

EMAT30007 Applied Statistics

Lecture 11: revision and further models

Nikolai Bode

Department of Engineering Mathematics, University of Bristol

Revision 1

Simple linear regression and multiple linear regression: you will NOT need to perform any calculations, but rather understand and interpret MATLAB outputs

- a) Recall the structure of simple and multiple linear regression models (LMs) and be able to use and interpret (1) alternative representations (such as algebraic notation, matrix notation and random variable notation) and (2) residual plots.
- b) Understand the assumptions underlying both linear regression and multiple linear regression models.
- c) Estimate parameters (MLE) and perform hypothesis testing (AIC, BIC, likelihood, R^2).
- d) Model selection.

Model building: you will NOT need to perform any calculations, but rather understand and interpret MATLAB outputs

- a) Understand how qualitative and quantitative predictors can be combined in models.
- b) Be able to interpret non-linear relationships between variables using polynomials of predictors.

Revision 2

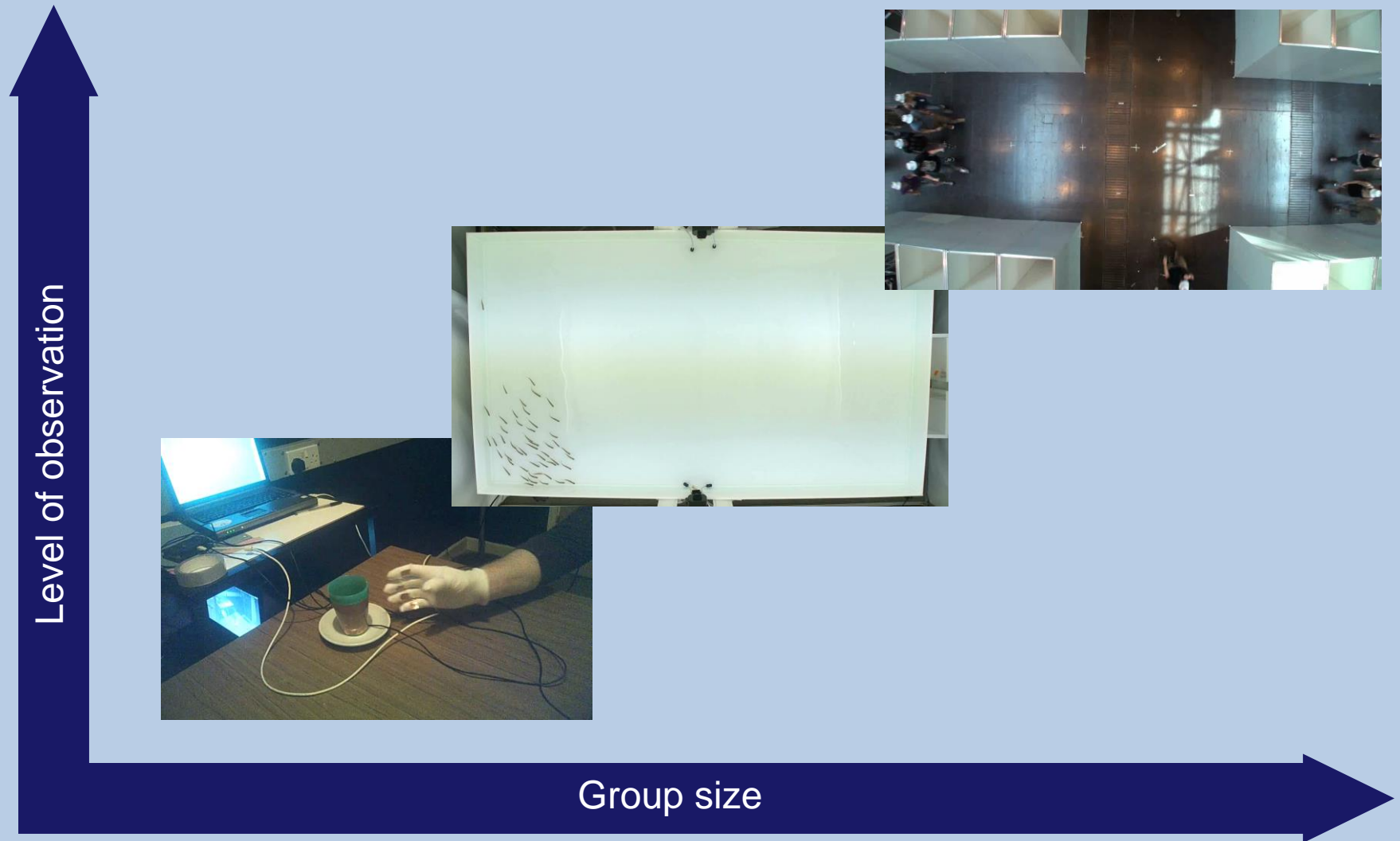
Experimental design and ANOVA: you will NOT need to perform any calculations, but rather understand and interpret MATLAB outputs

- a) Understand four major steps in the statistical experimental design.
- b) Be able to interpret one-way Anova and two-way Anova results.

Generalised linear models (Logistic regression): you will NOT need to perform any calculations, but rather understand and interpret MATLAB outputs

- a) Understand the assumptions underlying generalised linear models (GLMs) including interpretation of two types of residuals.
- b) Estimate parameters (MLE) and perform hypothesis testing (AIC, BIC, likelihood, deviance).

Scales of collective movements



Collective movements

Animals + humans:

- spread of diseases
- conservation
- ...



**Why is studying
social movement
important?**



Humans:

- behavioural diagnostics
- building design
- ...

Studying collective movement



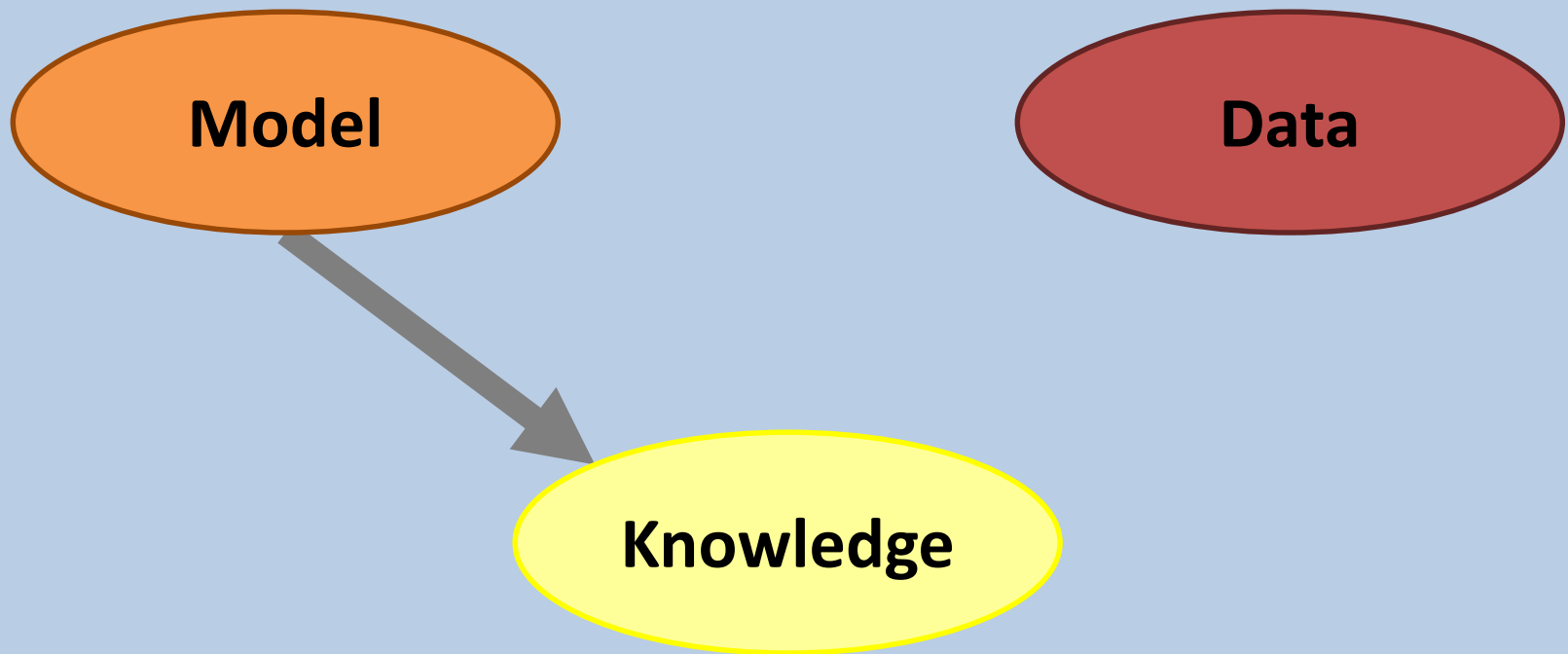
The diagram consists of three ovals on a light blue background. An orange oval labeled 'Model' is on the left, a red oval labeled 'Data' is on the right, and a yellow oval labeled 'Knowledge' is centered below them. The ovals are arranged in a triangular pattern, suggesting a cycle or relationship between the three concepts.

