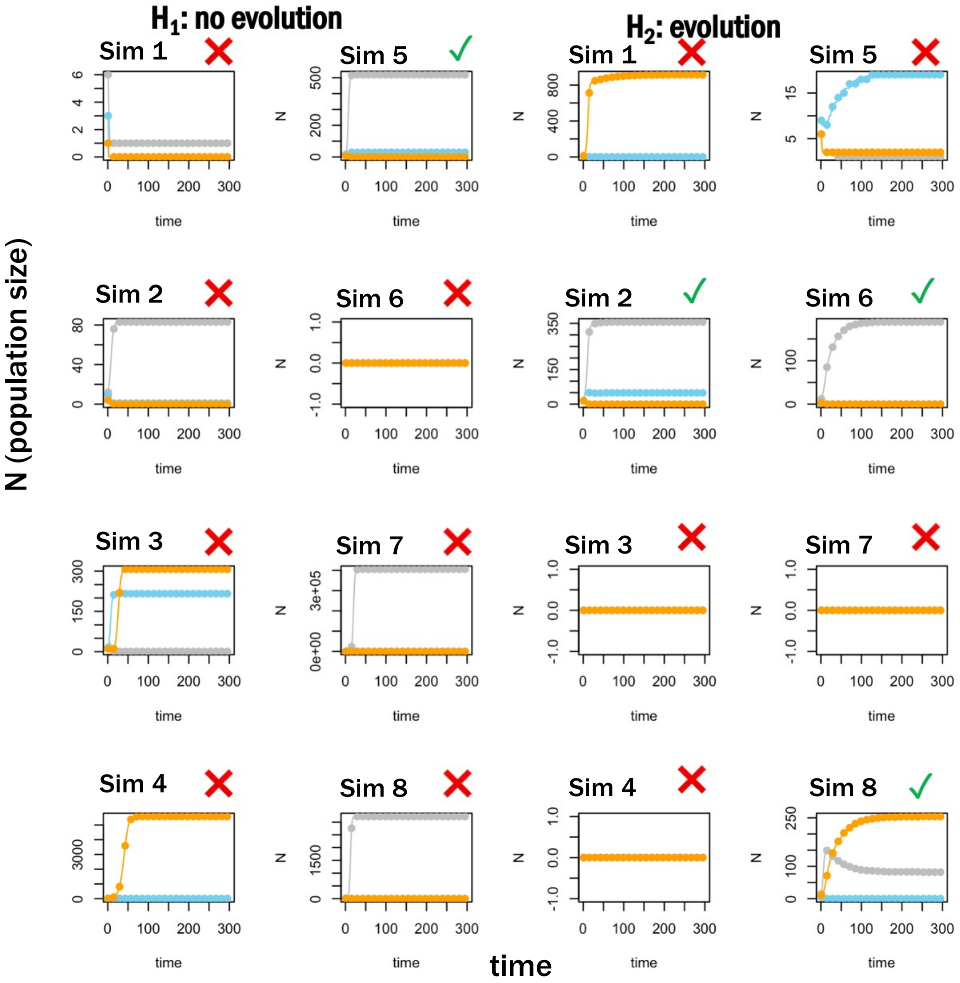


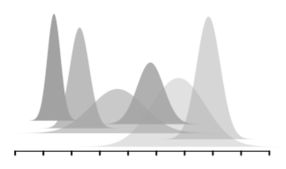
Posterior model probabilities for Observed Data

