

ENMPG21:

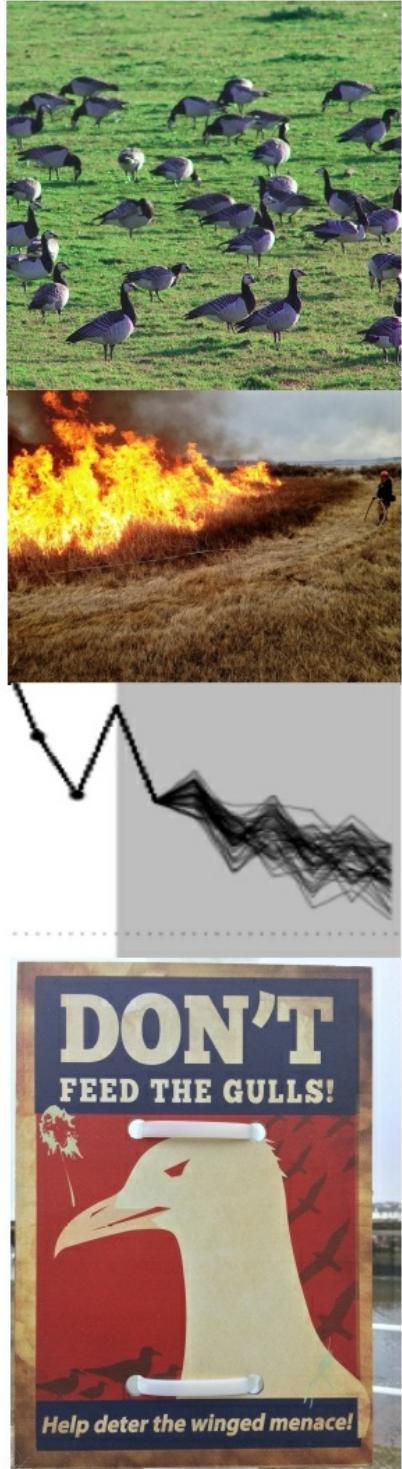
Biodiversity & Ecosystem Services 2019

Simulation modelling in conservation decision making: why and what?

Jeroen Minderman (jeroen.minderman2@stir.ac.uk)

13 March 2019 (*updated: 12/03/19*)

Overview



- What and why?
- Types of model
 - Conceptual
 - Quantitative models
 - Individual-based models (simulation)
- Example: oystercatcher IBM
- Modelling process: steps and complexity
- Tea break!
- Exercises & discussion

Why modelling?

What is it anyway?

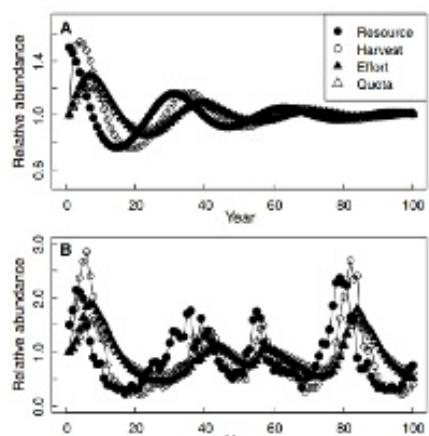
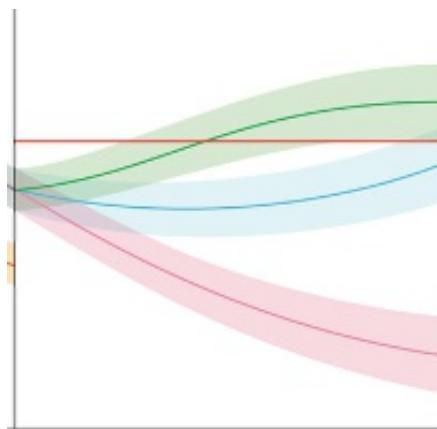
Definitions?

"*a representation of a particular thing, idea, or condition.. can be as simple as a verbal statement about a subject, or two boxes connected by an arrow to represent some relationship.*" (Jackson et al 2000)

"*Models represent real world phenomena in simplified forms in order to generate understanding of those phenomena; in ecology, models are typically mathematical objects*" (Evans 2012)

Why modelling?

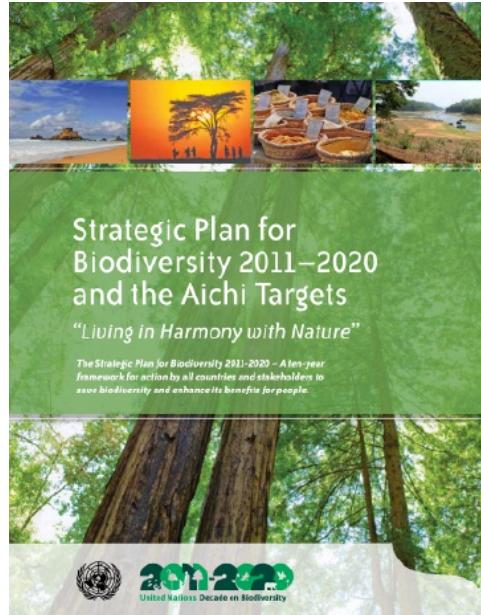
What is it anyway?



Examples illustrate different purposes

- **Predicting** animal distributions and/or population dynamics following disturbance or management interventions (e.g. Stillman et al. 2001, Nabe-Nielsen et al. 2014)
- **Evaluating** effect of policy interventions on species conservation (e.g. Nicholson et al. 2019)
- **Understanding** effect of delayed management responses (e.g. Fryxell et al. 2010)]

Why modelling? Evaluation and uncertainty



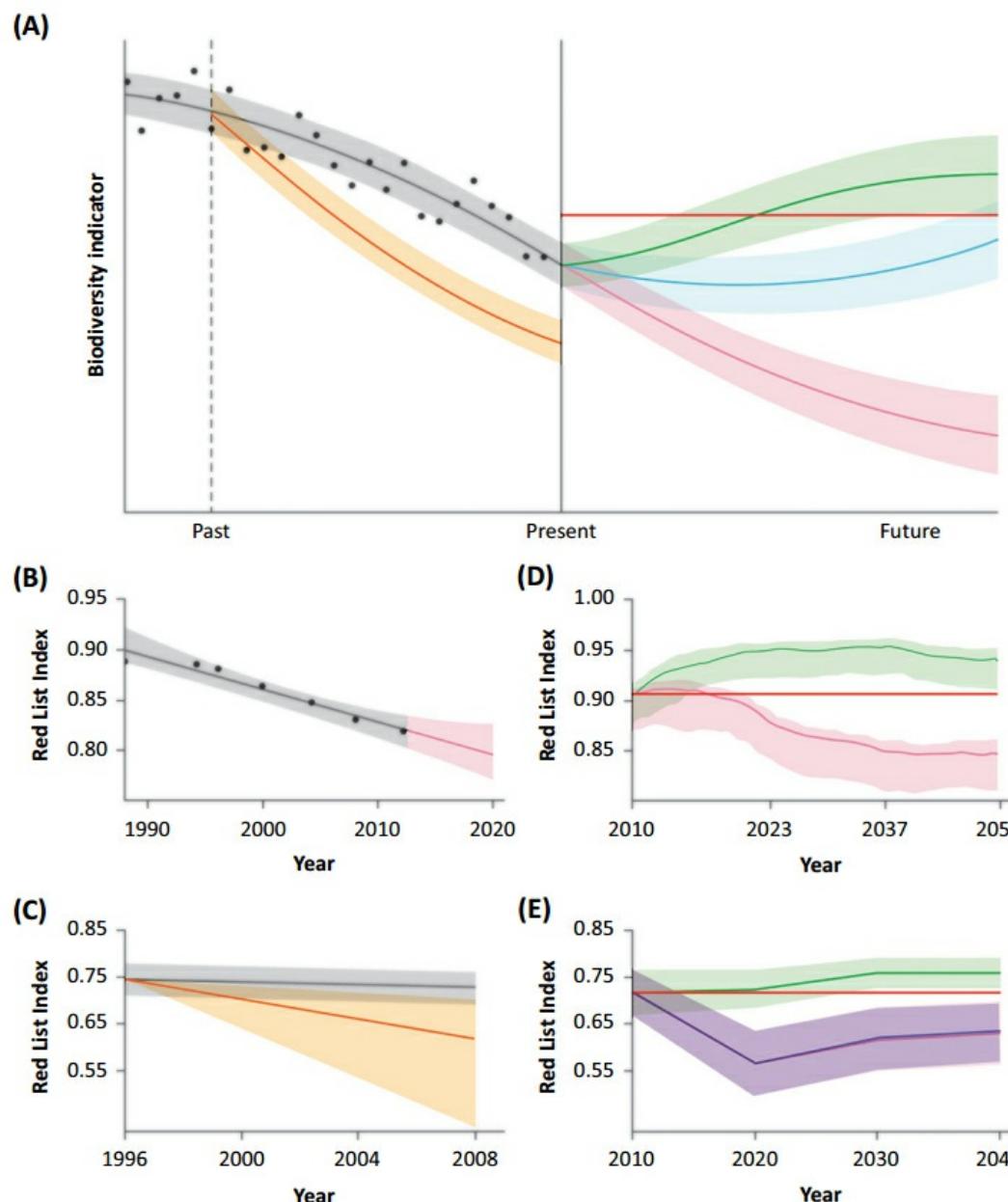
The Aichi Biodiversity Targets

Convention on Biological Diversity, e.g...

- **Target 12:** "By 2020 the extinction of known threatened species has been prevented and their conservation status, particularly of those most in decline, has been improved and sustained."
- **Target 14:** "By 2020, ecosystems that provide essential services, including services related to water, and contribute to health, livelihoods and well-being, are restored and safeguarded, taking into account the needs of women, indigenous and local communities, and the poor and vulnerable."

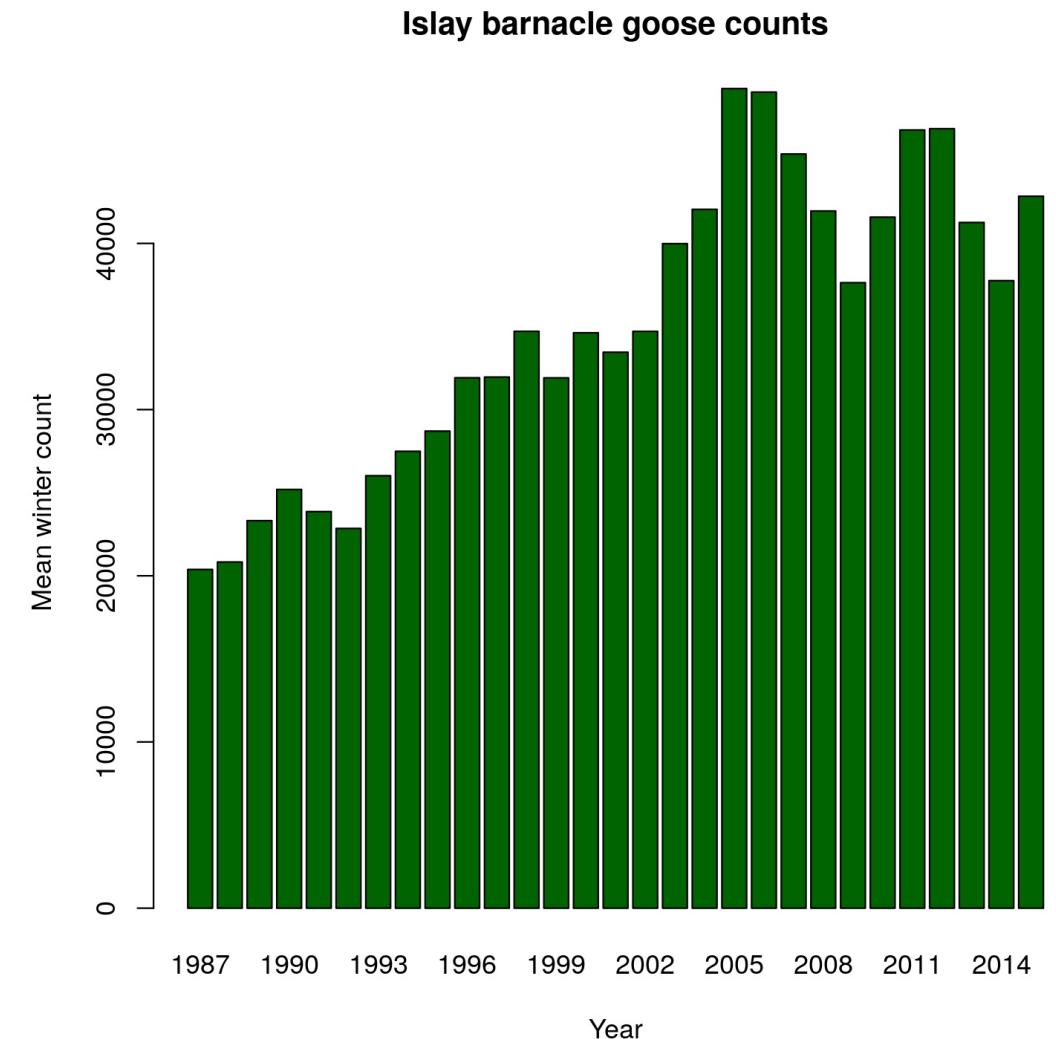
Why modelling? Evaluation and uncertainty

Scenarios and Models to Support Global Conservation Targets (Nicholson et al. 2019)



- Targets can shape policy and action...
- ... **BUT** bad wording or poor understanding can lead to poor conservation outcomes
- Model predictions may help evaluate possible outcomes (scenarios)
- Facilitates systematic use of data & representation of uncertainty