Model

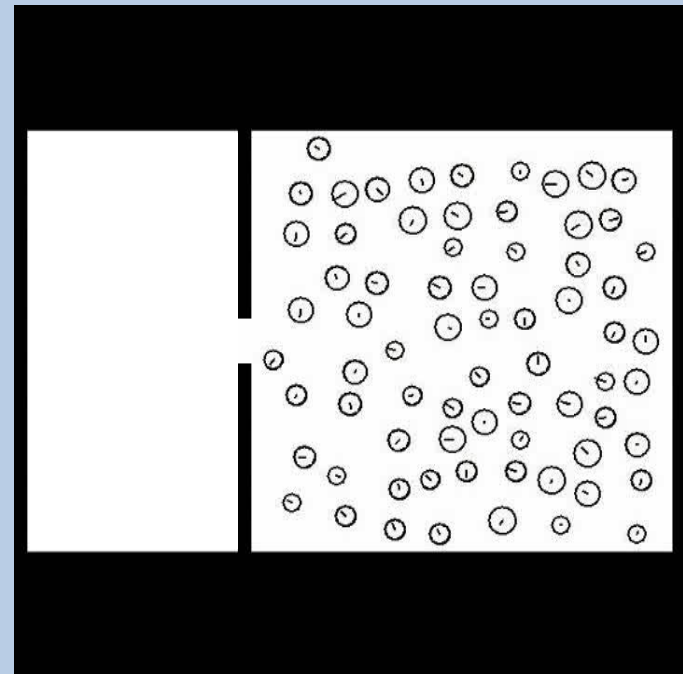
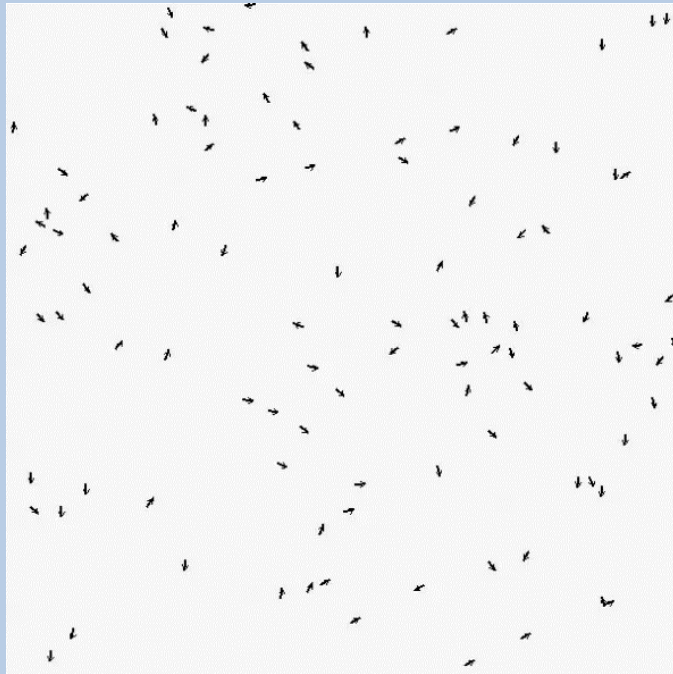
Data

Knowledge

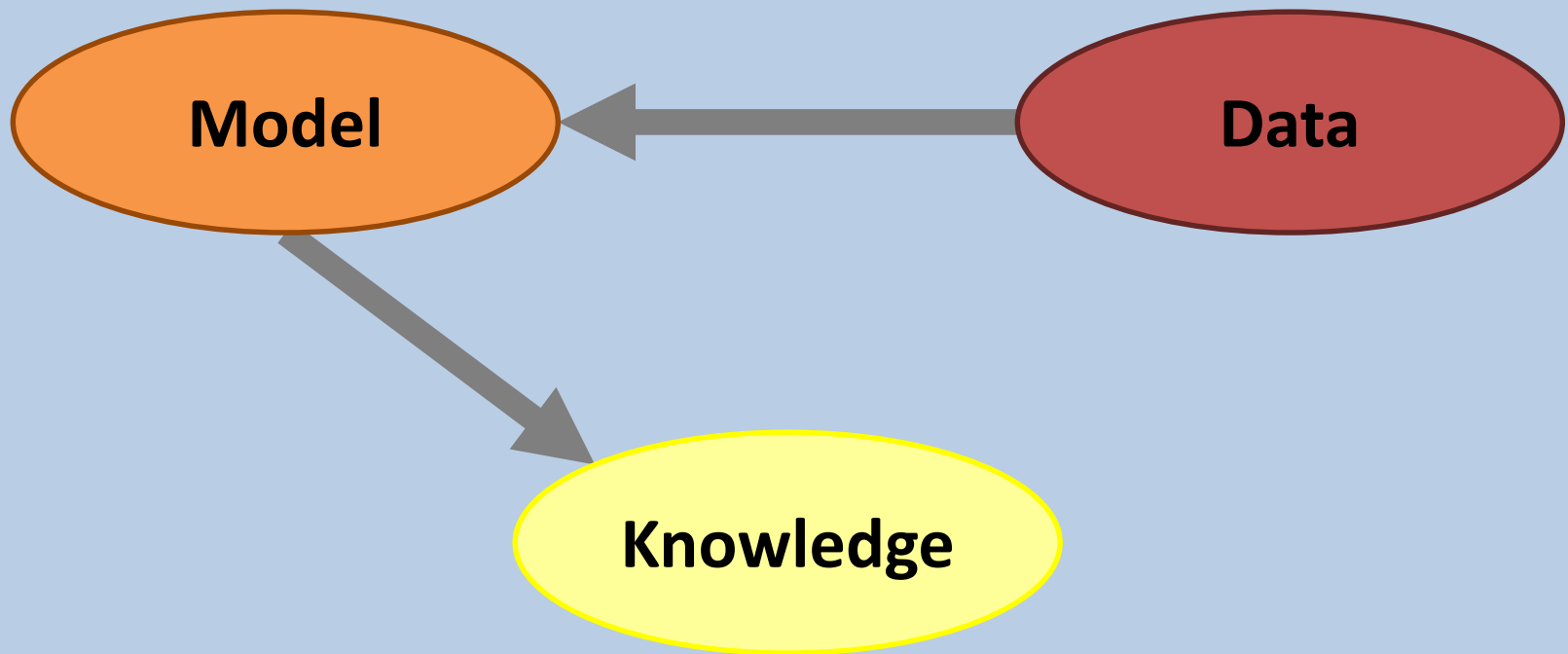
Studying collective movement



Models for collective movement



Studying collective movement



Context – pedestrian crowds



- Route choice
- Evacuation timing
- Risk taking
- Helping behaviour

Decision-making in evacuations

Observational data and experiments with real crowds are difficult to obtain.



Decision-making in evacuations

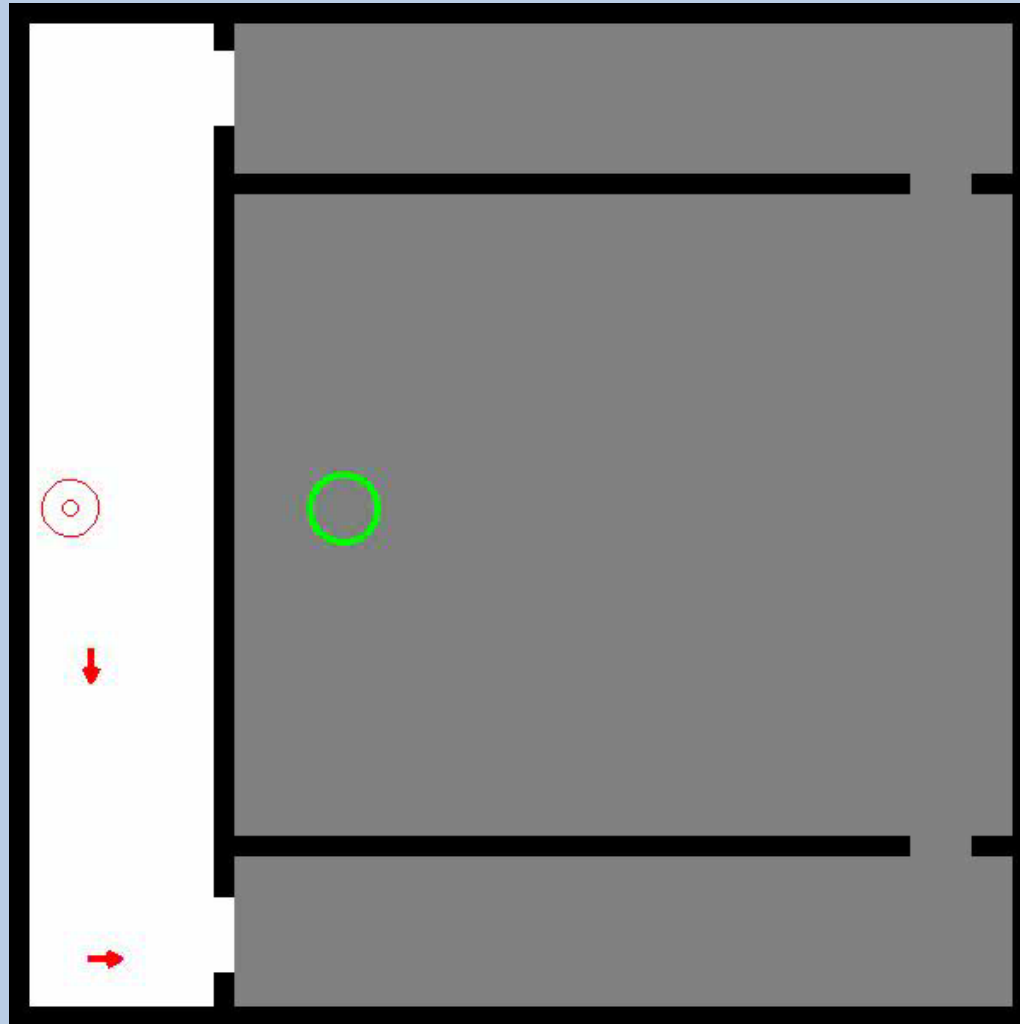
Observational data and experiments with real crowds are difficult to obtain.

Instead, use a *virtual environment* to investigate this.