H_{eco} = 0.4676

$H_{eco\text{-}evo}$ = 0.5324

Based on % Accepted vs. Rejected per H_A model





Research approach –eco-evolutionary hypothesis testing to fit data to models

Compare to observed data

4. Compare observed data to alternative hypothesis simulations

(i) Estimate posterior probability of alternative model hypotheses

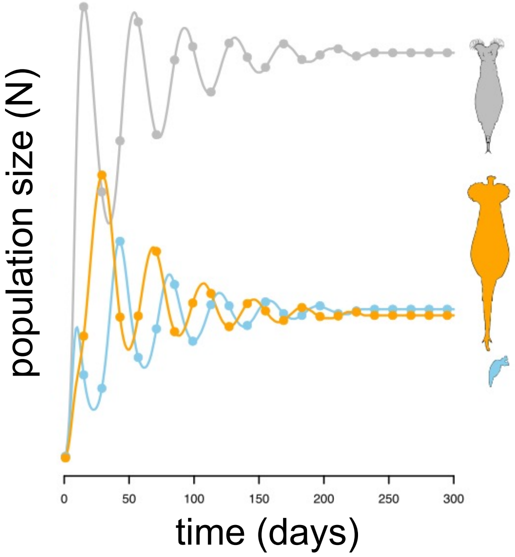
H_{eco}

$$\frac{n_{i,t+1}}{n_{i,t}} = \frac{\lambda_i}{1 + \alpha_{ii}N_{i,t} + \alpha_{ij}N_{j,t}}$$

$H_{eco\text{-}evo}$

$$N_{i,t+1} = \frac{\hat{W}e^{\frac{-[(\frac{w+(1-h^2)P}{P+w})(E-x_t)]^2}{2(P+w)}}N_{i,t}}{1 + \alpha_{ii}N_{i,t} + \sum_j \alpha_{ij}N_{j,t}}$$

Case 2. With simulated model + data
With x_{300} trait values only (!!)



Posterior model probabilities for Observed Data

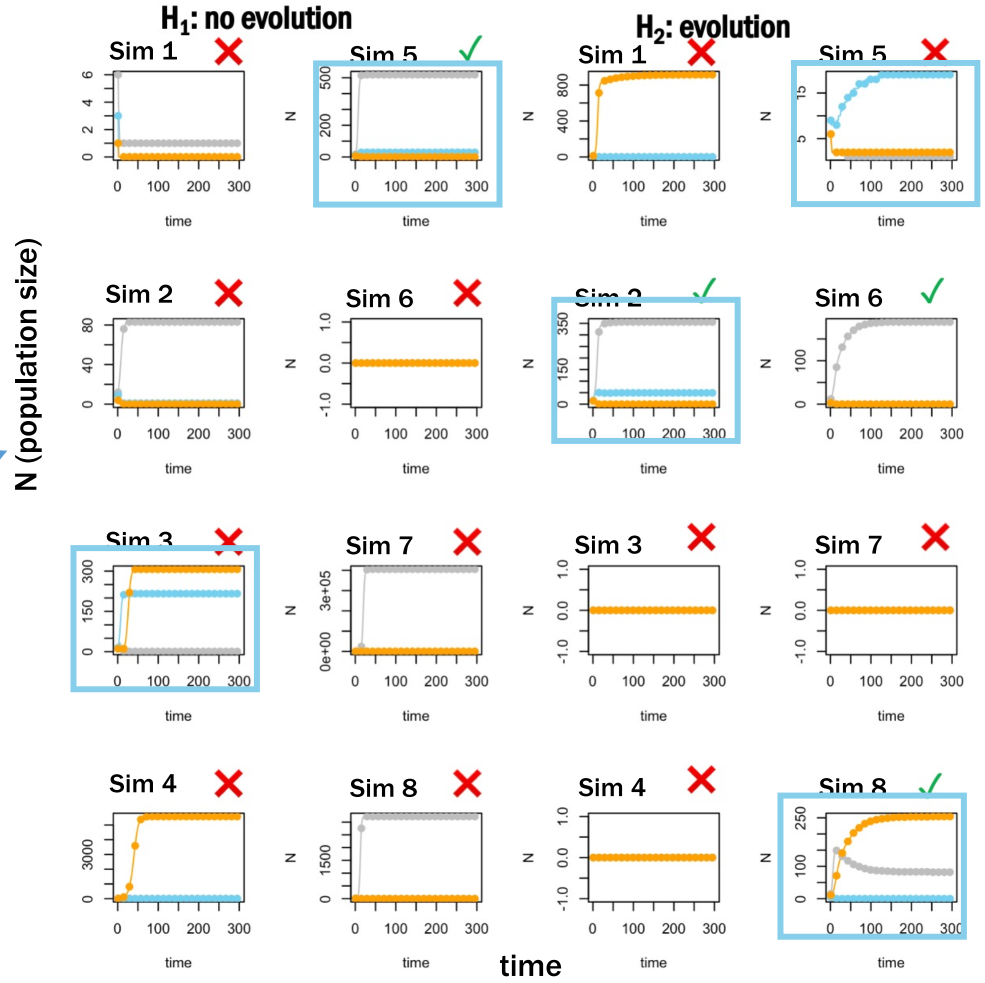
H_{eco} = 0.4676
$H_{eco\text{-}evo}$ = 0.5324