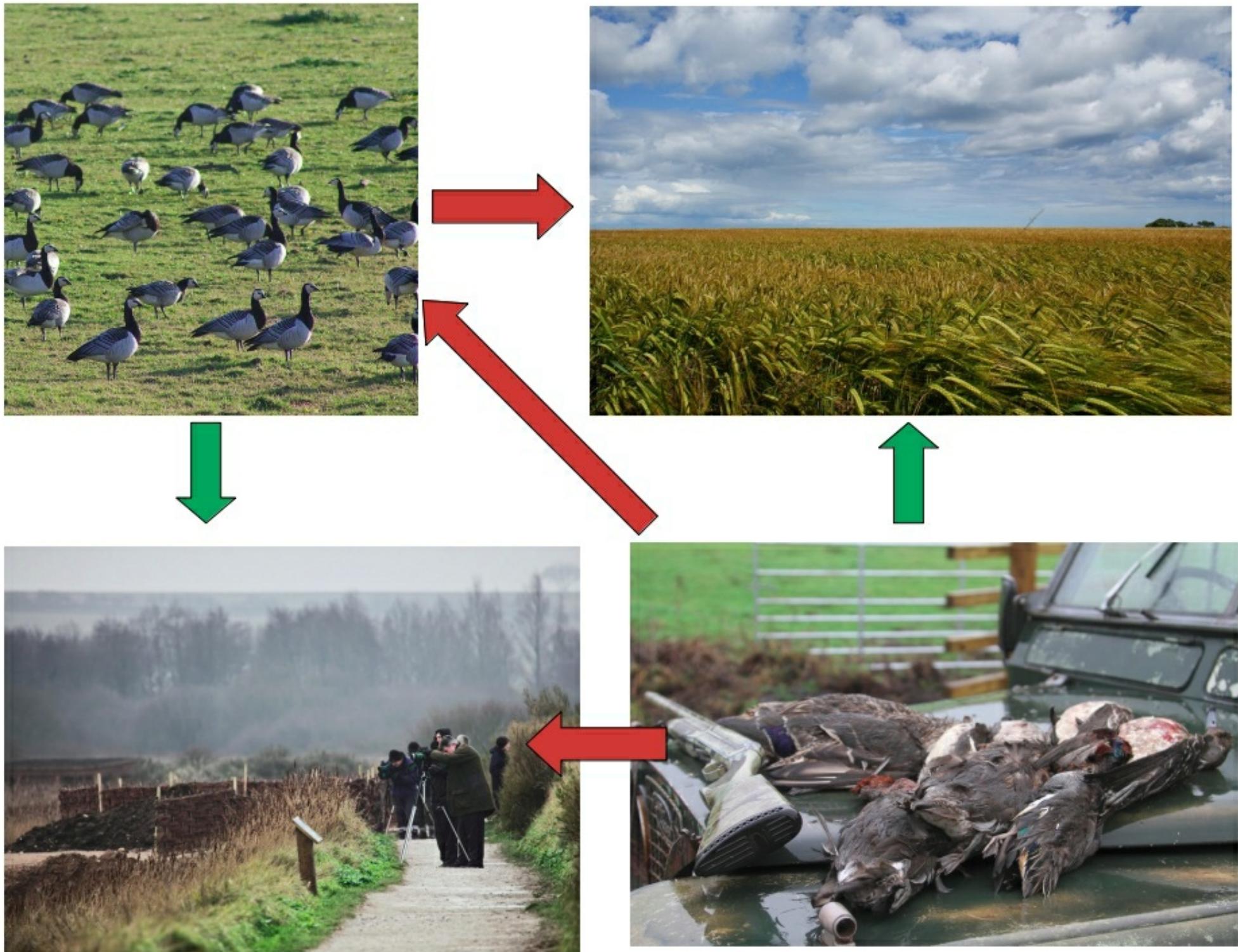
Why modelling? Management complexity



Why modelling? Management complexity



Why modelling? Management complexity



Why modelling? Management complexity

The Scotsman logo: THE SCOTSMAN, SCOTLAND'S NATIONAL NEWSPAPER

News Environment Politics Transport Education Health UK World

Islay's barnacle geese battle: 'I can't shoot enough to make a difference'



The strategy aims to reduce crop damage by an estimated 25% to 35% by decreasing the number of Barnacle Geese. Picture: John Devlin/JPIMedia

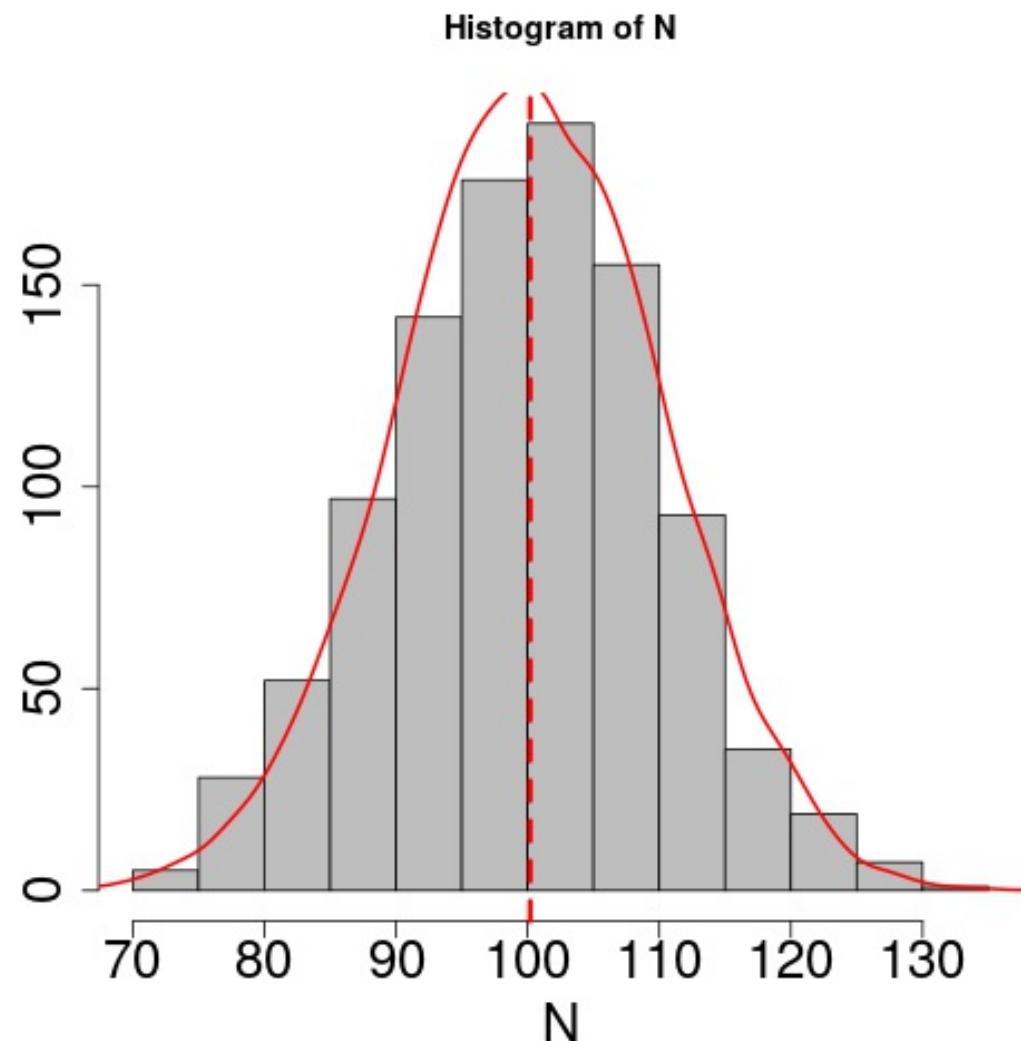
The Scotsman, November 2018



Film clips of geese being shot on the island of Islay have prompted renewed allegations that many are left to suffer slow, painful deaths.

theferret.scot, January 2019

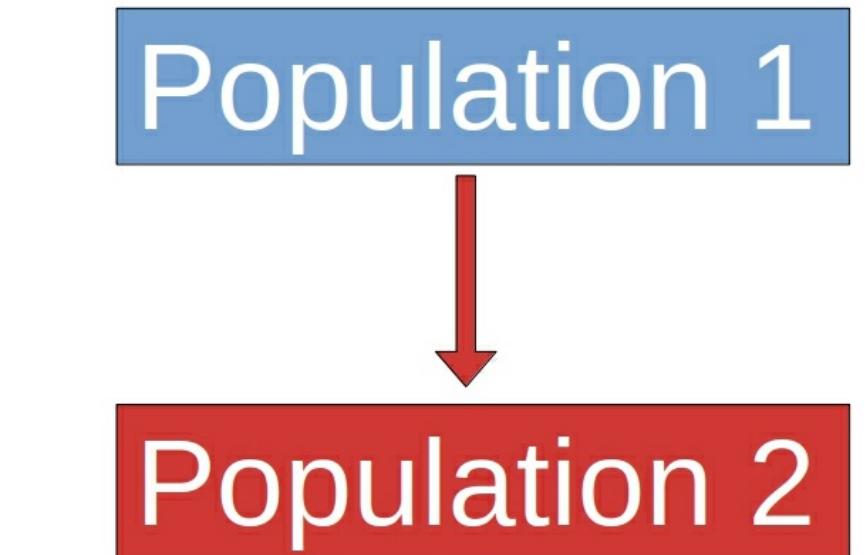
We're all modellers! (sort of)



```
N = rpois(1000, 100) # Sample counts  
rnorm(10000, 100, 10) # Normal distribution
```

- A mean of N is a model!
- Makes assumptions
- "Predicts" the most likely "true" value, given assumptions hold

Conceptual models



- **State variables**

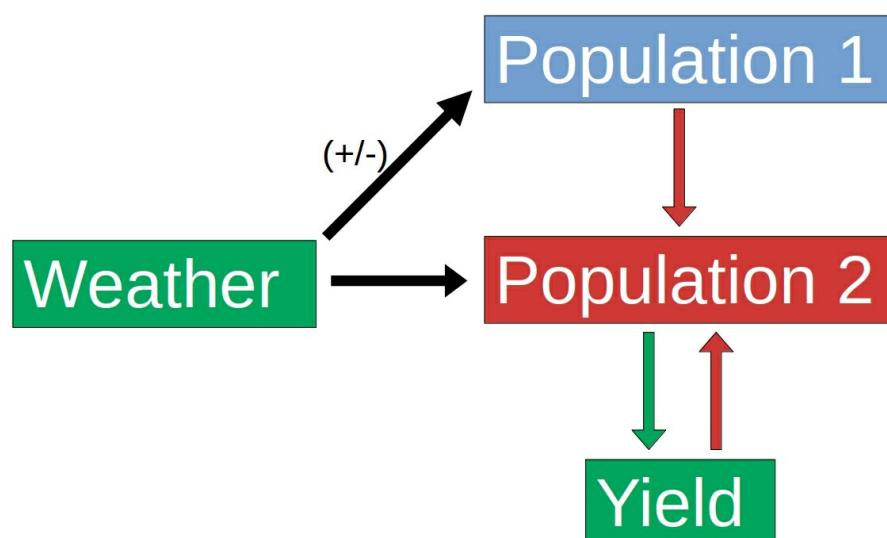
Represent condition/state, e.g.

- Population size
- Stakeholder response

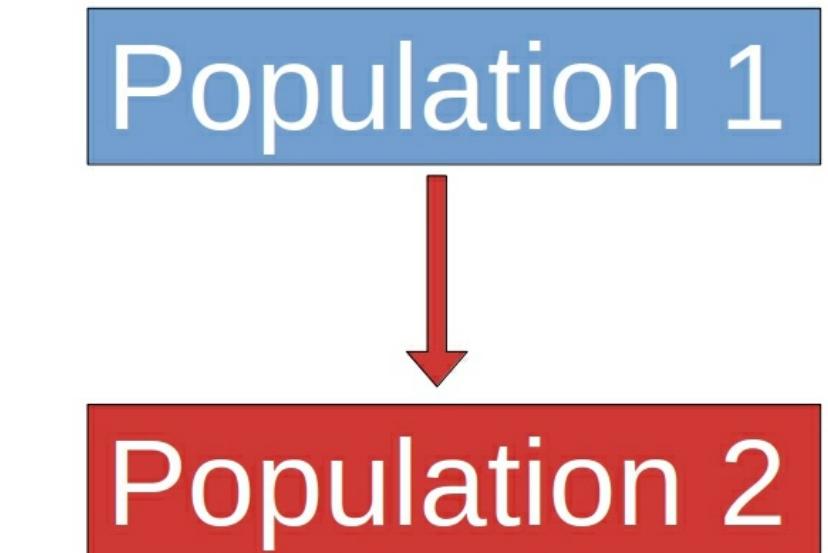
- **Relationships**

Represent relationships or effects, e.g.