Here, give one example, study:

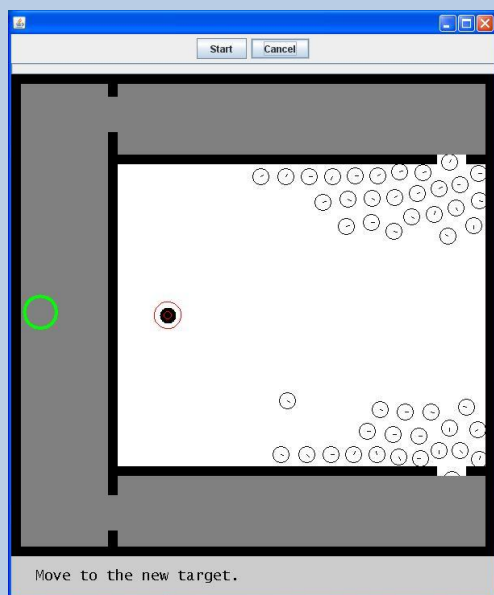
- route choice
- following others
- ability to change decisions
- the effect of motivation/stress

Experiments

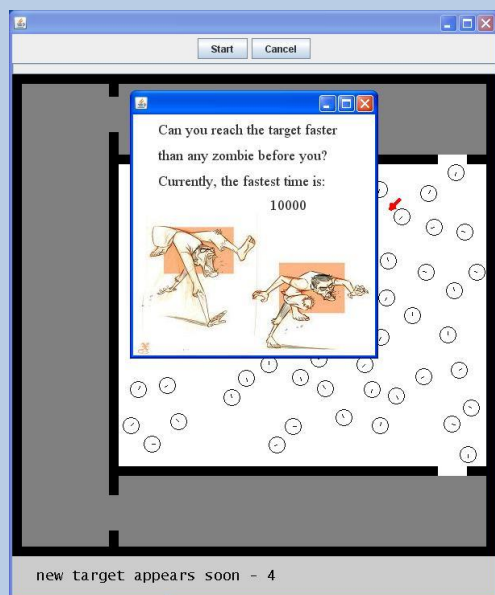


Treatments

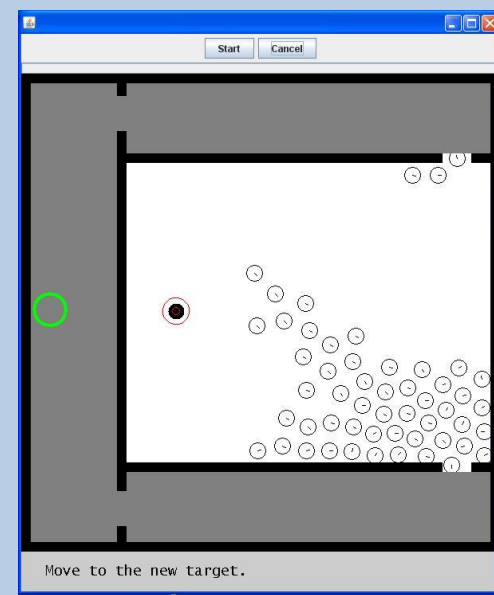
Control



Motivation (M)

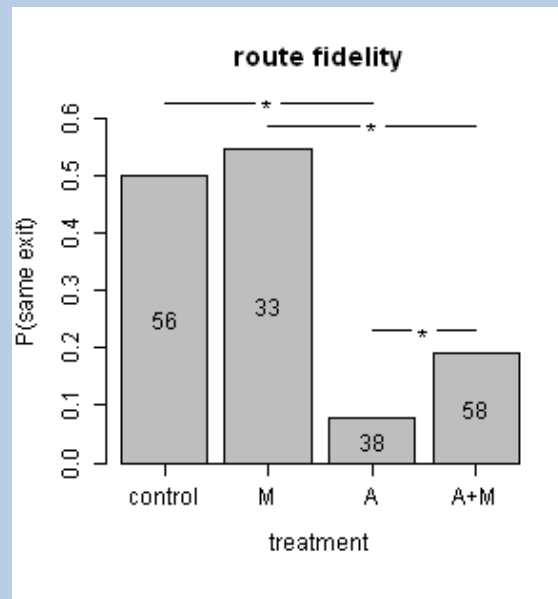


Asymmetric (A)



Four treatments: control, M, A, A+M

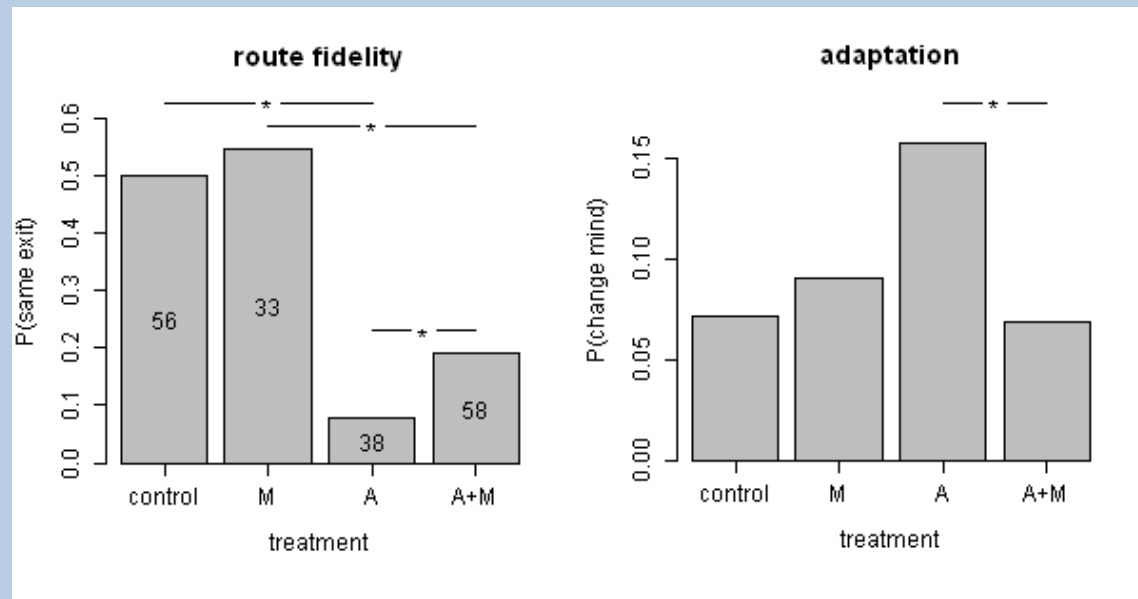
Results



185 participants

* $P < 0.1$

Results



185 participants

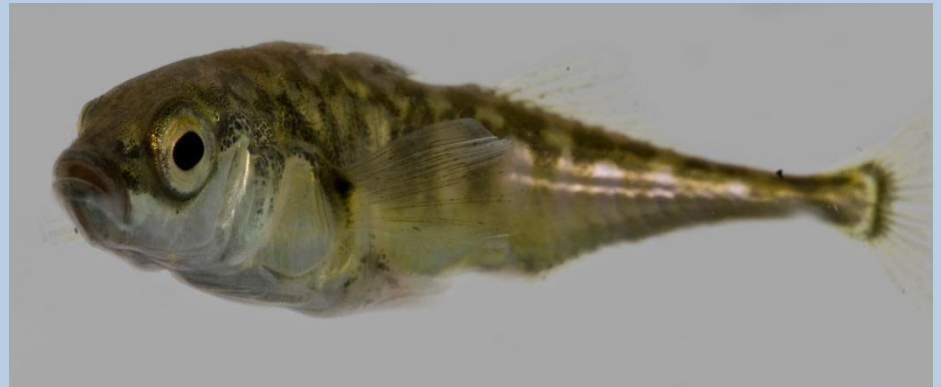
* $P < 0.1$

Summary

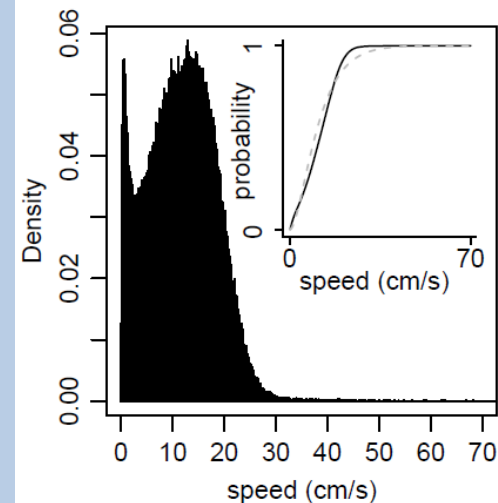
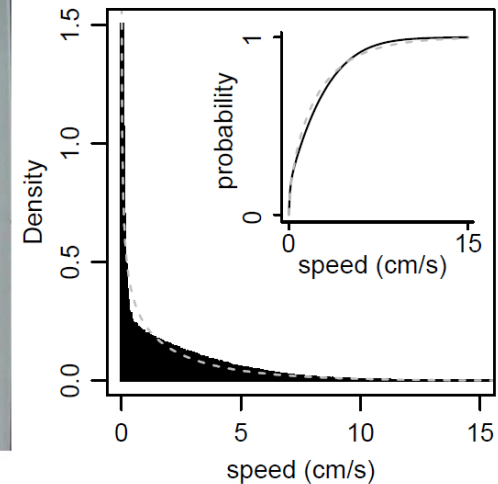
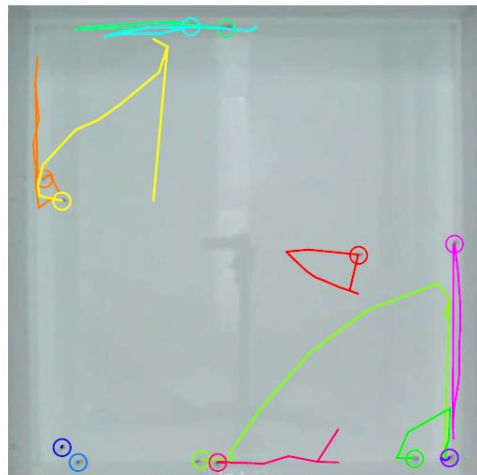
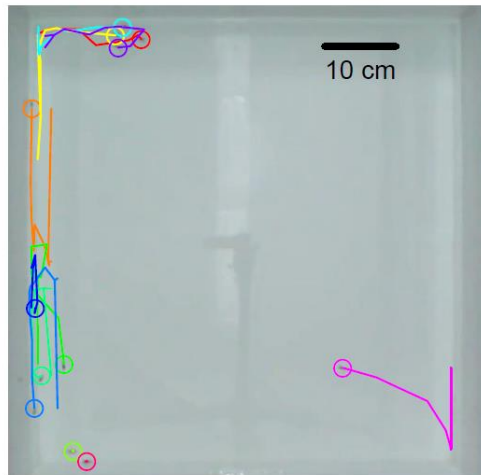
Motivation affects decision-making

- Other experiments:
 - Reactions to combinations of different sources of information
 - Helping behaviour
 - Following instructions
 - Risk-taking