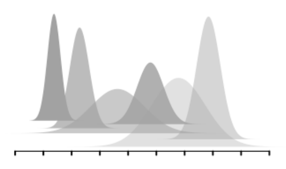
Based on % Accepted vs. Rejected per H_A model

Case 3. With simulated model + data
With x_{300} trait values only (!!)
Restricted to 3-species persisting simulations only

Posterior model probabilities for Observed Data

H_{eco} = 0.0783
$H_{eco\text{-}evo}$ = 0.9217





Research approach –eco-evolutionary hypothesis testing to fit data to models

Compare to observed data

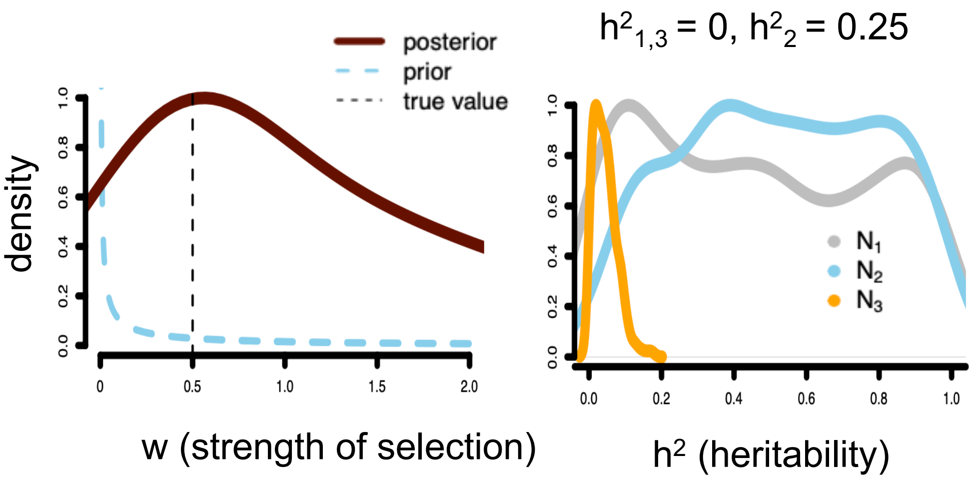
4. Compare observed data to alternative hypothesis simulations