- Effect of predation
- Management effects



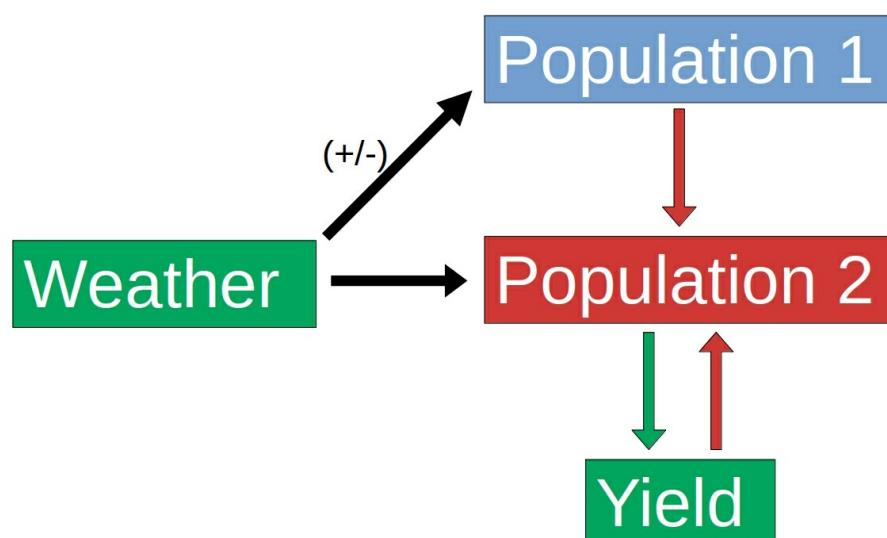
Conceptual models



- **Advantages**

- Easy to understand and to communicate
- Very flexible and quick to develop
- Useful tool for planning/designing work

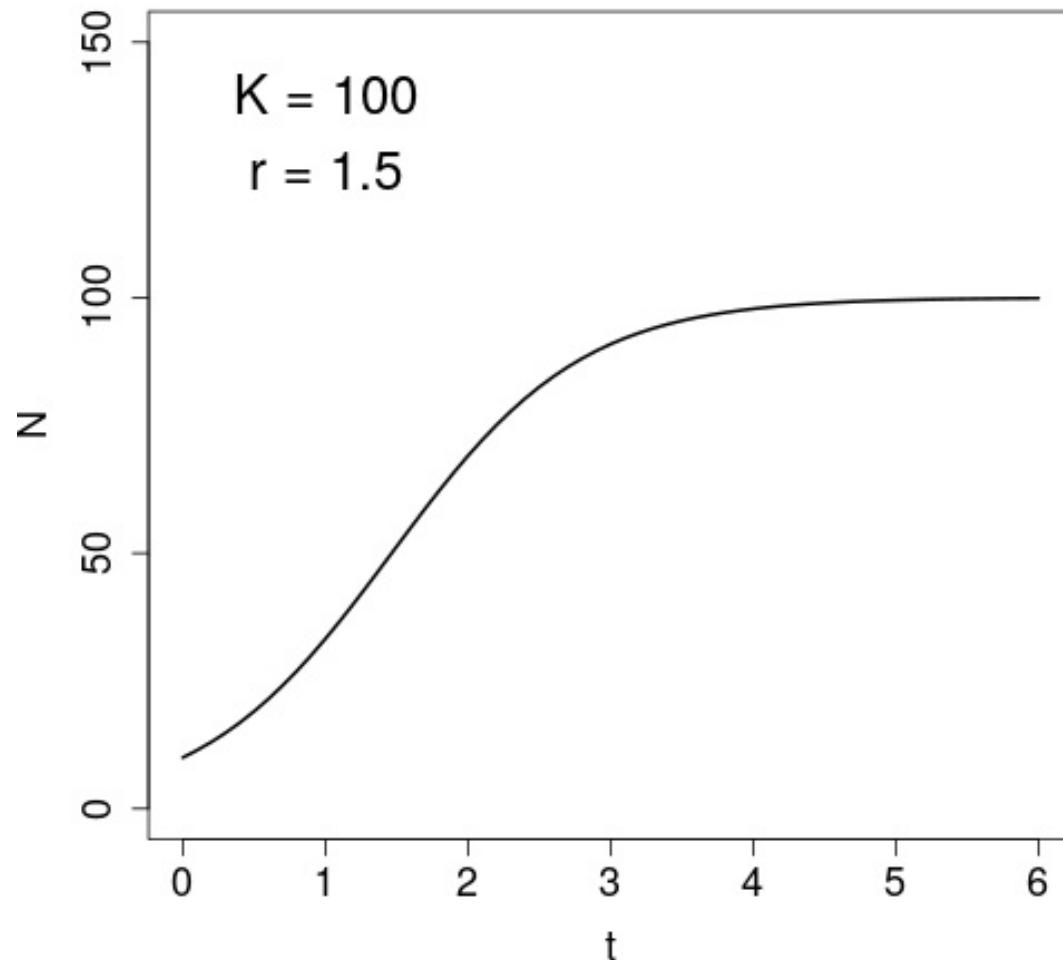
- **Disadvantages**



- Not usually quantitative
- Can be deceptively simple

Quantitative models

Logistic population growth model



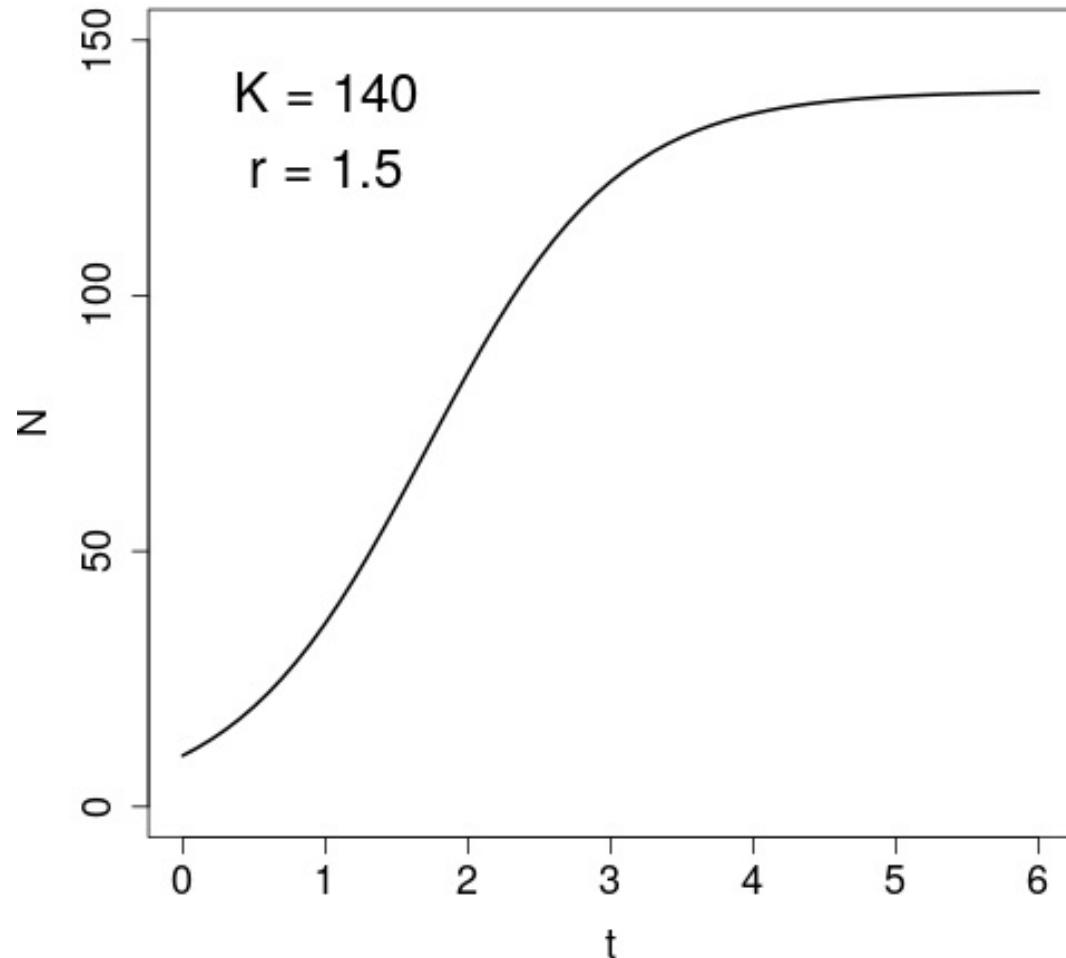
$$\frac{dN}{dt} = rN\left(1 - \frac{N}{K}\right)$$

$$N(t) = \frac{KN_0}{(K-N_0)e^{-rt}+N_0}$$

- $N(t)$ = population size at time t
- N_0 = initial population size
- r = intrinsic population growth rate
- K = carrying capacity

Quantitative models

Logistic population growth model



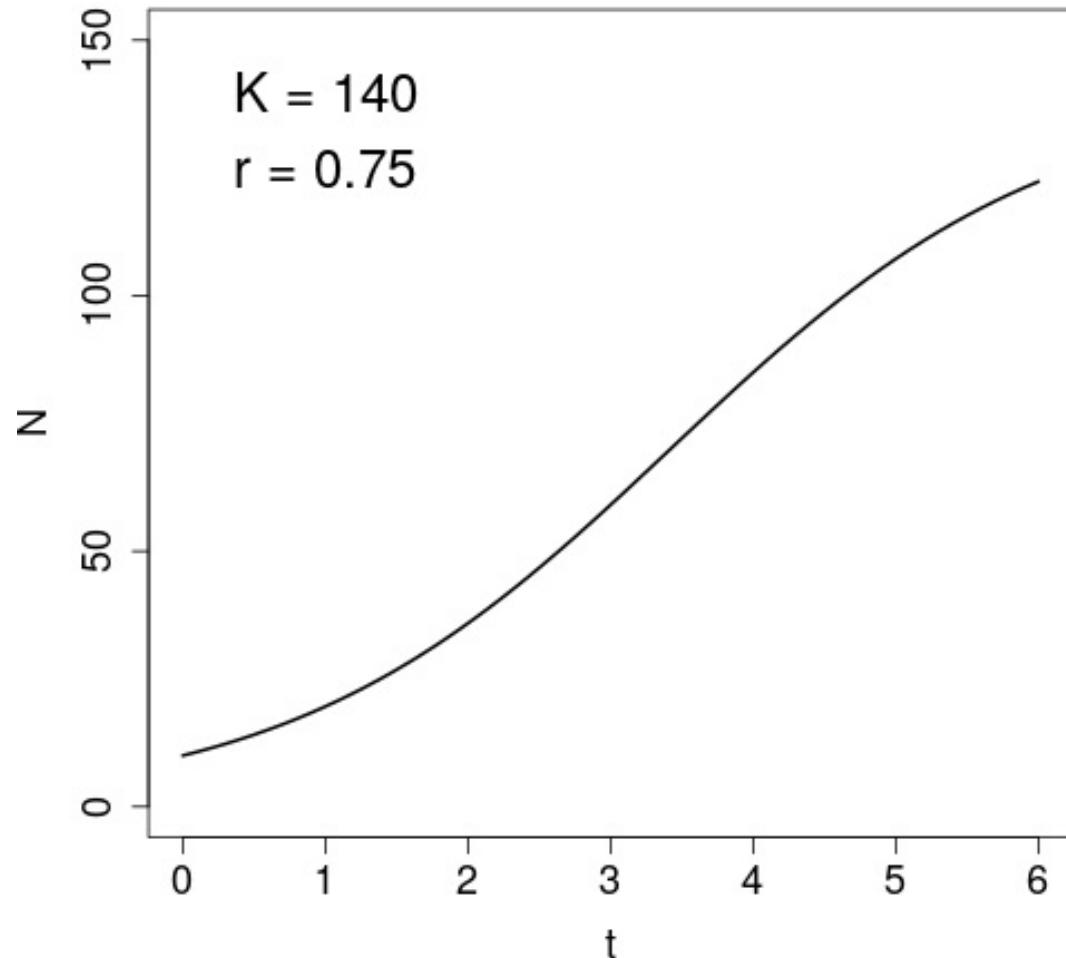
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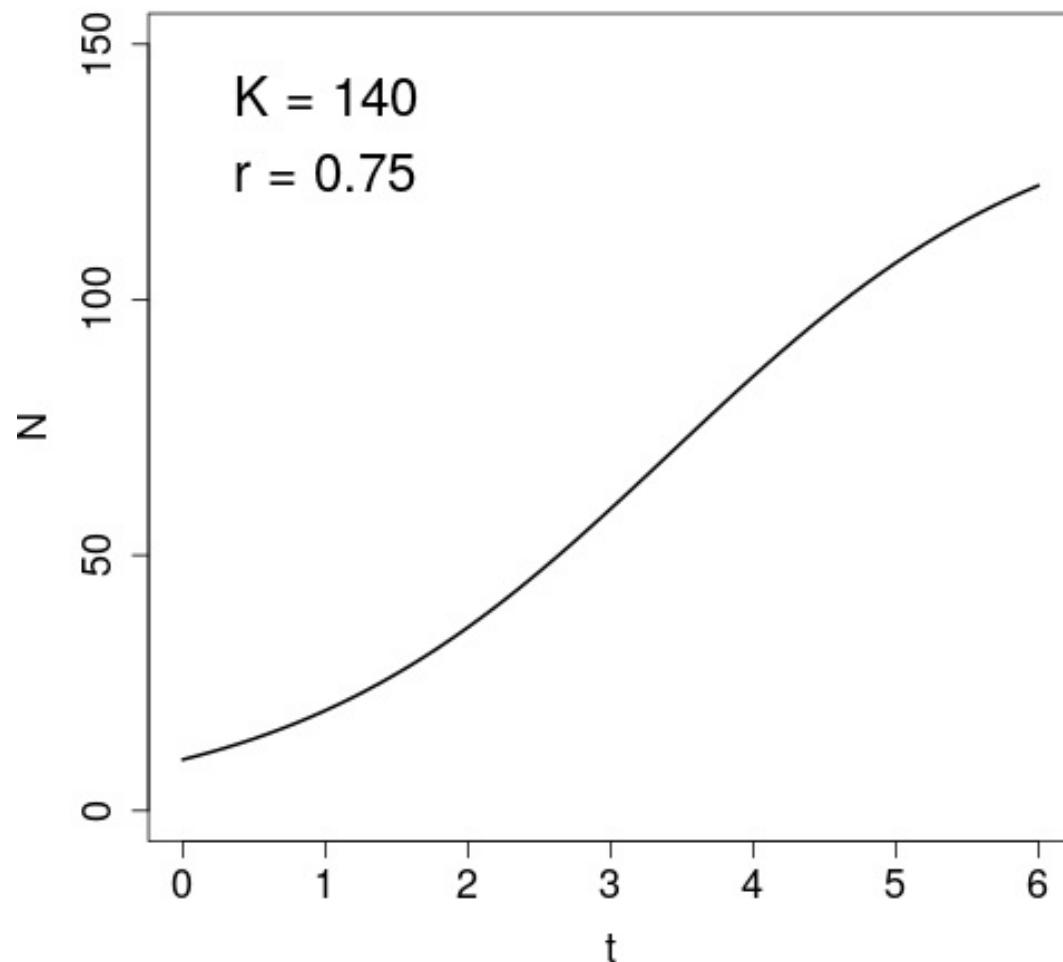
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Quantitative models

Logistic population growth model



Advantages

- Basic quantitative models very simple
- Relatively easy to fit to data

Disadvantages

- N function of only one "explanatory variable"
- Expanding explanatory variables can require significant maths skills
- Difficult to extrapolate beyond parameterised range

Quantitative models

More realism?