Intermittent social movement in shoaling guppies and sticklebacks

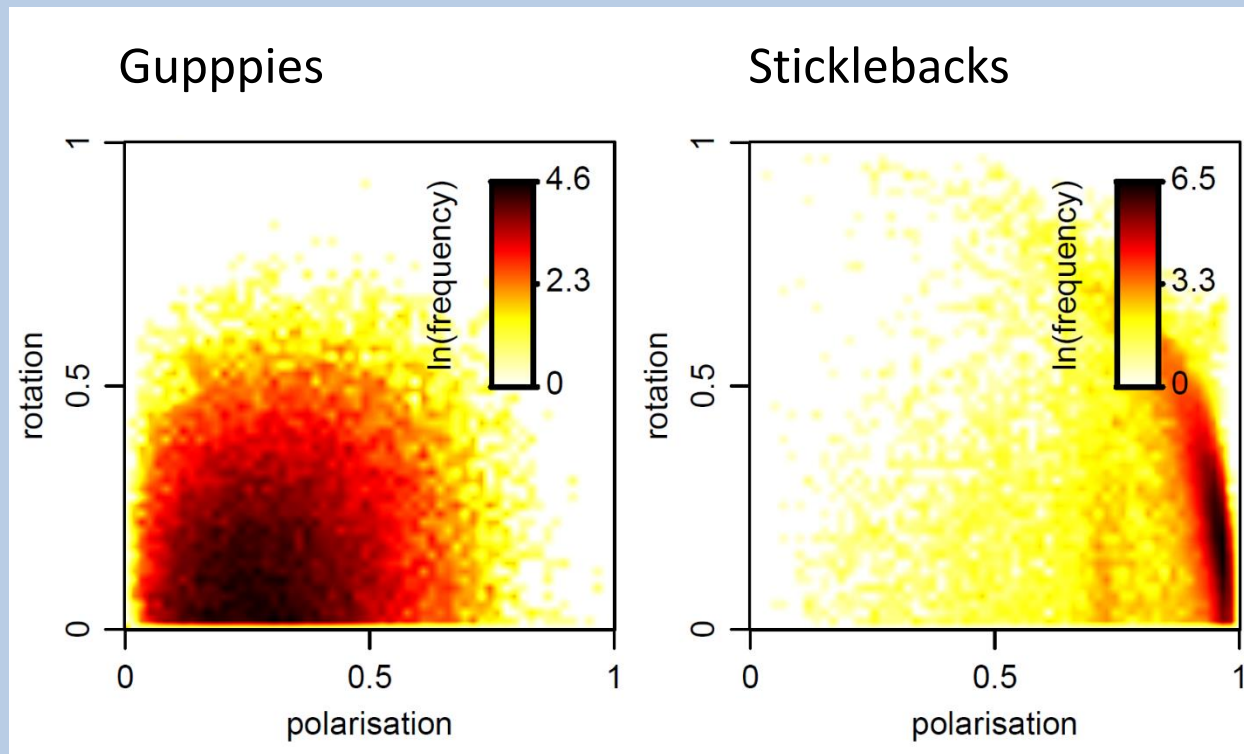


Movement of fish shoals

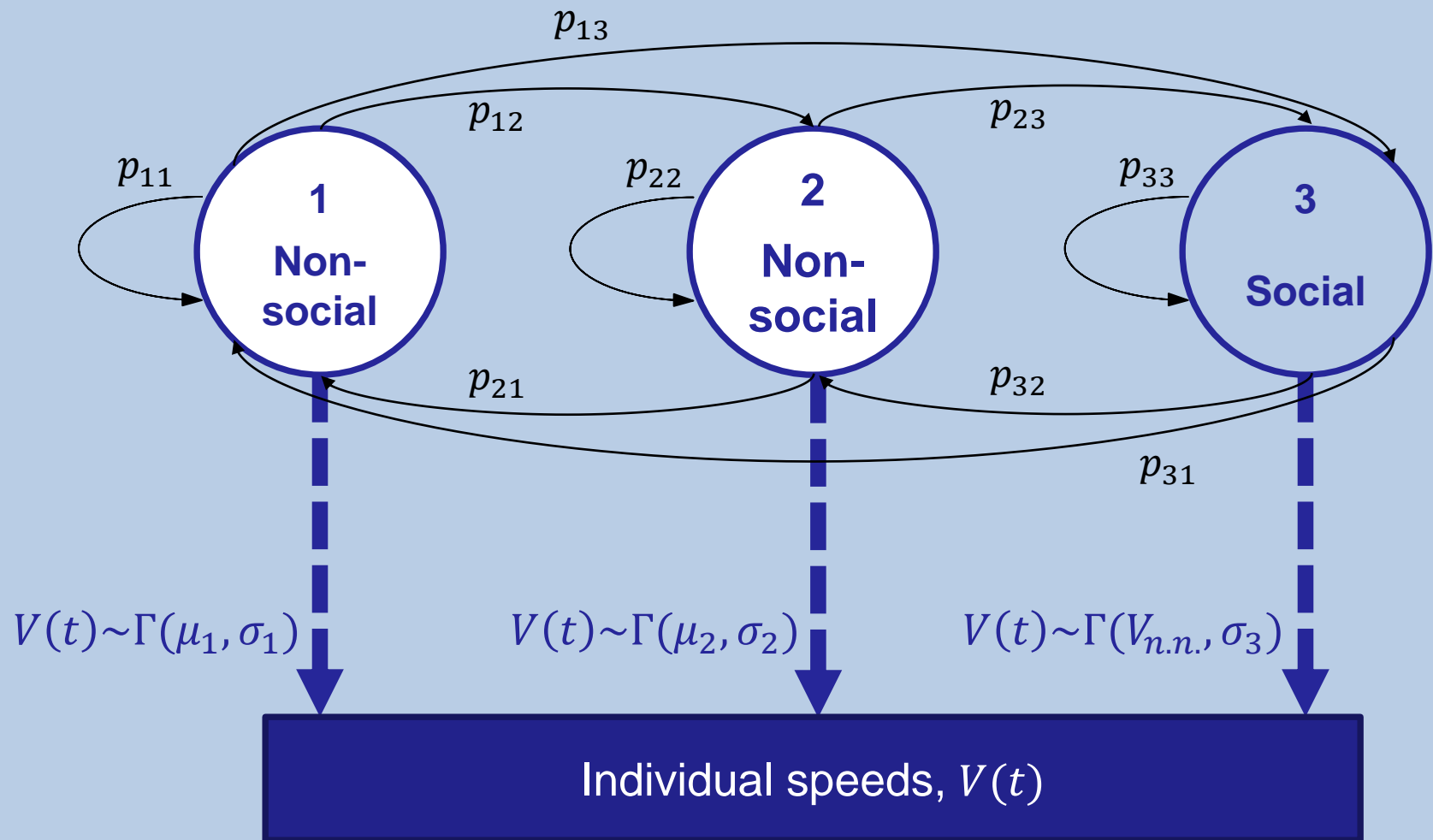


- Shoals of 12 guppies or 8 sticklebacks
- Obtain trajectories
- Square (guppies) and circular (sticklebacks) tank

Shoal-level movement



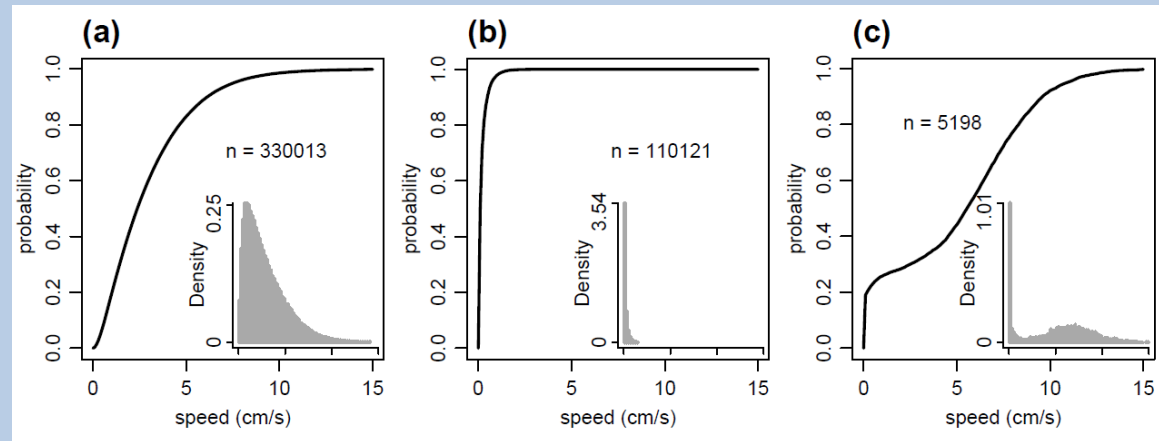
Behaviour characterisation using HMMs



Evidence for intermittent social behaviour

AIC of social model is better than expected by chance for both species ($P \ll 0.01$).