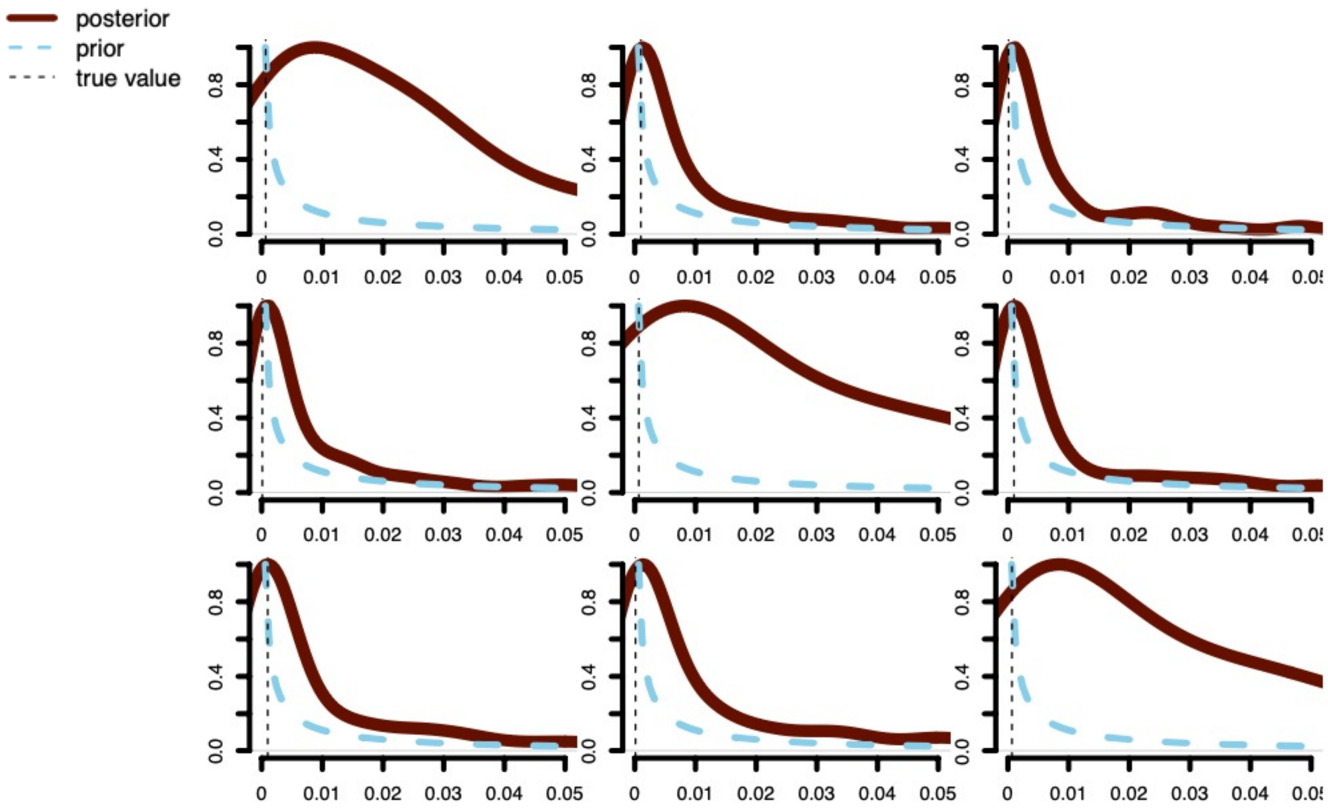
(i) Estimate posterior probability of alternative model hypotheses

(ii) Use best-fit (or consensus) models to estimate parameters for observed data, make predictions for future cases

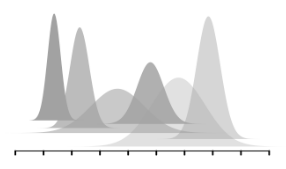
Posterior parameter values (unobserved)

$$\begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix} = \begin{bmatrix} 0.000666 & 0.001 & 0.000111 \\ 0.000111 & 0.000666 & 0.001 \\ 0.001 & 0.000111 & 0.000666 \end{bmatrix}$$





Pantel & Becks (in review, Trends Ecology & Evolution)

