Fitting Models to Data in Ecology and Evolution

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October 28, 2019

What does "modelling data" mean to you?

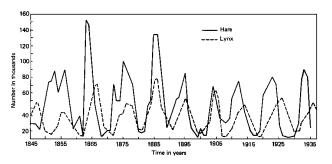
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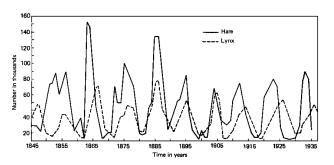
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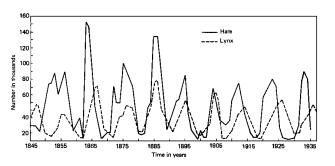


source: https://www.cds.caltech.edu/~murray/amwiki/images/8/8f/LHgraph.gif



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- Phenomenological model: The Lynx and Hare Cycles have a significant asynchrony (period shift) of x years

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- Ultimately, successful, EMPIRICALLY-GROUNDED mechanistic models are the best path towards a THEORY in any scientific discipline (including ecology and evolution)

Individuals

Mechanisms ⇒
Metabolic rate,
Temperature response,
Growth rate



Interactions

Mechanisms ⇒
Consumer-resource

interactions, Competition, Density dependence



Communities

Mechanisms ⇒

Trophic cascades, Bottom-up & Top-down regulation



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 - For example, disease outbreaks: Do we really need to care about the underlying mechanisms if we can predict a future event using phenomenological modelling (e.g., Machine-learning of time series patterns)?

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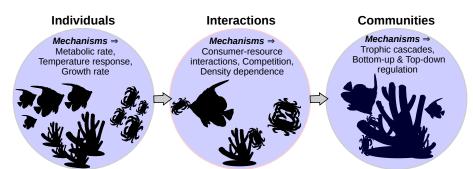
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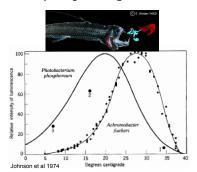
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- But is this REALLY mechanistic? What are r and k really?

 Proponents of Ecological Metabolic Theory (AKA "Metabolic Theory of Ecology") argue that we have not progressed far enough towards mechanistic modelling because metabolism has been ignored

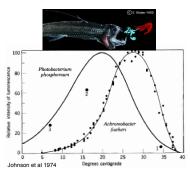


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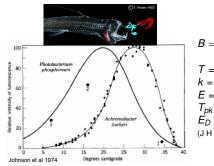
E = Activation energy (eV)

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EXAMPLE OF A FUNDAMENTAL MECHANISM: METABOLIC RATE

 The mechanistic basis of thermal performance curves (https://youtu.be/6n8fCuDwn74)



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- Surely there is more to thermal responses?
- What about alternative models?

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- Phenomenological/statistical models often perform better than mechanistic ones. Why? — because they have lest restrictive assumptions

MODELS: HOW TO BUILD THEM?

- It's an art, takes practice (Levins' paper on the strategy of model building in biology)
- Build models one mechanism at a time in biology, it means start at the right level of organization!
- Always consider an alternative that is more parsimonious, even if it is phenomenological!
- For example, the Boltzmann-Arrhenius model is a good first try describe and uncover mechanisms underlying individual level "traits" that are rates (e.g., fecundity or development rate)
- The next step would be to include species interactions with temperature dependence of individuals (or go in an evolutionary direction)

FITTING MODELS TO DATA

Multiple ways to do it:

- Least Squares methods
 - Linear
 - Non-linear
- Likelihood-based methods
 - Maximum Likelihood Estimation (MLE)
 - Bayesian
- Artificial intelligence and Machine learning
 - Focus in on maximizing ability to discover pattern and predict at the cost of mechanistic insights

METHODS YOU CAN USE

- Least squares: along with Linear Model fitting, Non-linear Least Squares (NLLS) fitting is a particularly versatile and powerful approach because many mechanisms in biology and inherently non-linear
- MLE/Bayesian methods: more robust if you are able to calculate the likelihood function analytically or numerically.
- Al/machine Learning: most versatile for large amounts of noisy data

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- Necessary for understanding the mechanisms underlying biological patterns/phenomena

 It's all about the "Likelihood" of a model: the set of parameter values of the model (θ) given outcomes (x), equals the probability of those observed outcomes given those parameter values, that is,

$$\mathcal{L}(\theta|\mathbf{x}) = P(\mathbf{x}|\theta)$$

- The easiest thing to do for you is to use information theory (including AIC and BIC) to compare models.
- Both AIC and BIC use the estimated (log-) likelihood of a model:
 - AIC: $-2 \ln[\mathcal{L}(\theta|x)] + 2p$
 - BIC (Schwartz criterion): $-2ln[\mathcal{L}(\theta|x)] + p\ln(n)$ (n = sample size, p = number of free parameters)
- The lower the AIC or BIC, the better.

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AIC AND BIC

• In models fitted with least squares and normally-distributed errors, $\ln[\mathcal{L}(\theta|x)] = -\frac{n}{2}\ln\left(\frac{RSS}{n}\right)$

Thus

AIC =
$$-2 \ln[\mathcal{L}(\theta|x)] + 2p$$

= $n + 2 + n \ln\left(\frac{2\pi}{n}\right) + n \ln(RSS) + 2p$

And

$$BIC = -2ln[\mathcal{L}(\theta|x)] + p \ln(n)$$

$$= n + 2 + n \ln\left(\frac{2\pi}{n}\right) + n \ln(RSS) + p \ln(n)$$

 The small sample AIC can also be calculated similarly (see Johnson & Omland 2004)

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- And BIC = n + 2 + n * log((2 * pi) / n) + n * log(rss) + (log(n)) * (p + 1)
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Also note that:

 R² = 1 - (rss/tss), where tss is total sum of squares: tss = sum((Observations - mean(Predictions)) ** 2) (a useful measure of goodness of fit)

COMPARING AND SELECTING MODELS: MORE STUFF

- You can also calculate Akaike Weights, which is very useful/important when comparing > 2 models. These weights can then be used to perform model averaging.
- Model selection using the Likelihood-Ratio test (LRT) is another option when you are comparing 2 models.
- Adjusted R² can be used to get a rigorous "idea" about how alternative models are performing.
- Very often, you will end up doing model simplification, especially in for linear least squares model fitting — starting with a complex model and then dropping terms till you have found a the most parsimonious version of the original model. There are functions in R to do this (of course!).

READINGS

- Levins, R. (1966) The strategy of model building in population biology. Am. Sci. 54, 421–431.
- Johnson, J. B. & Omland, K. S. (2004) Model selection in ecology and evolution. Trends Ecol. Evol. 19, 101–108.
- Bolker, B. M. et al. (2013) Strategies for fitting nonlinear ecological models in R, AD Model Builder, and BUGS. Methods Ecol. Evol. 4, 501–512.
- Additional readings on the TheMulQuaBio git repository