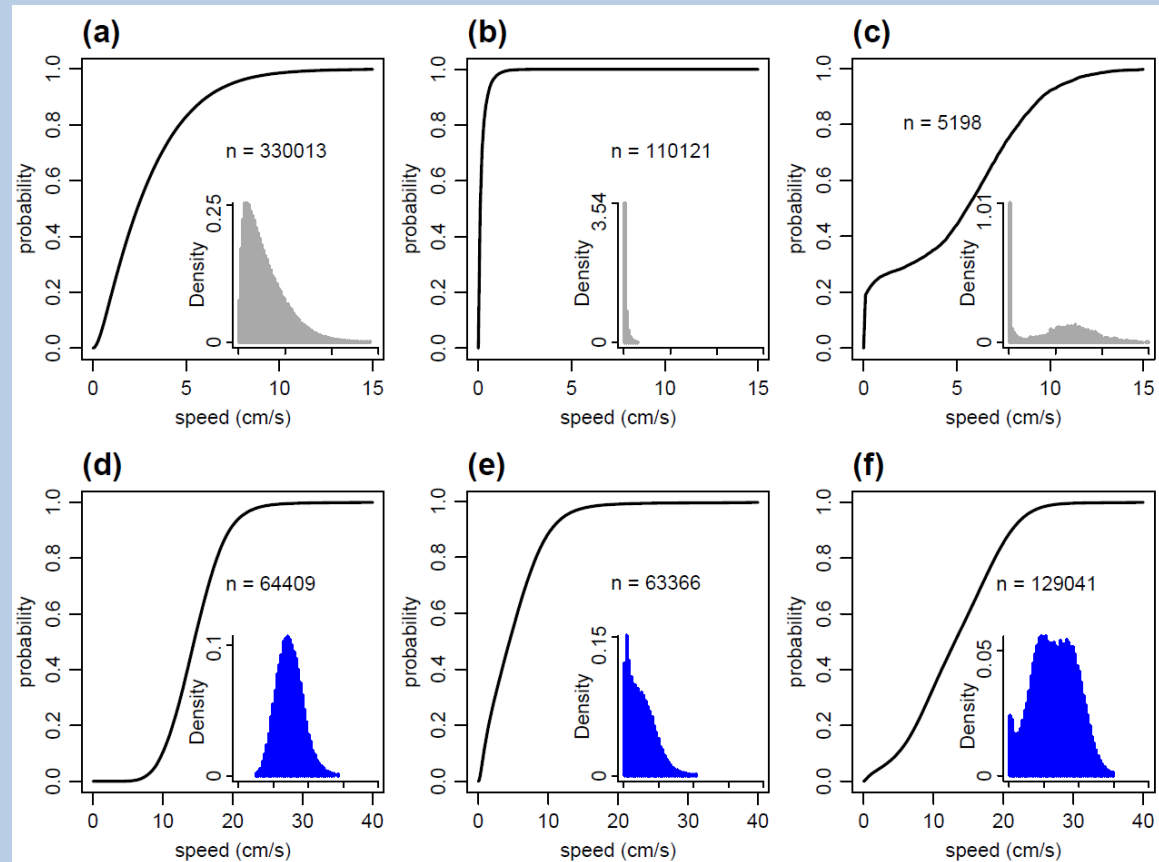
Guppies



Evidence for intermittent social behaviour

AIC of social model is better than expected by chance for both species ($P \ll 0.01$).

Guppies



Sticklebacks

Fishy discussion

**Intermittent social
movement in fish
shoals**

Microscopic
analysis of
interactions

Direct contrast
of hypotheses
for behaviour

Models are
simple, but
versatile

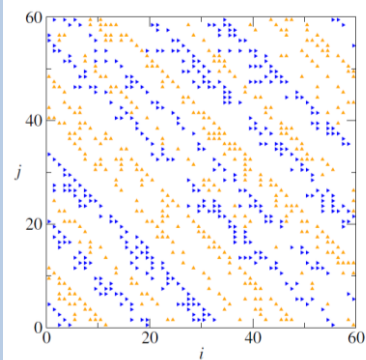
Detailed
investigation
of social
movement?

Interactions at the infrastructure level: intersecting pedestrian streams

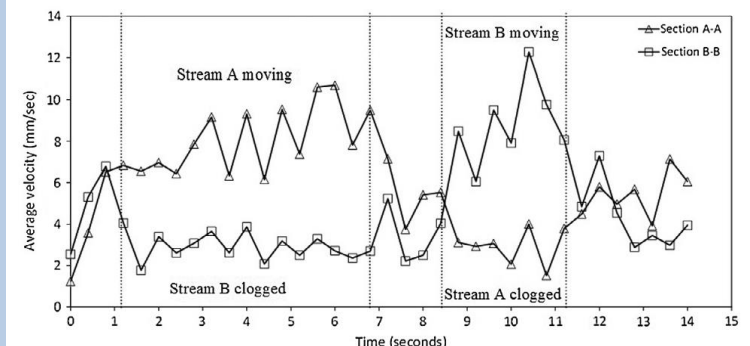
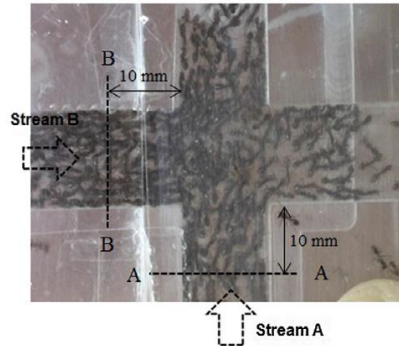


© The Guardian UK

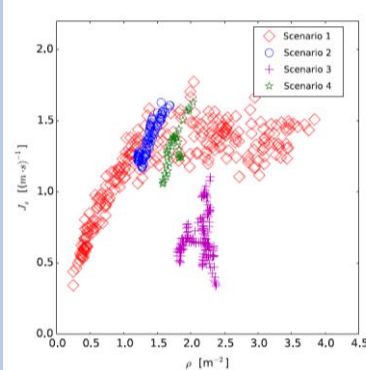
Previous Work



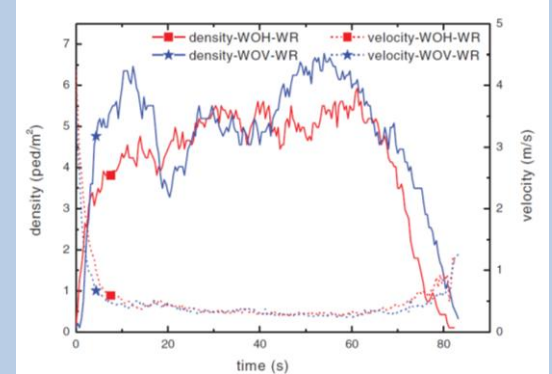
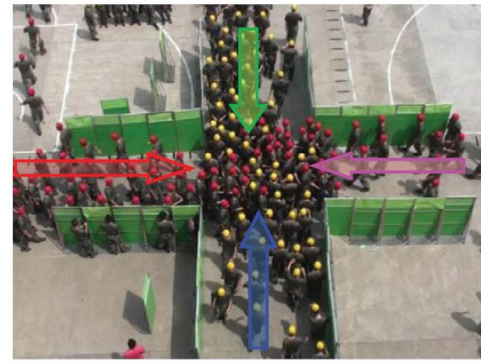
Cividini, Appert-Rolland, et al. (2013)



Dias, Sarvi, et al. (2013)



Zhang, Seyfried (2014)



Lian et al. (2015)

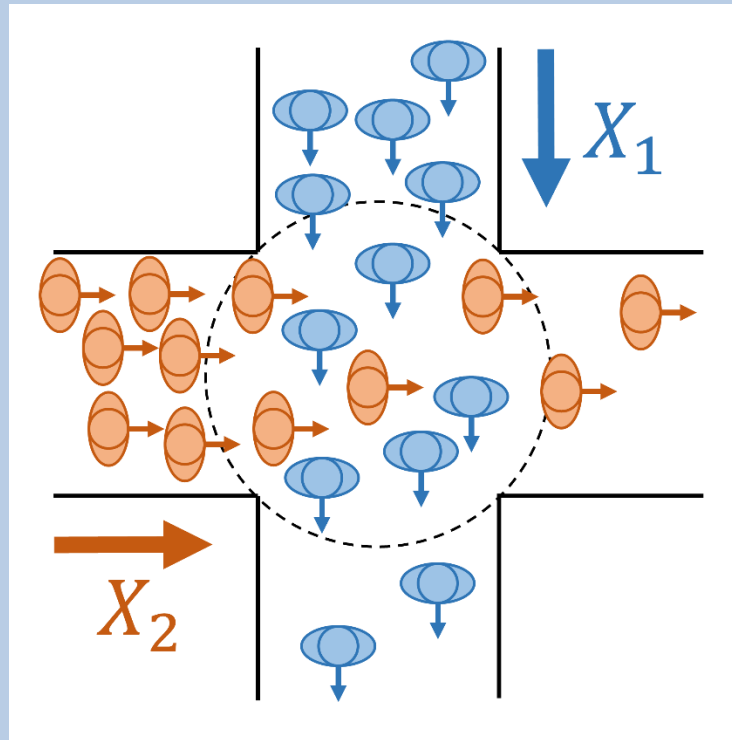
My Approach

... to test for interactions at the infrastructure level:

- Different scenarios we might reasonably expect
 - Stable states
 - Densities
 - Dynamics

→ *macroscopic models*
- Which model is the most plausible, given empirical evidence

Stream Populations

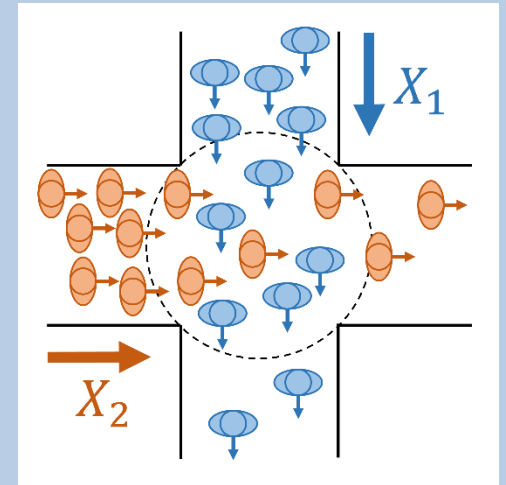


Here $X_1 = 5$ and $X_2 = 4$.