Effects of noise and by-catch on a Danish harbour porpoise population (Nabe-Nielsen et al. 2014)

$$\mathbf{V}_k[t] = \begin{cases} \text{ci} * (n_k d_{deter} - \text{dist}(p, k)[t]) & \text{if } \text{dist}(p, k)[t] < d_{deter}; \\ \mathbf{V}_k[t-1]/2 & \text{if } \text{dist}(p, k)[t] \geq d_{deter} \text{ and } \mathbf{V}_k[t-1] > 0; \\ 0 & \text{if } \text{dist}(p, k)[t] \geq d_{deter} \text{ and } \mathbf{V}_k[t-1] = 0. \end{cases}$$

Eqn. A1a

$$\mathbf{V}_D = \sum_k \mathbf{V}_k \quad \mathbf{V}^* = \frac{\mathbf{V}_R + \mathbf{V}_S + \mathbf{V}_D}{\|\mathbf{V}_R + \mathbf{V}_S + \mathbf{V}_D\|} \times \|\mathbf{V}_S\|$$

$$E_p^*[t+1] = \begin{cases} E_p[t] + E_k[t]^{\frac{20-E_p[t]}{10}} & \text{if } E_p[t] \geq 10; \\ E_p[t] + E_k[t] & \text{if } E_p[t] < 10. \end{cases}$$

- Needs understanding of maths
- Not easy to communicate to non-specialists
- Usually very specific to case study

Quantitative models

More realism?

Effect of marine reserve establishment on non-cooperative fisheries management
(Takashina *et al.* 2017)

$$\frac{dx}{dt} = rx \left(1 - \frac{x}{K}\right) - \sum_i^n q_i e_i x.$$

$$\pi_i = (p_i q_i x^* - c_i) e_i$$

$$\frac{dx_1}{dt} = rx_1 \left(1 - \frac{x_1}{K_1}\right) - \sum_i^2 q_i e_i x_1 + M(x_1, x_2),$$

$$\frac{dx_2}{dt} = rx_2 \left(1 - \frac{x_2}{K_2}\right) - M(x_1, x_2),$$

$$M(x_1, x_2) = m\{(1 - \alpha)x_2 - \alpha x_1\},$$

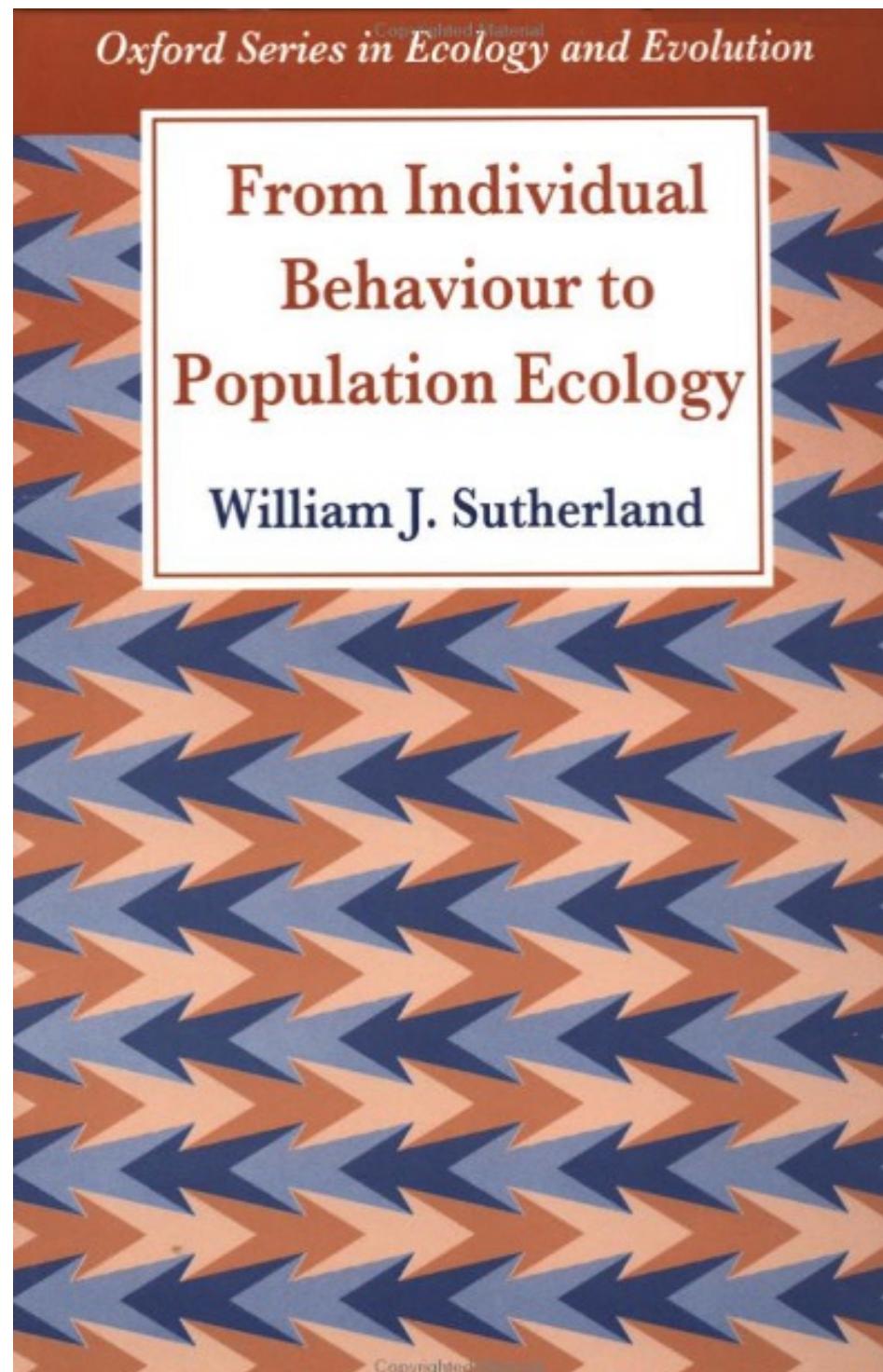
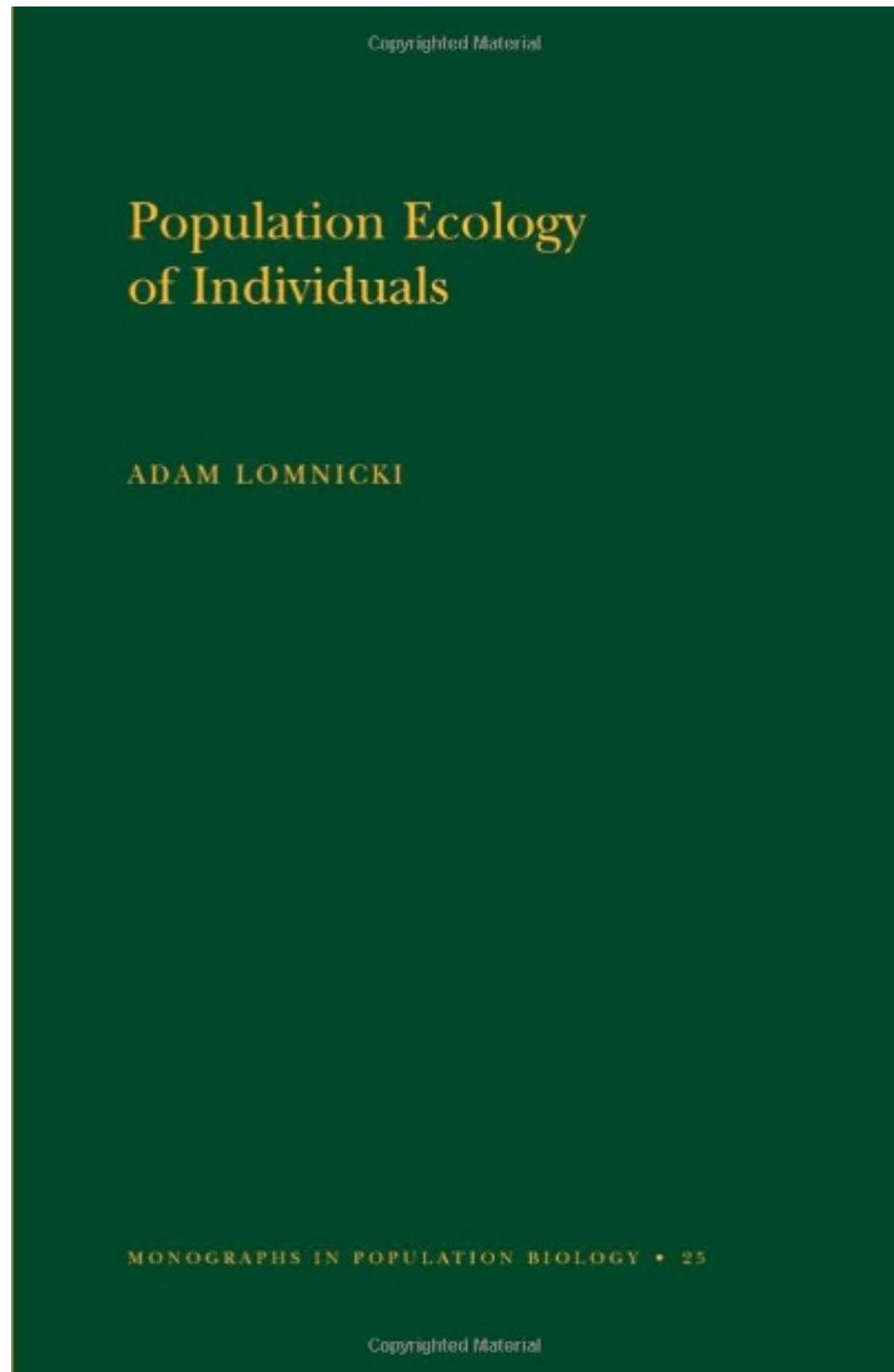
$$\pi_i^{\text{Nash}_2} = \max_{e_i} (p_i q_i x_1^{\text{Nash}_2} - c_i) e_i, \quad (i = 1, 2)$$



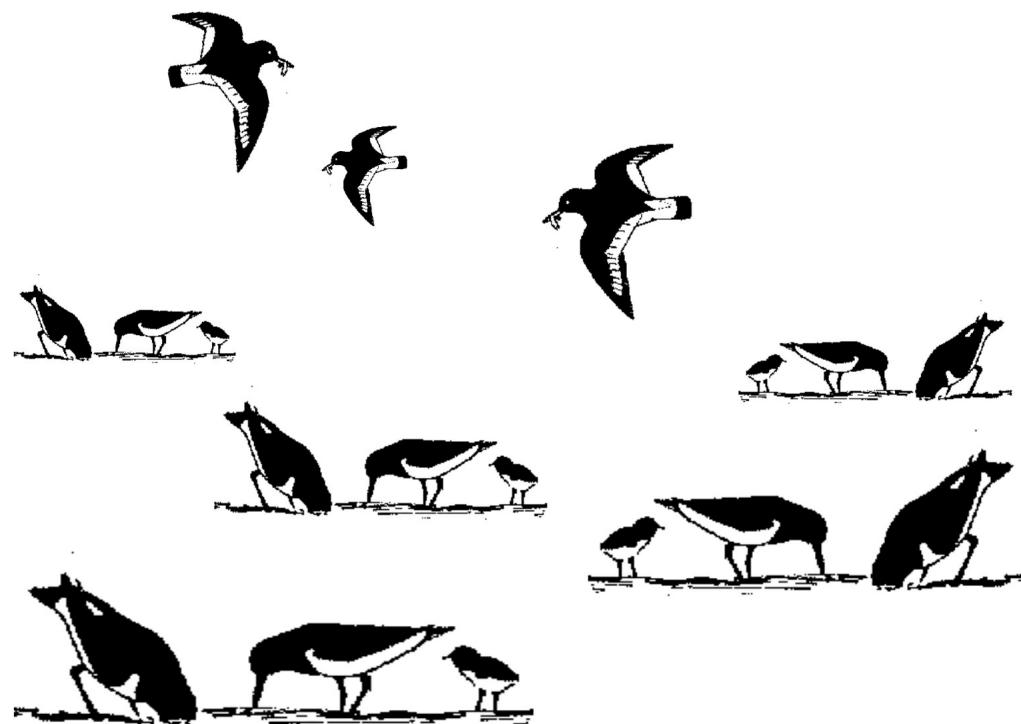
- Increased realism = increased complexity
- Hard to communicate?
- Needs extensive technical skills to implement