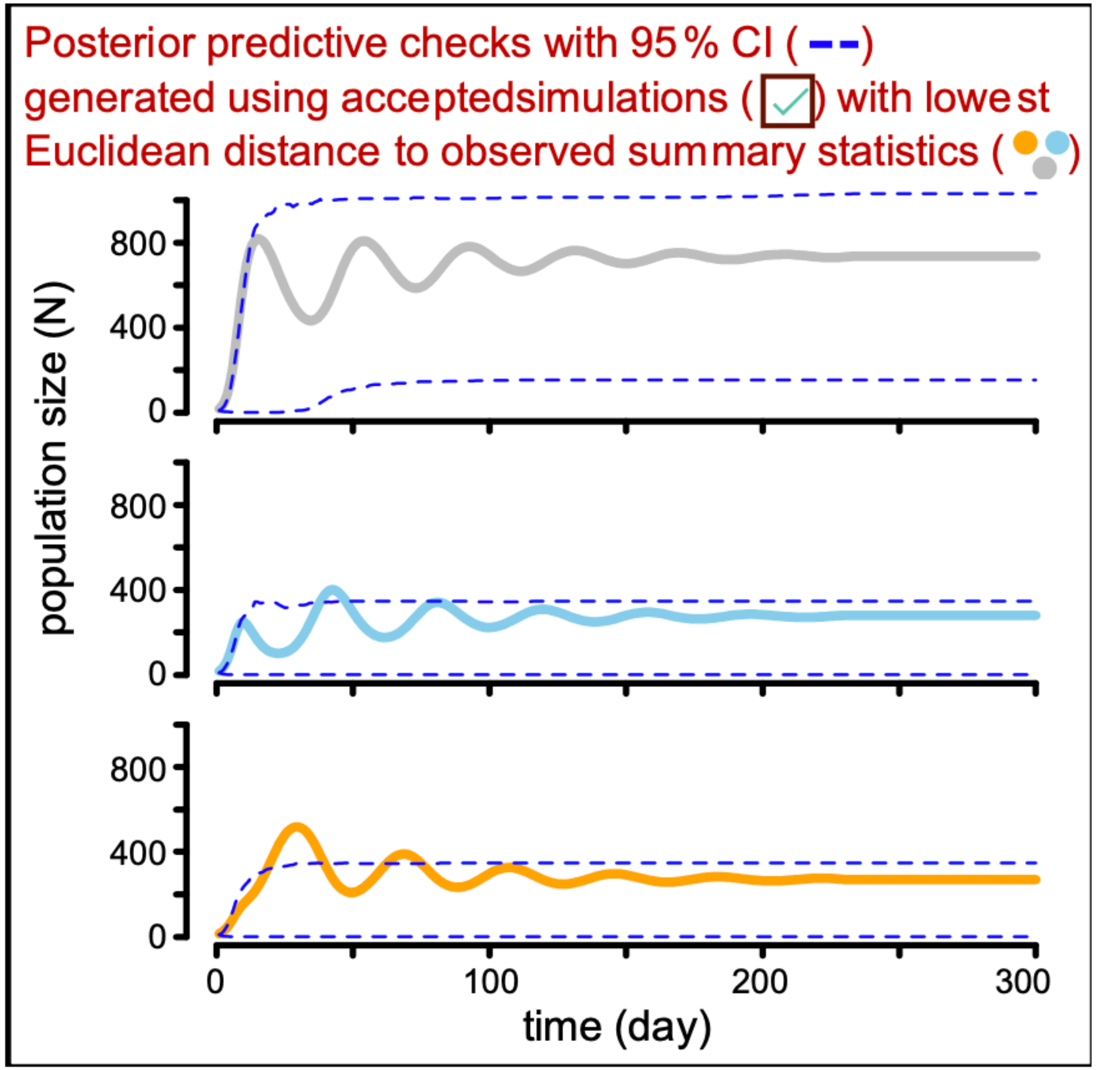


Research approach –eco-evolutionary hypothesis testing to fit data to models

Compare to observed data

4. Compare observed data to alternative hypothesis simulations

(i) Estimate posterior probability of alternative model hypotheses
(ii) Use best-fit (or consensus) models to estimate parameters for observed data, make predictions for future cases



Pantel & Becks (in review, Trends Ecology & Evolution)