Modelling Stream Populations

$$\frac{dX_1}{dt} = f_{in}(X_1, X_2) - f_{out}(X_1, X_2)$$

$$\frac{dX_2}{dt} = f_{in}(X_2, X_1) - f_{out}(X_2, X_1)$$



Assumptions:

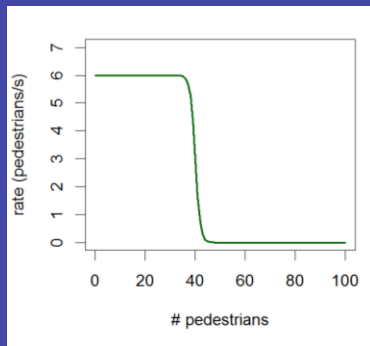
- Streams are symmetric
- Density inside intersection drives dynamics

Modelling Stream Populations

$$\frac{dX_1}{dt} = f_{in}(X_1, X_2) - f_{out}(X_1, X_2)$$

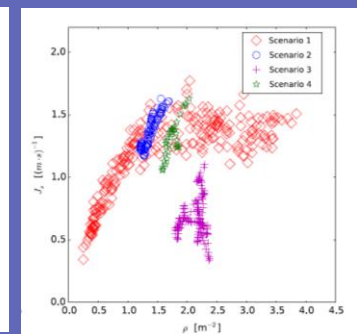
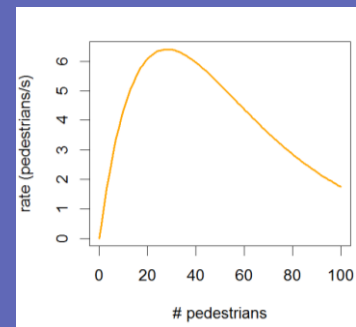
INFLOW

$$f_{in}(X_1, X_2) = \frac{\alpha}{1 + e^{(X_1 - \gamma)}}$$



OUTFLOW

$$f_{out}(X_1, X_2) = \mu X_1 e^{-\varepsilon X_1}$$



Zhang, Seyfried (2014)

Different Models

Null Model (no interaction), model 1:

$$f_{in}(X_1, X_2) = \frac{\alpha}{1 + e^{(X_1 - \gamma)}}$$

$$f_{out}(X_1, X_2) = \mu X_1 e^{-\varepsilon X_1}$$

Linear density interaction, model 2:

$$f_{in}(X_1, X_2) = \frac{\alpha}{1 + e^{(X_1 + X_2 - \gamma)}}$$

$$f_{out}(X_1, X_2) = \mu X_1 e^{-\varepsilon [X_1 + X_2]}$$

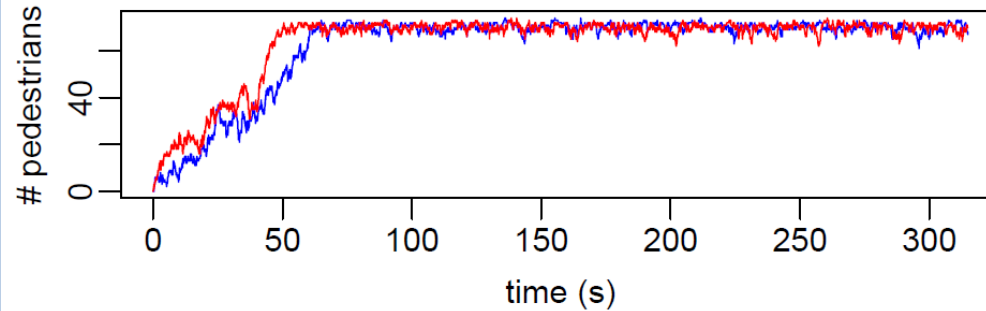
Non-linear density interaction, model 3:

$$f_{in}(X_1, X_2) = \frac{\alpha}{1 + e^{(X_1 + X_2 - \gamma)}}$$

$$f_{out}(X_1, X_2) = \mu X_1 e^{-\varepsilon X_1 - \delta \sqrt{X_1 X_2}}$$

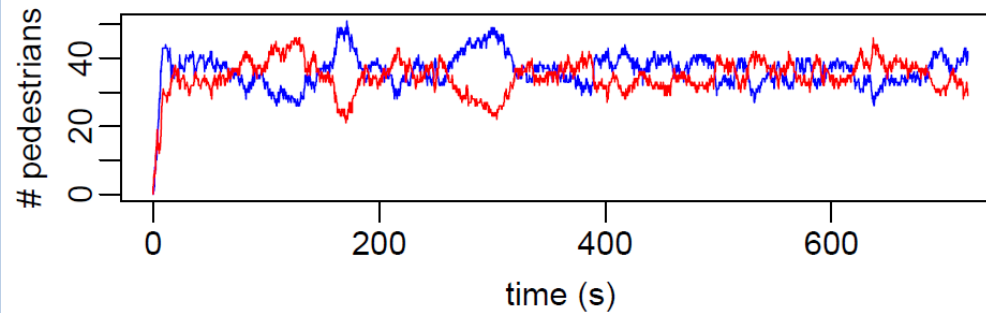
Simulations - Pedestrian Numbers

Model 1



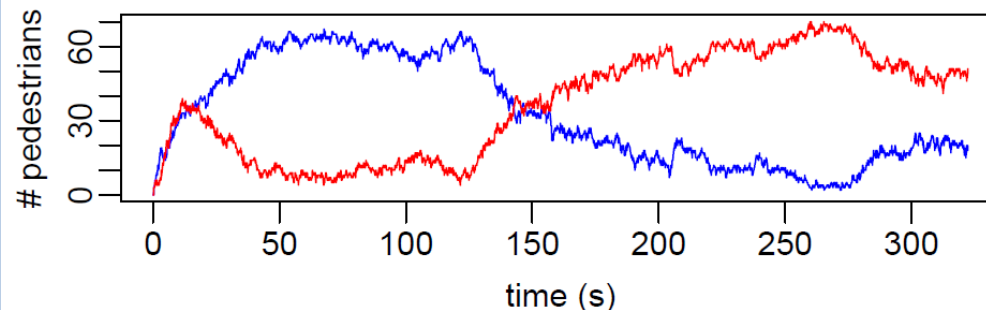
$$\alpha = 7; \gamma = 70; \\ \mu = 0.039; \varepsilon = 0.036.$$

Model 2



$$\alpha = 8; \gamma = 70; \\ \mu = 0.039; \varepsilon = 0.036.$$

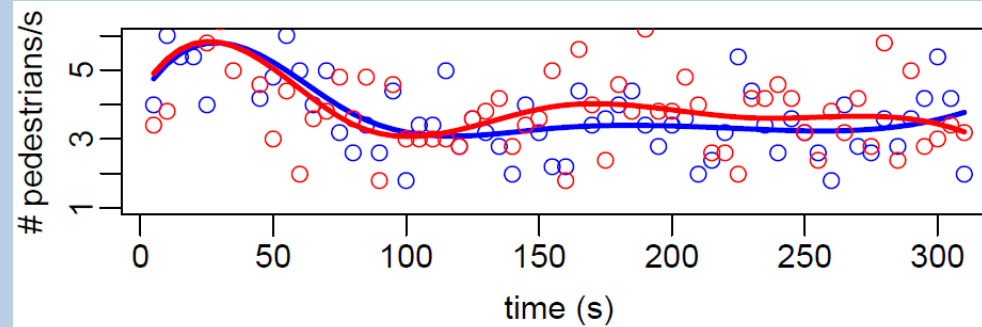
Model 3



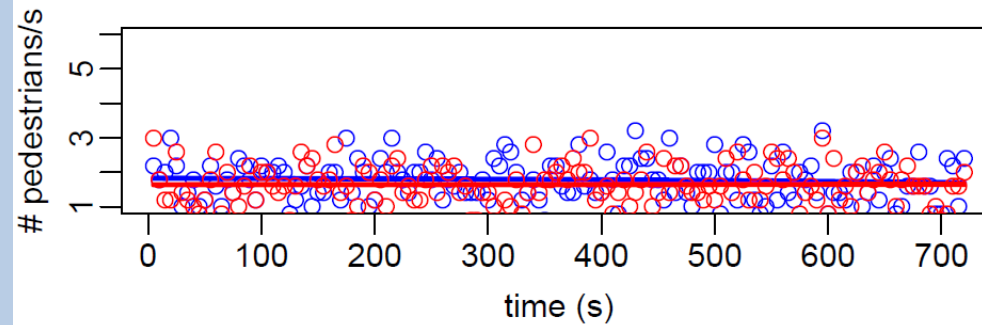
$$\alpha = 8; \gamma = 70; \\ \mu = 0.039; \\ \varepsilon = 0.036; \delta = 0.01.$$

Simulations - Outflows

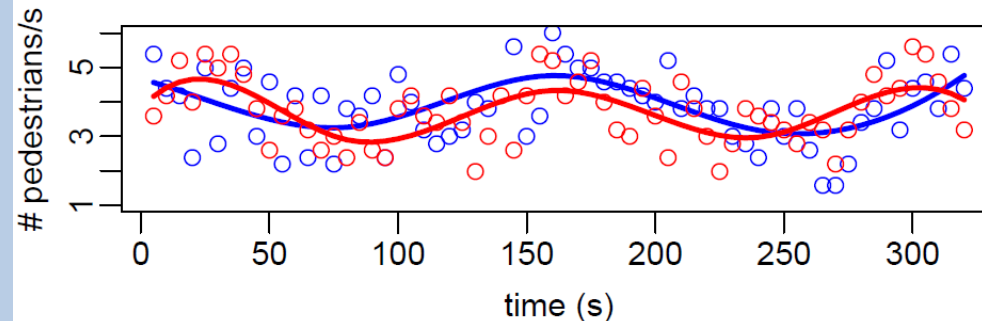
Model 1



Model 2

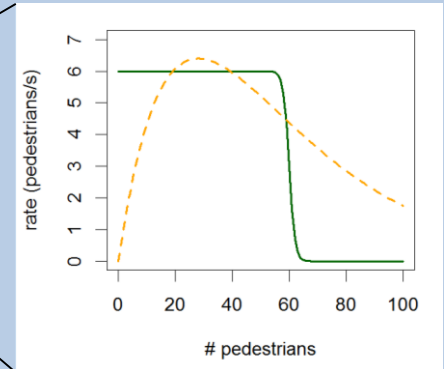
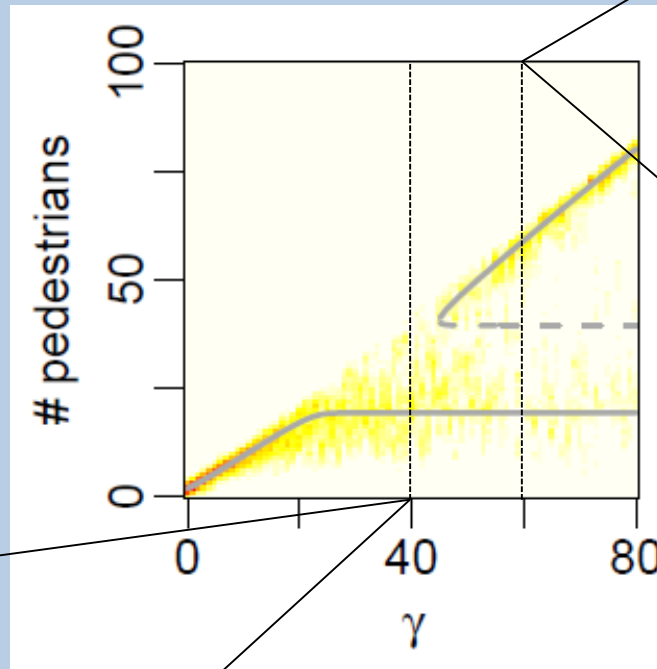
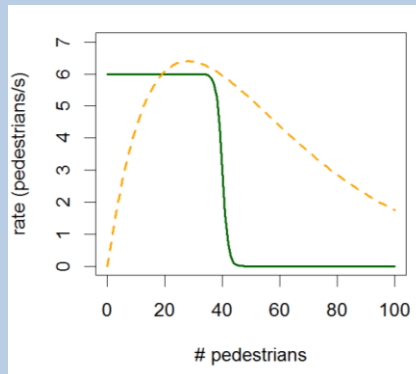