Individual-based models

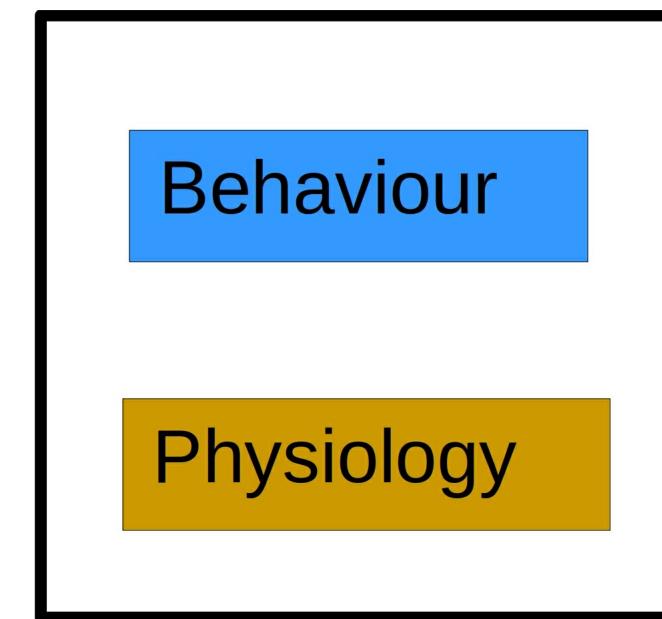
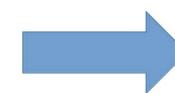
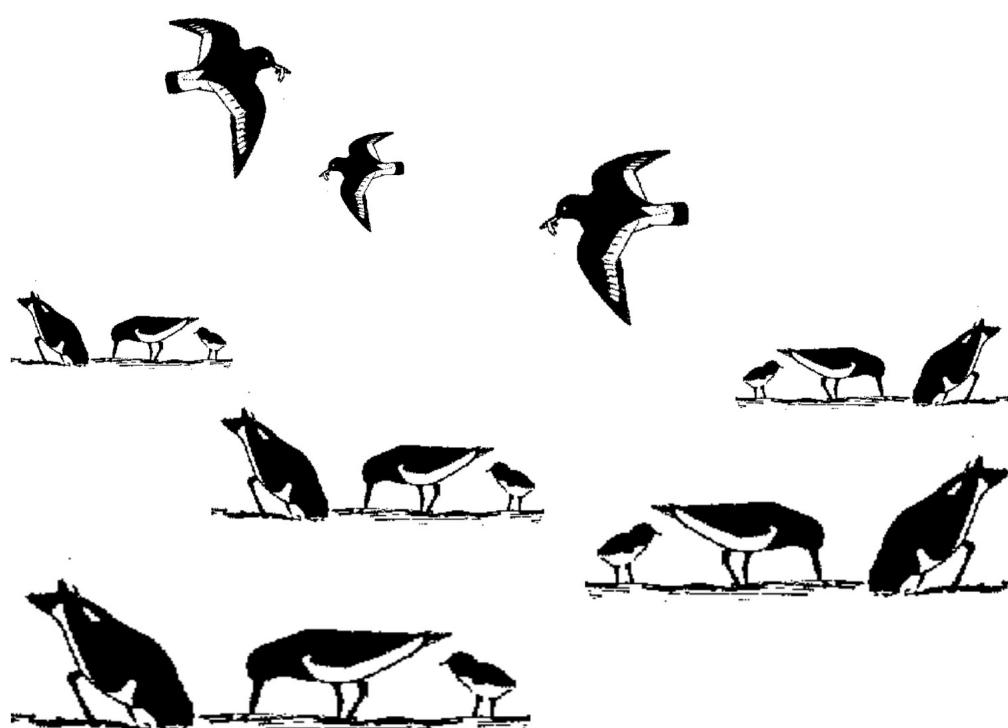
IBMs, "Agent-based" models



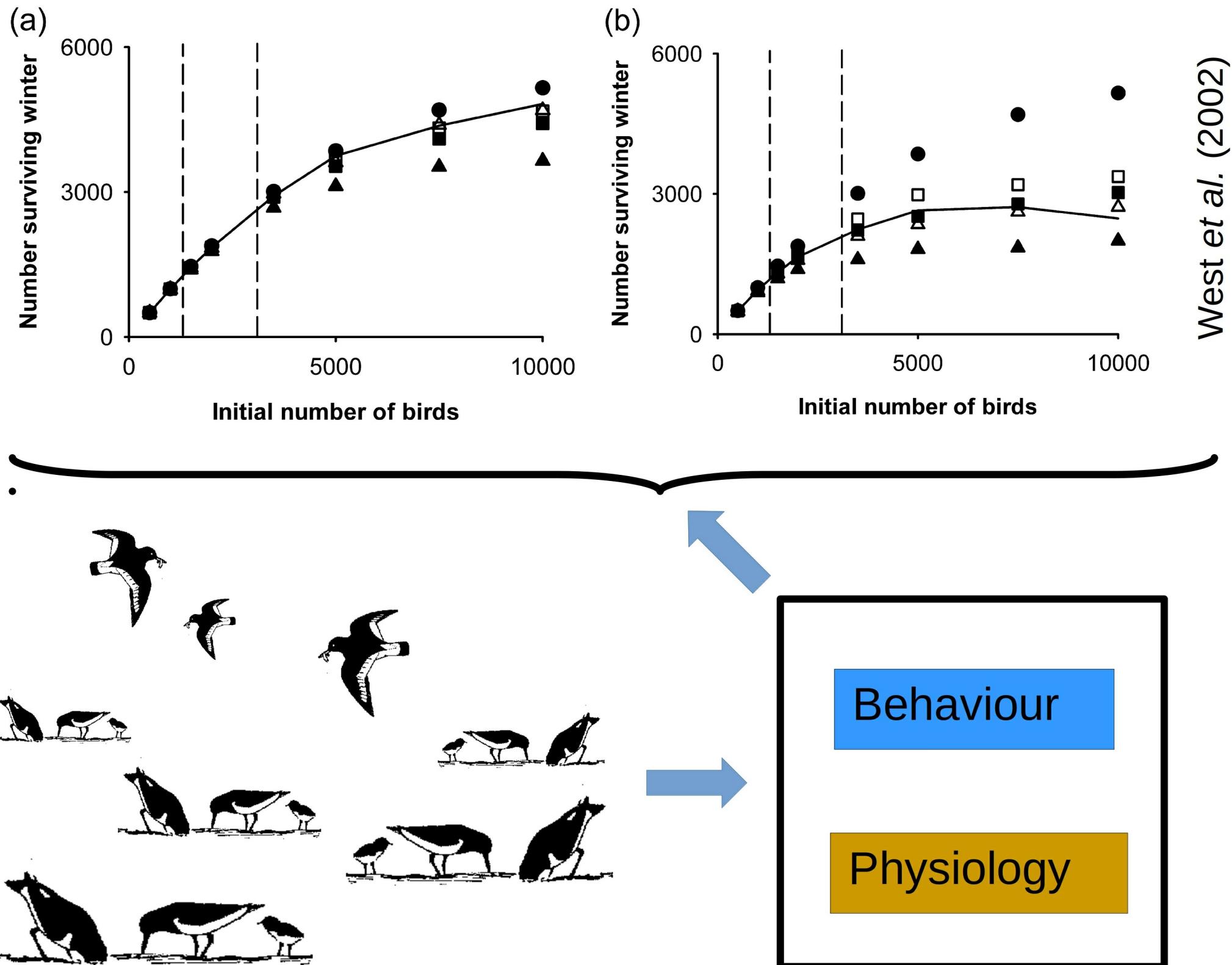
Individual-based models



Individual-based models



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Individual-based models

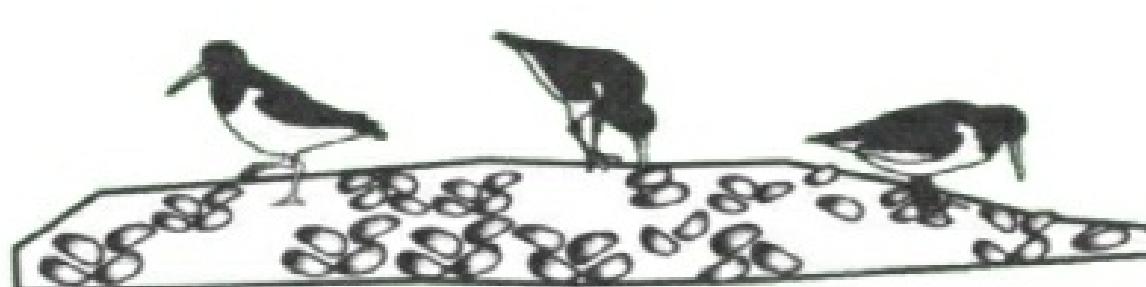
Based around **two key principles** (per Stillman et al. 2015)

1. Emergence

- Population properties arise from individuals:
- e.g. behaviour, physiology, genotype

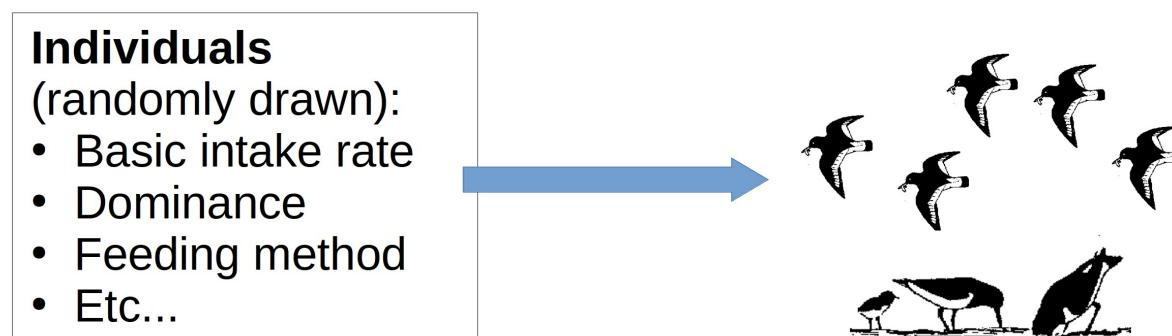
2. Fitness

- Individual fitness determines success (survival/reproduction)
- Individuals aim to maximise fitness
- Fitness & environment linked by functions



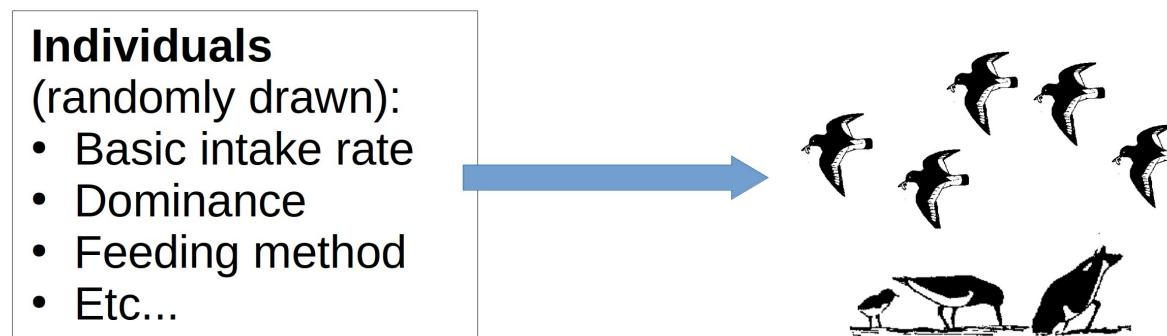
Individual-based models: Oystercatchers

IBM to predict winter mortality in Oystercatchers (*Haematopus ostralegus*)
(Stillman et al. 2000)