Model 3



Stability Analysis 1

Find *fixed points*:

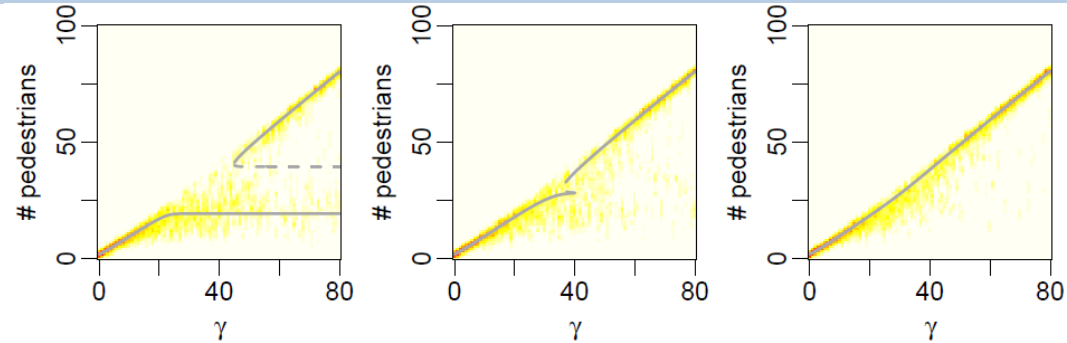


Bifurcation diagram for
varying γ (model 1);

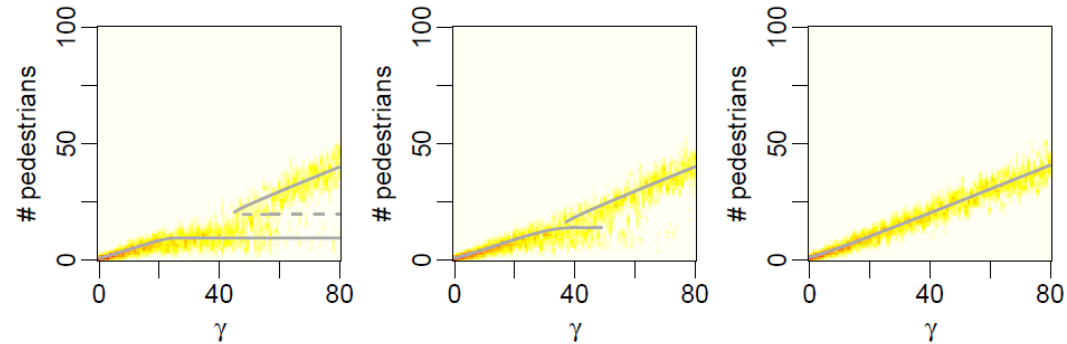
$$f_{in} = \frac{\alpha}{1 + e^{(X_1 - \gamma)}}$$

Stability Analysis 2

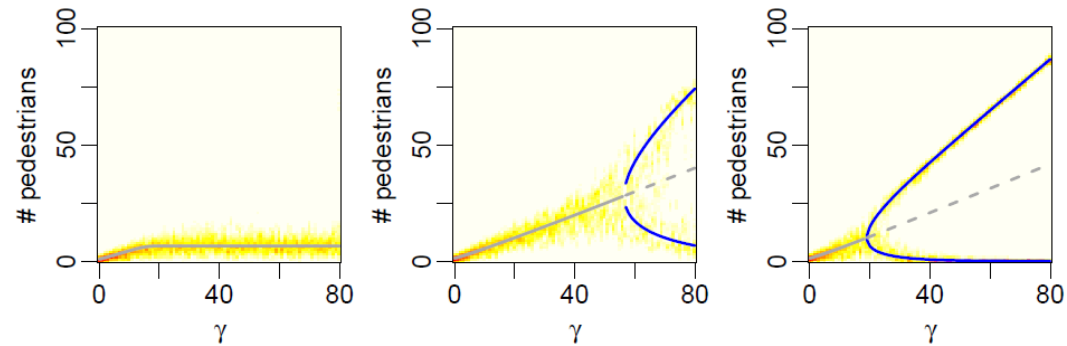
Model 1



Model 2



Model 3



Model Fitting using ABC

Exploring the parameter space comprehensively is difficult, so models need to be fitted to data.

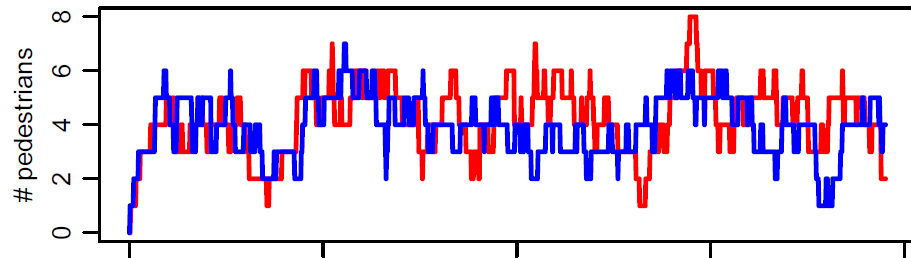
Pedestrian data



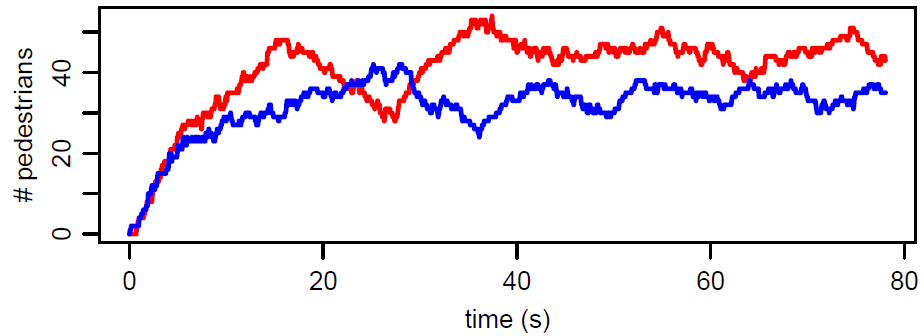
Courtesy BaSiGo Project

Pedestrian data

Inflow gate 1m wide



Inflow gate 4m wide



Model Fitting using ABC

Exploring the parameter space comprehensively is difficult, so models need to be fitted to data.

Discreteness and multi-dimensionality of data (# pedestrians and time) mean likelihood functions of models are not readily available.

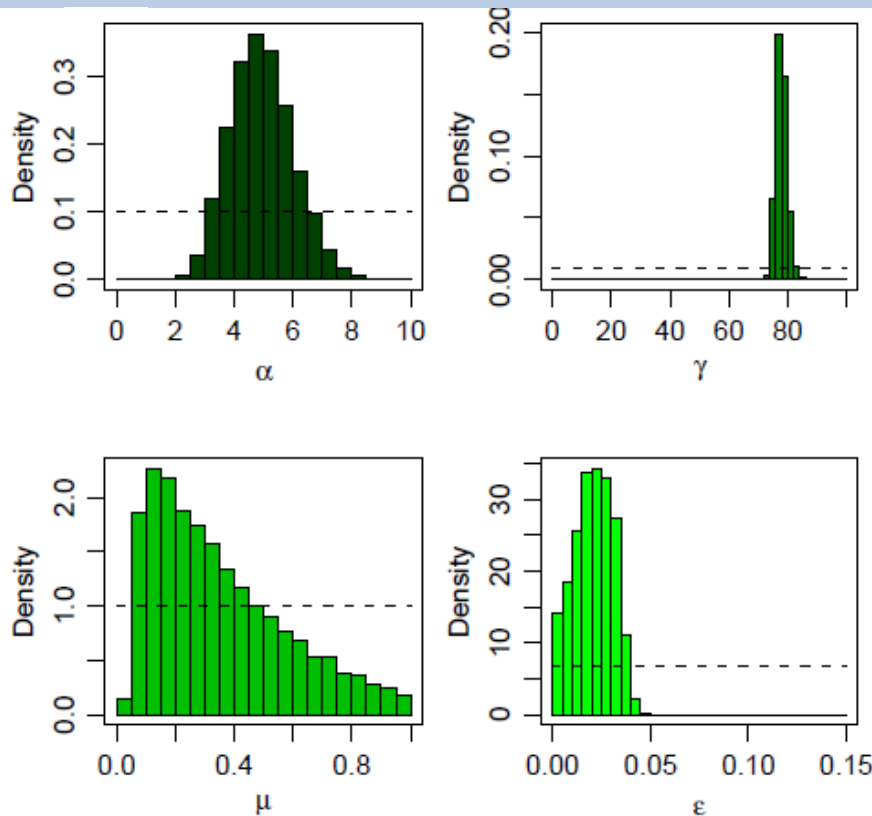
Use *Approximate Bayesian Computation*:

- 1) Sample parameters from prior distribution
- 2) Simulate from model using these parameter values
- 3) If *difference* between simulation and data is below a threshold, accept priors, otherwise reject
- 4) Return to (1)

... do this LOTS of times to get posterior distribution of parameters.