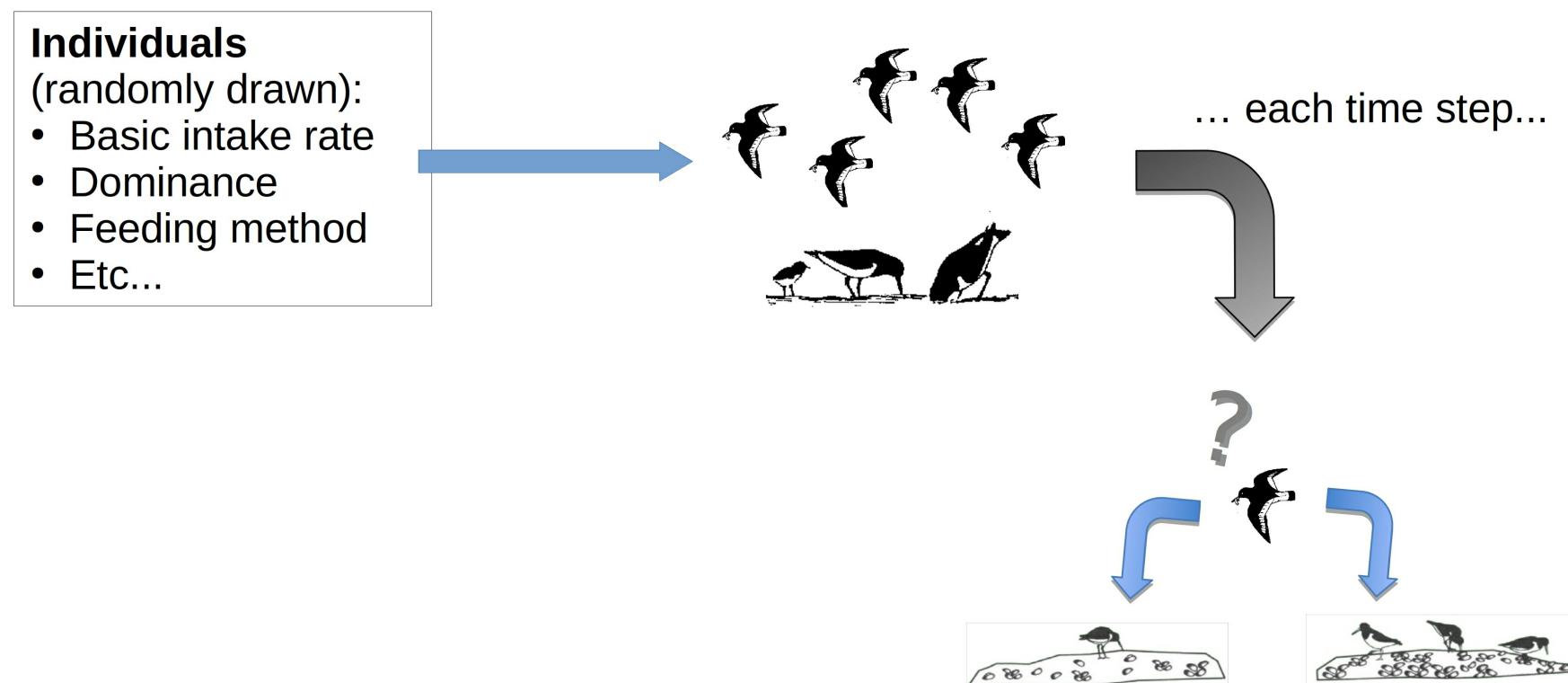
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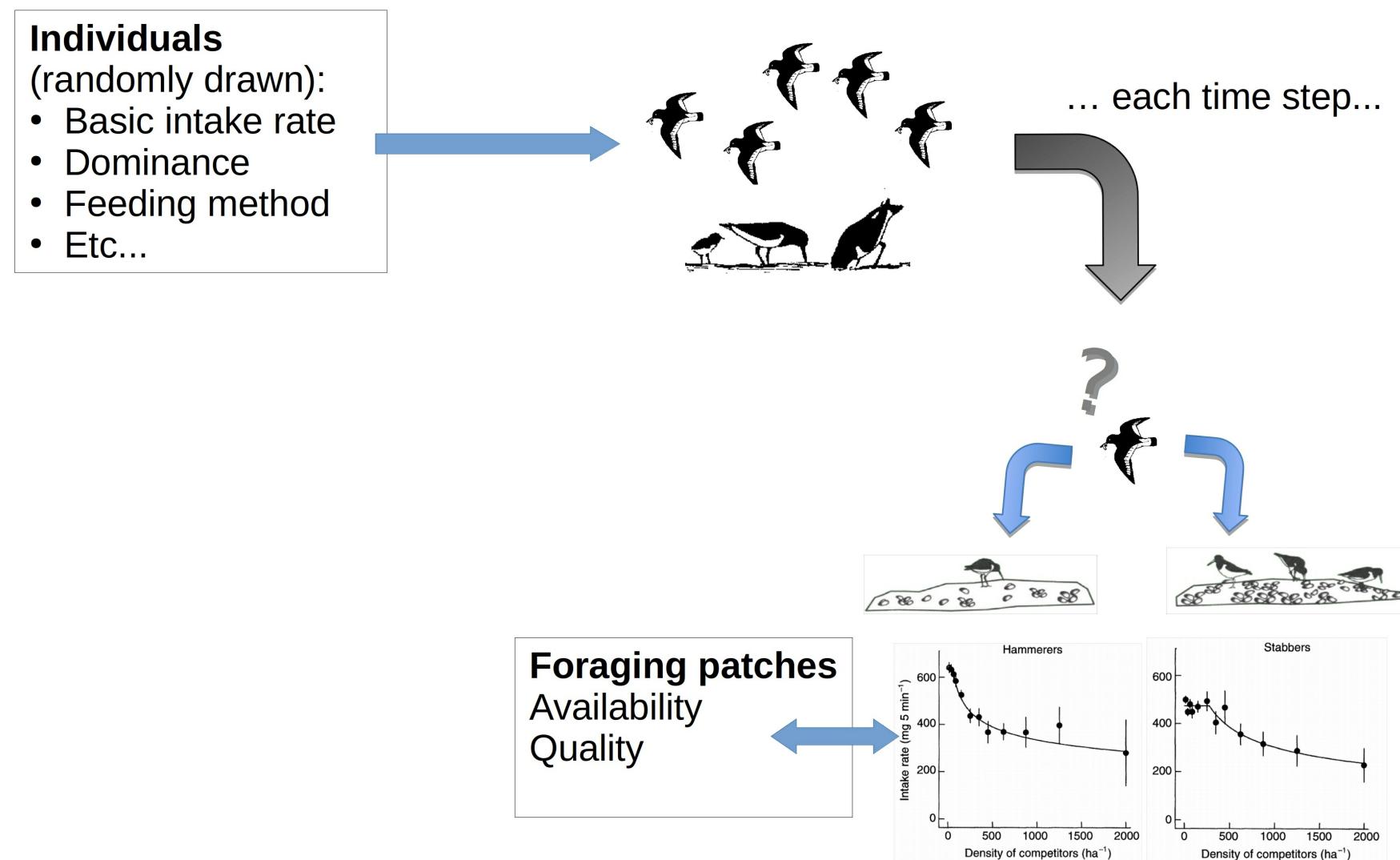
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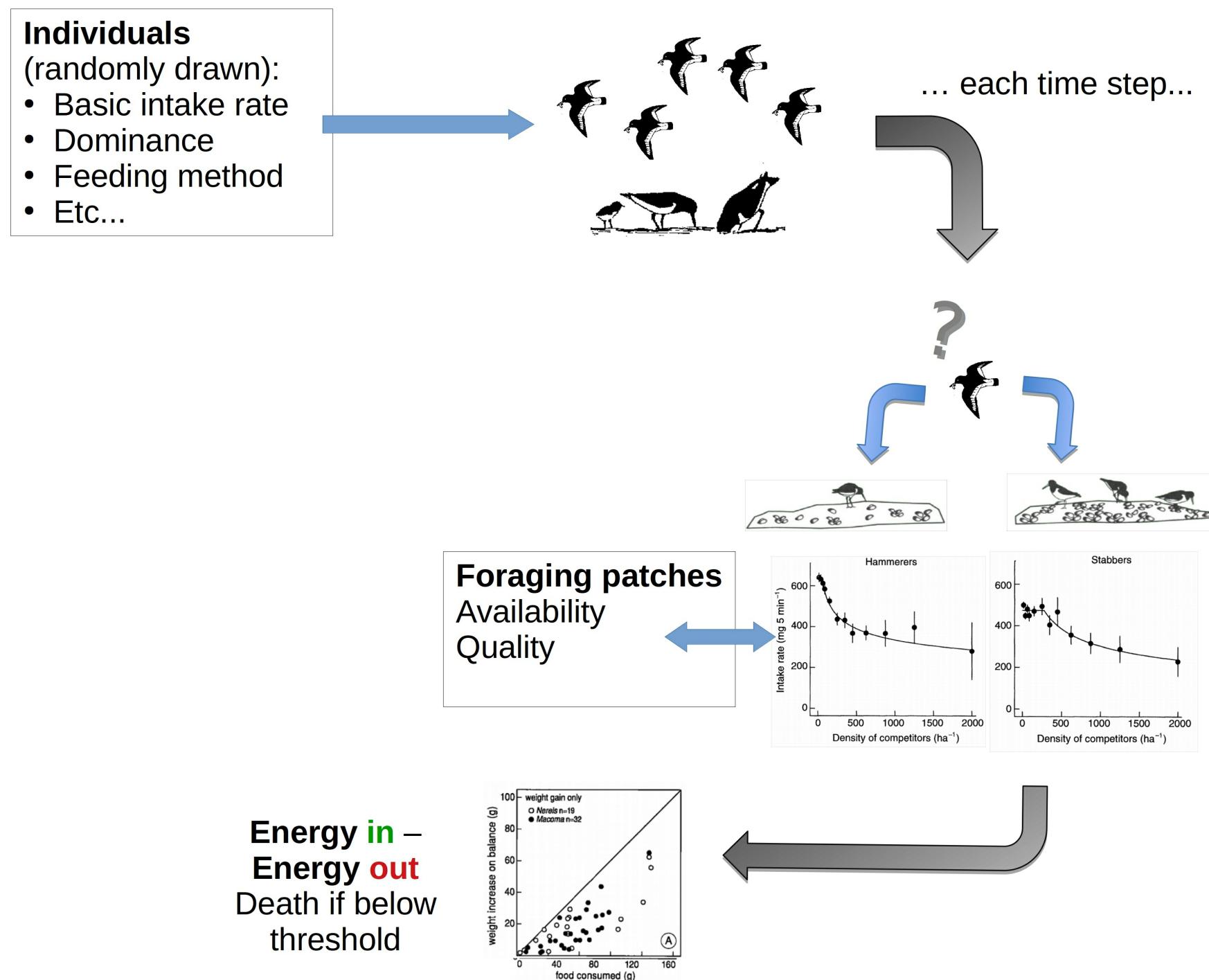
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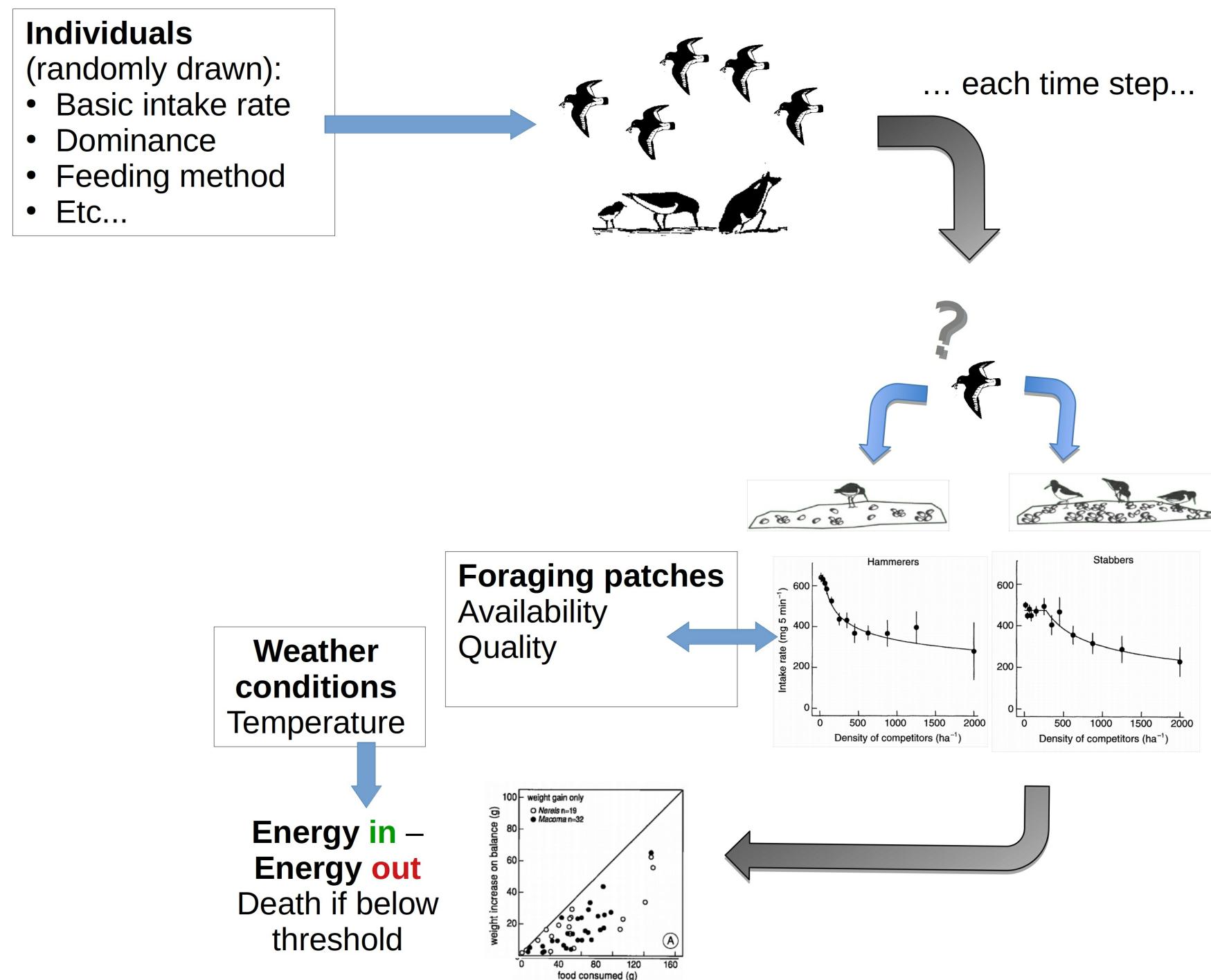
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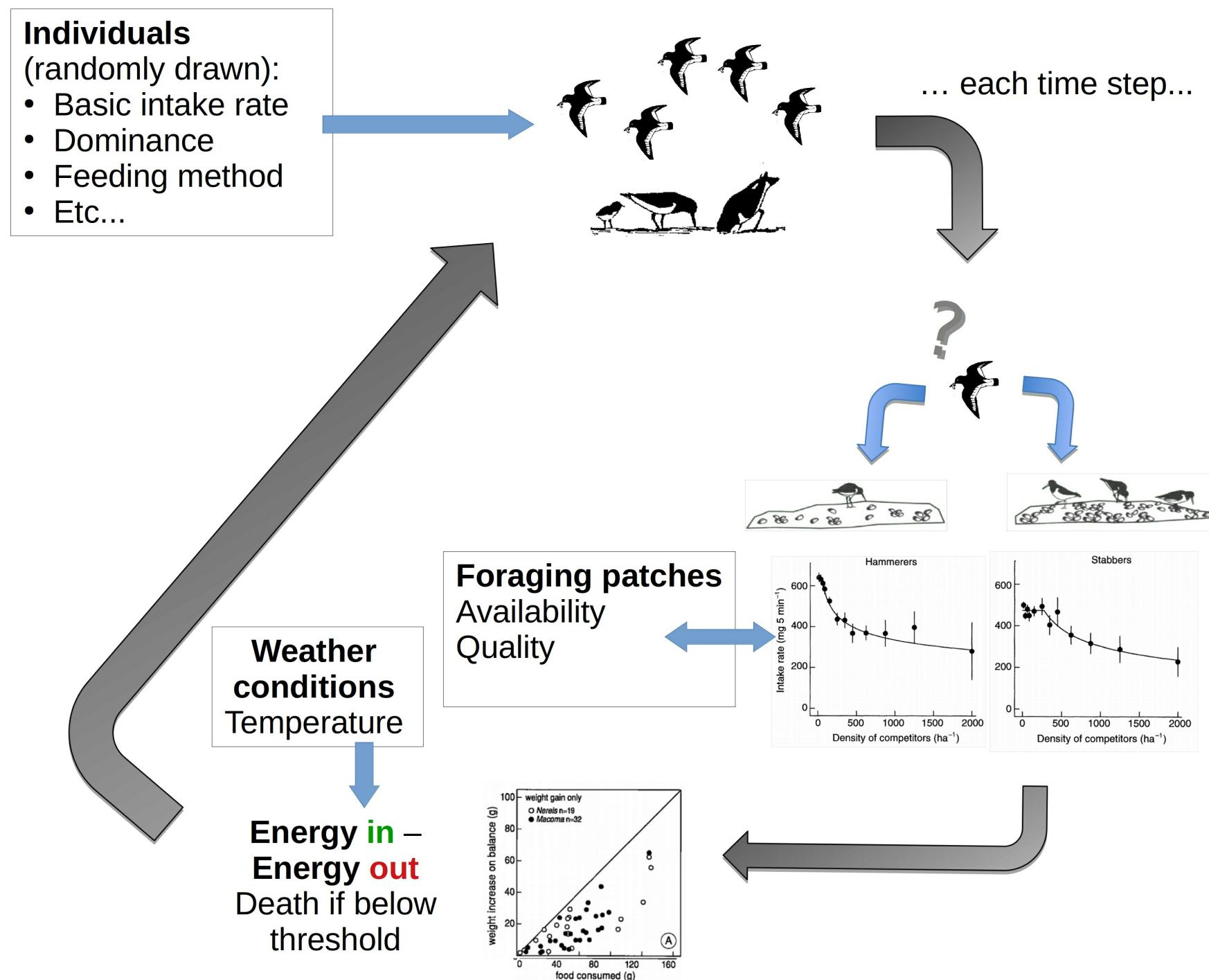
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Individual-based models: Oystercatchers

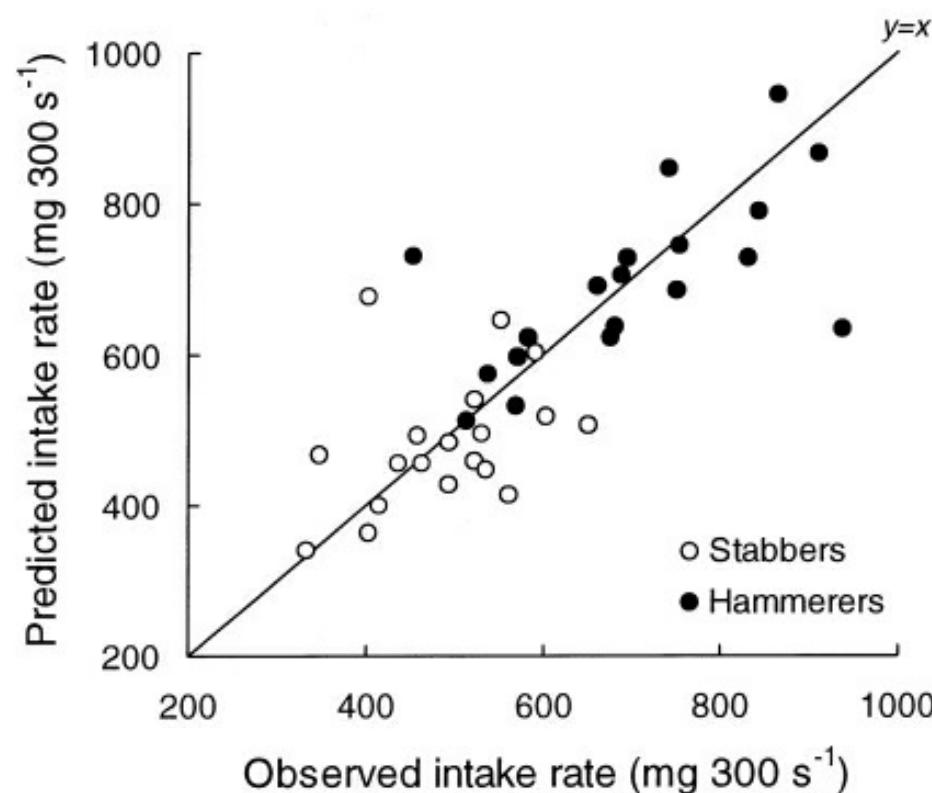
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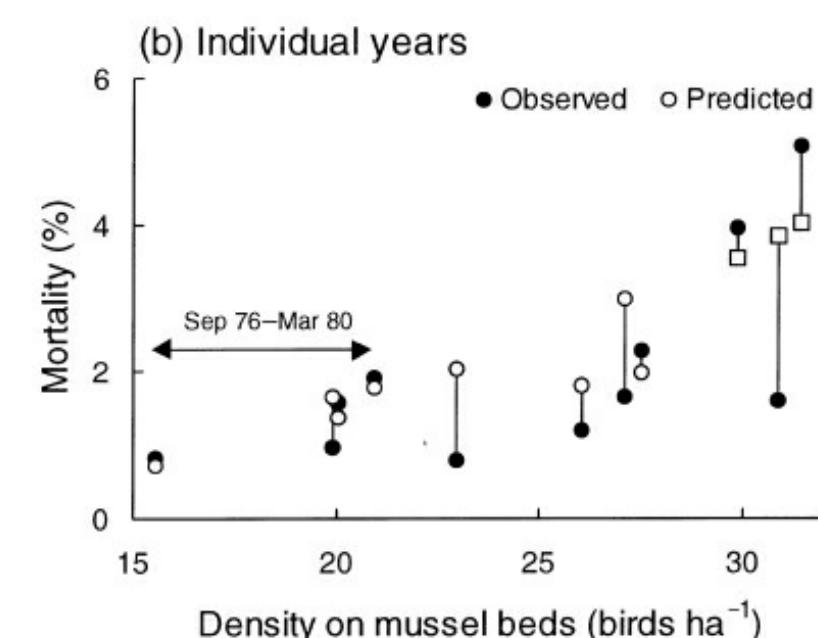
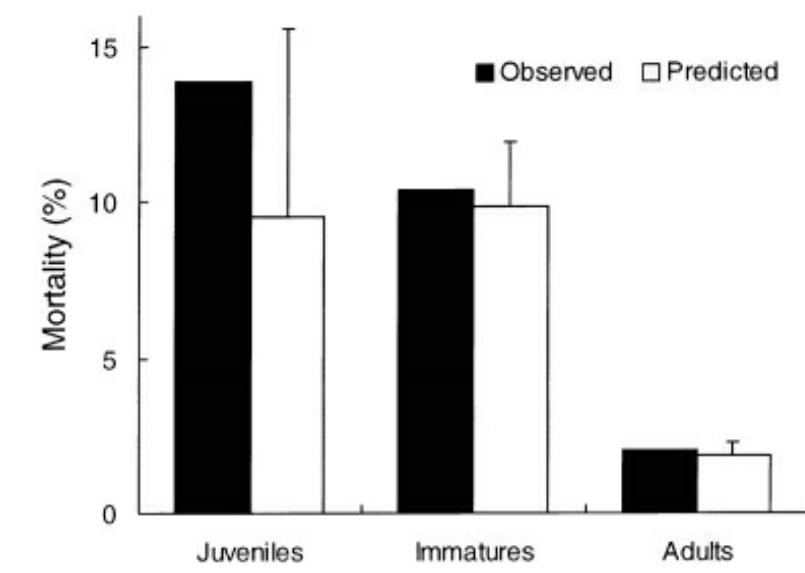
Individual-based models: Oystercatchers

Model validation (Stillman et al. 2000)

Intake rate predictions



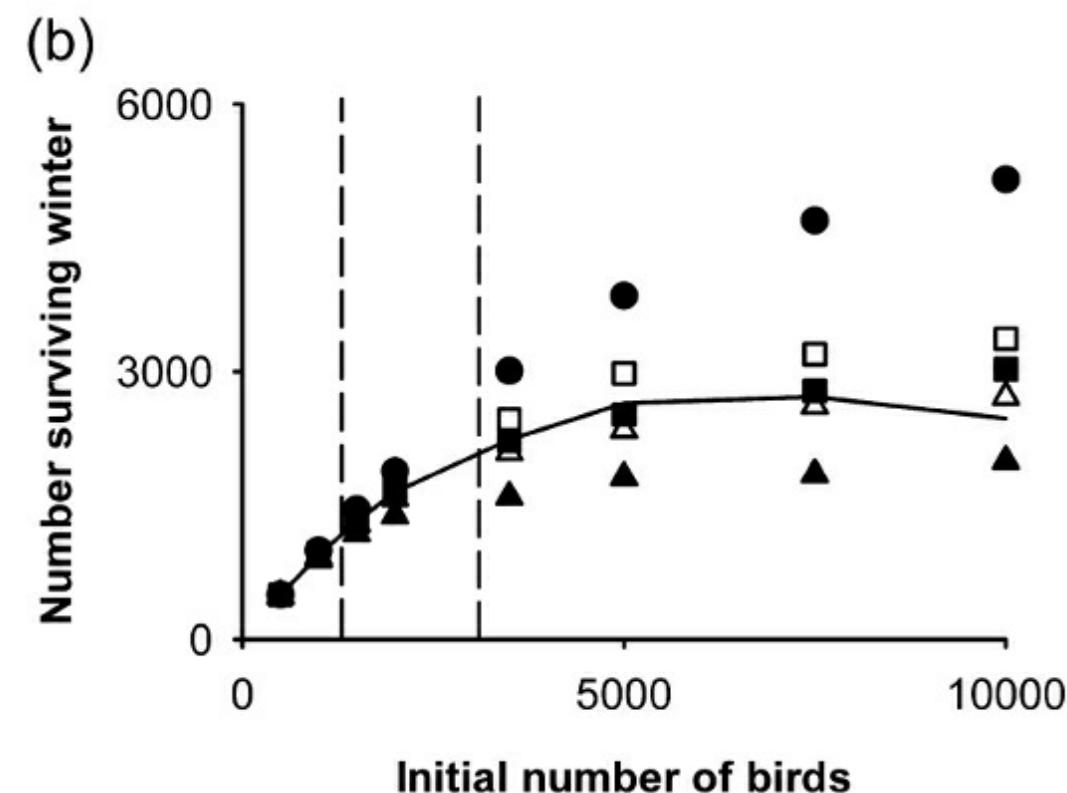
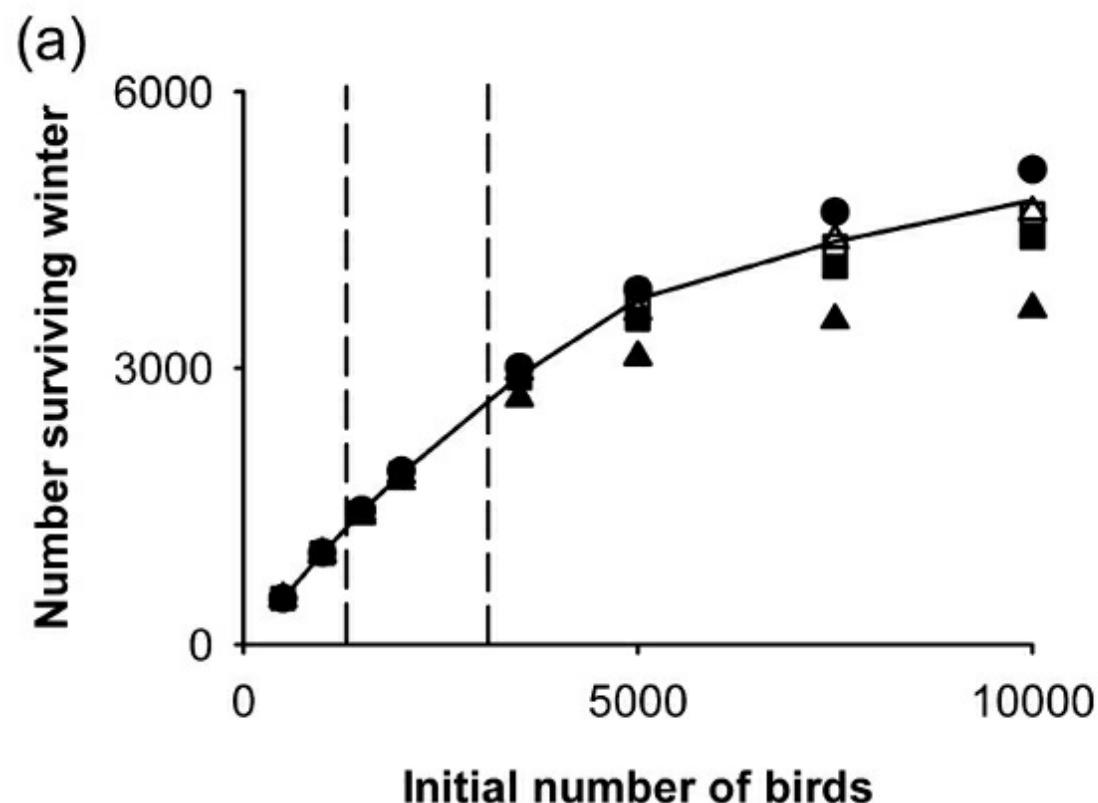
Mortality predictions



Individual-based models: Oystercatchers

IBM assessing effects of disturbance ([West et al. 2000](#))

Disturbance scenarios on feeding areas: (a) 10% of area; (b) 50% of area

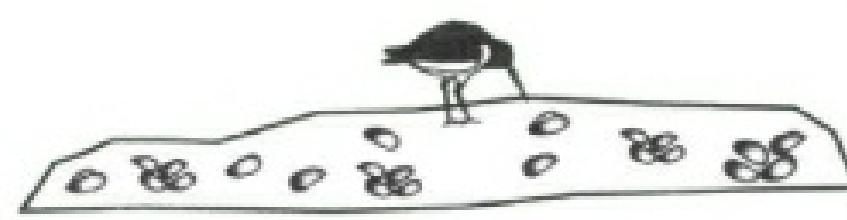


[West et al. \(2002\)](#)

Individual-based models

Individual-based models

- Usually need fewer historical population data.
- Fitness maximisation likely to hold in future - extrapolation possible
- Individual variability implicitly accounted for.
- Needs data on and understanding of behaviour
- Quickly becomes very complex



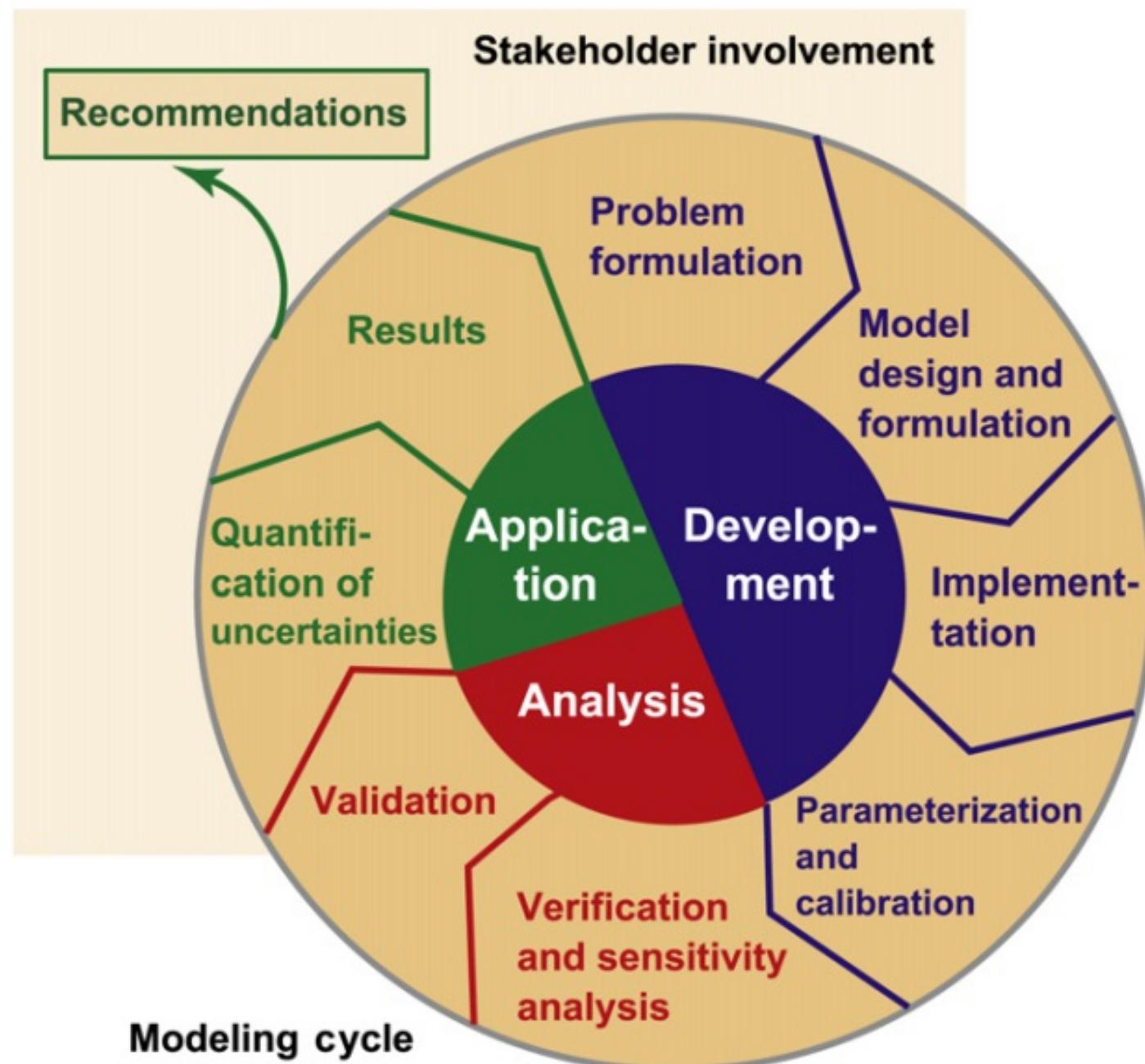
Population-level models

- Usually needs more historical data to "fit"
- Limited extrapolative power
- "Tyranny of the mean"
- No need for individual-level data
- Basic forms easy to build "out of the box"



Modelling process

The modelling cycle (*Schmolke et al. 2010*)



Modelling process

Model complexity (1): Extremes of complexity...

Both models predict population size....

Logistic population model

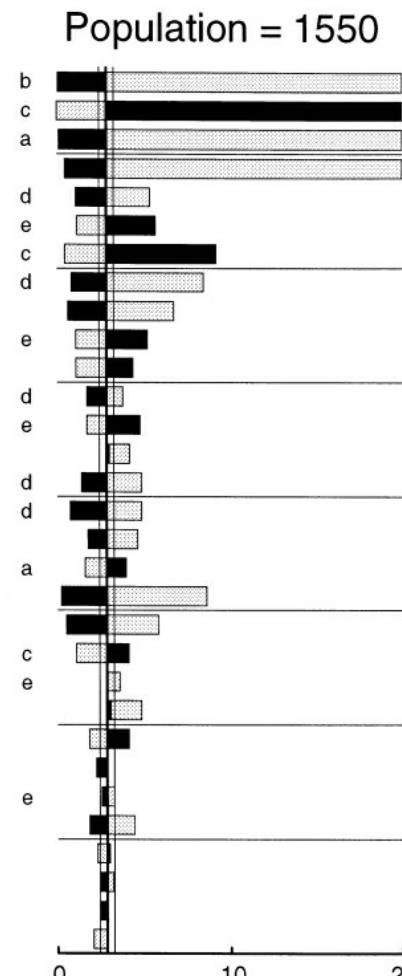
$$N(t) = \frac{KN_0}{(K-N_0)e^{-rt}+N_0}$$

- **Four** parameters (including time)

IB population model

(e.g. Stillman et al. 2000)

Assimilation efficiency (a_{assim})
General energy expenditure (E_{gen})
Mussel energy density (d_{prey})
Mussel ash-free dry mass (m)
Mussel day feeding efficiency
Seasonal interference (c)
Lower critical temperature (T_{crit})
Mussel night feeding efficiency
Mussel encounter rate (λ)
Aggregation factor
Mussel handling time (h)
Upshore night feeding efficiency
Interference intercept (a)
Mussel density
Field day feeding efficiency
Upshore day feeding efficiency
Field intake rate
Supplementary prey energy density (d_{prey})
Mussel inspection time (l)
Upshore intake rate
Thermoregulatory cost (E_{therm})
Dominance interference (b)
Gut processing rate
Mussel intake variation
Gut capacity
Adult interference threshold (C_0)
Storage tissue energy density (d_{store})
Mussel waste handling time (w)
Ambient temperature
Upshore intake variation
Field intake variation



Modelling process

Model complexity (1): Extremes of complexity...

Both models predict population size... directly or indirectly

Logistic population model

$$N(t) = \frac{KN_0}{(K-N_0)e^{-rt}+N_0}$$

- **Four** parameters (including *time*)

IB population model

(e.g. Stillman et al. 2000)

- At least **31 parameters** - likely more!

Advantages? Disadvantages?

Modelling process

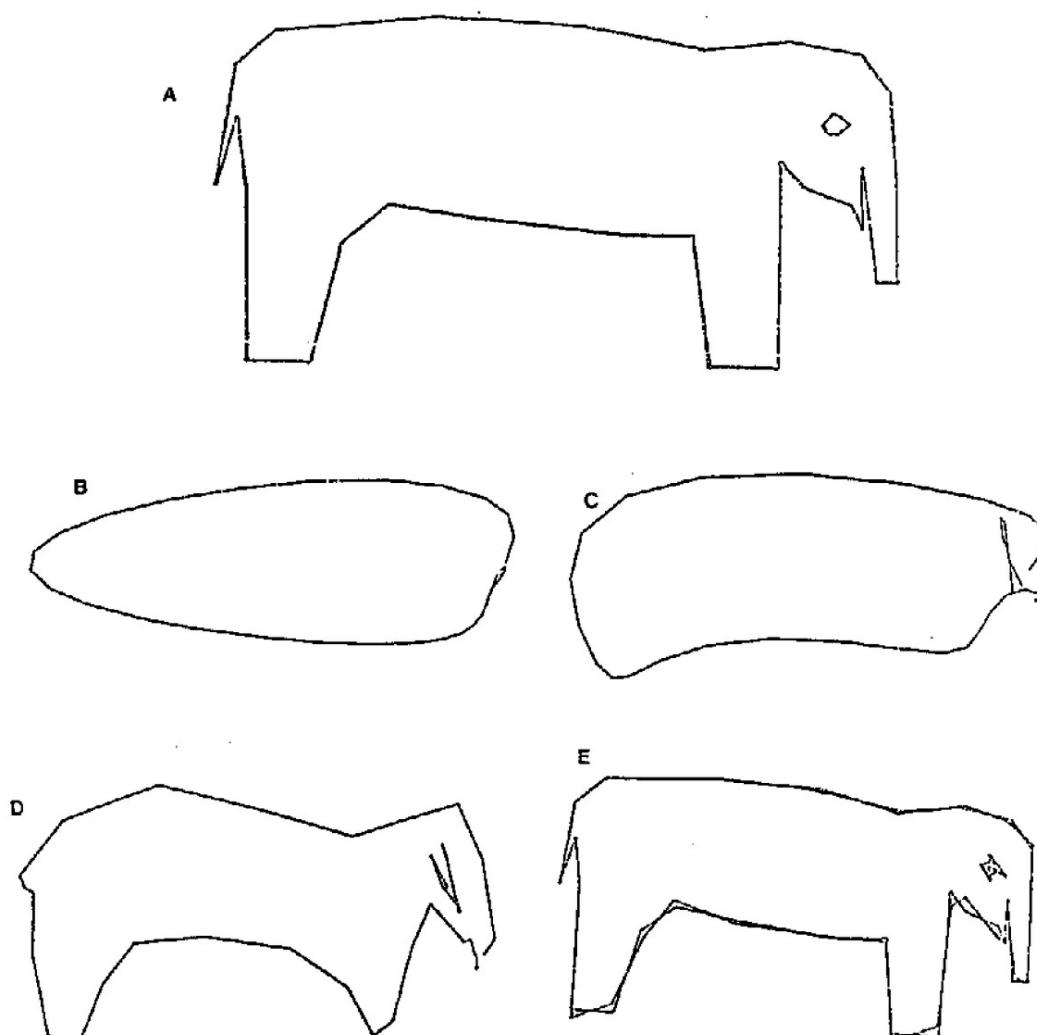
Model complexity (2): how many parameters to draw an elephant?



- Adapted from Burnham & Anderson (1998)

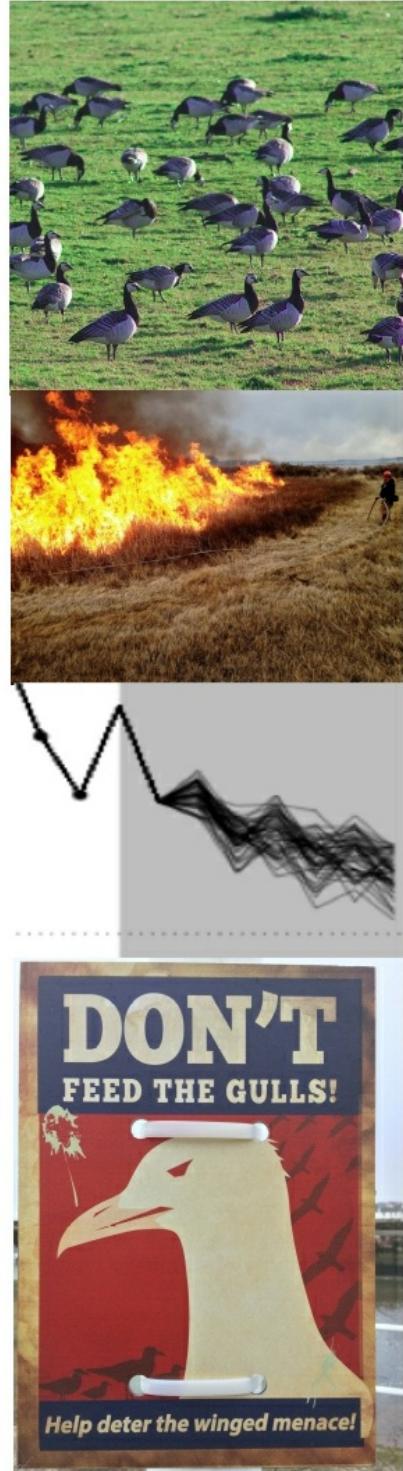
Modelling process

Model complexity (2): how many parameters to draw an elephant?



- Adapted from Burnham & Anderson (1998)
- "Bias" trades off with "variance"
- "Overfit" vs. "underfit"
- Complexity vs. practicality?
- Important in applied settings; e.g. conservation decision making.

Summary



- Models are formalised and simplified representations of states (e.g. populations) and relationships between states (e.g. effects)
- Models can provide...
 - Understanding of systems
 - Make and test predictions where otherwise not possible
 - Ability to evaluate alternative management options (e.g. scenarios)
- Many model types (e.g. conceptual to IBM)
- Need to balance complexity with practicality