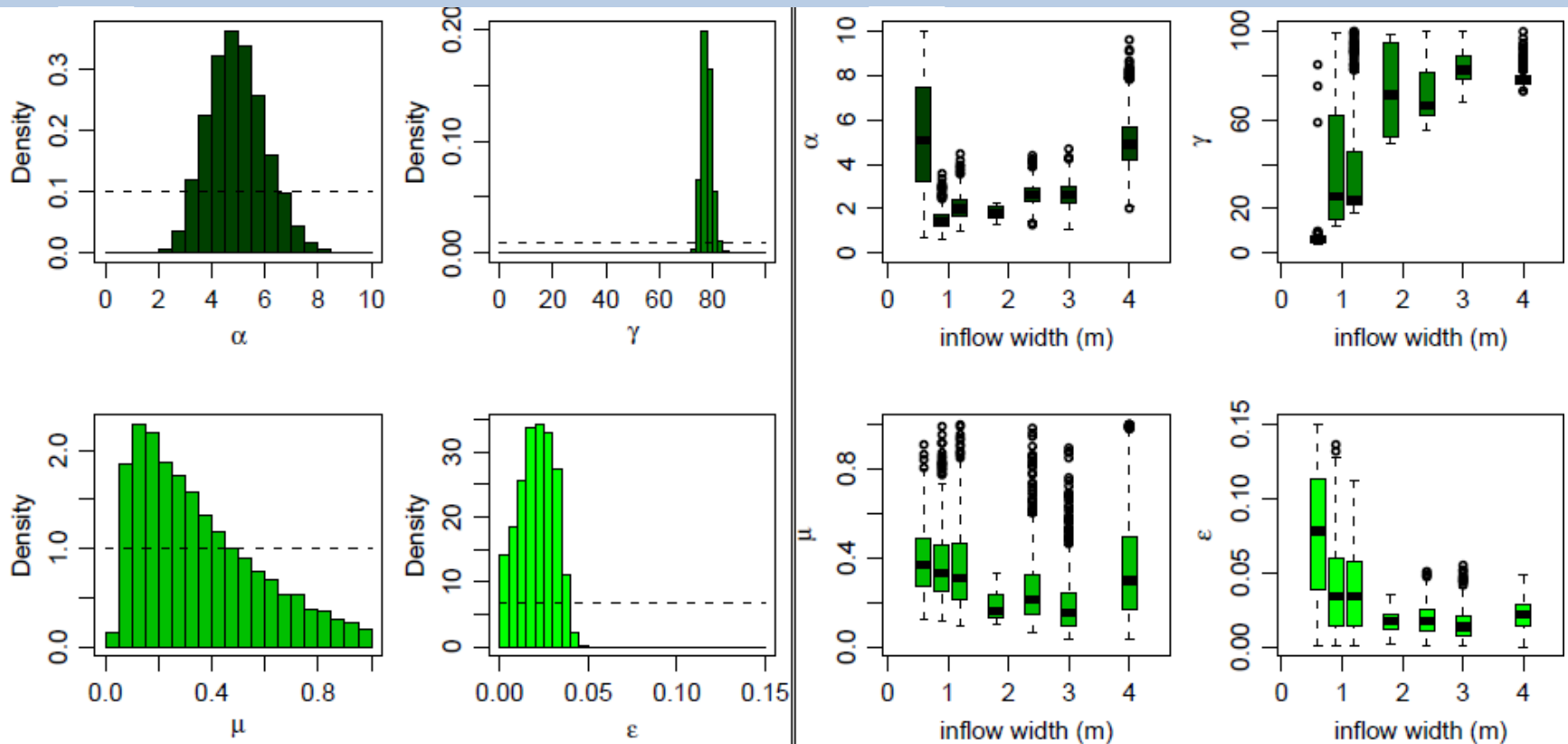
Model Fitting using ABC

Doing this for a given data set (courtesy Holl, Chraibi, BaSiGo project, FZ Jülich):

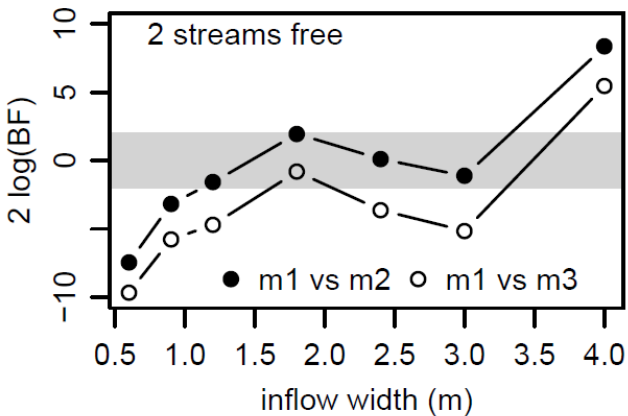


Model Fitting using ABC

Doing this for a given data set (courtesy Holl, Chraibi, BaSiGo project, FZ Jülich):



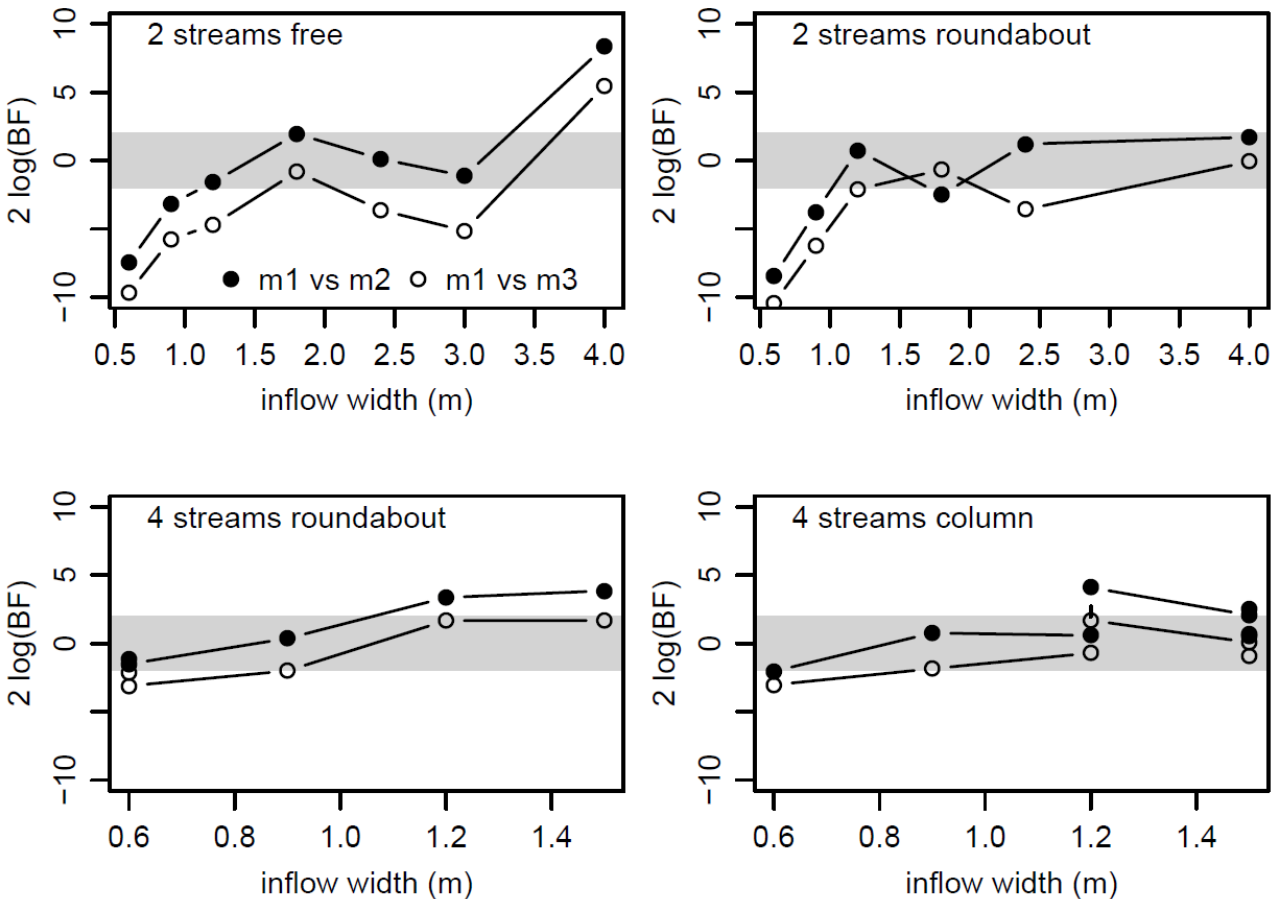
Model Selection using ABC



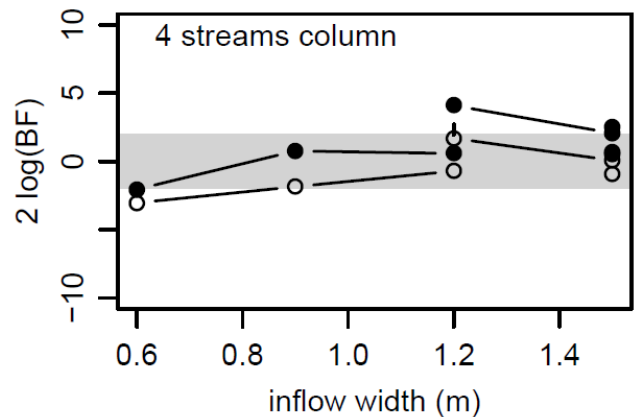
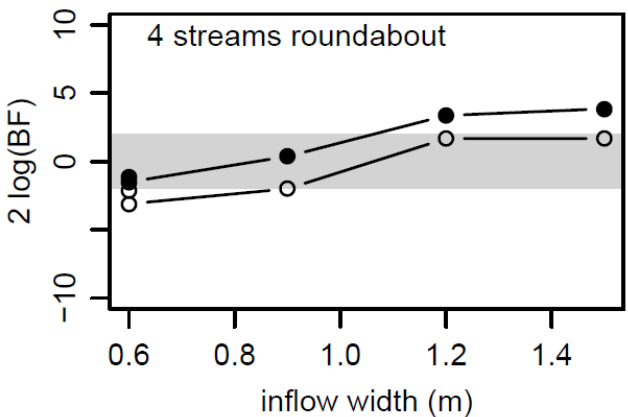
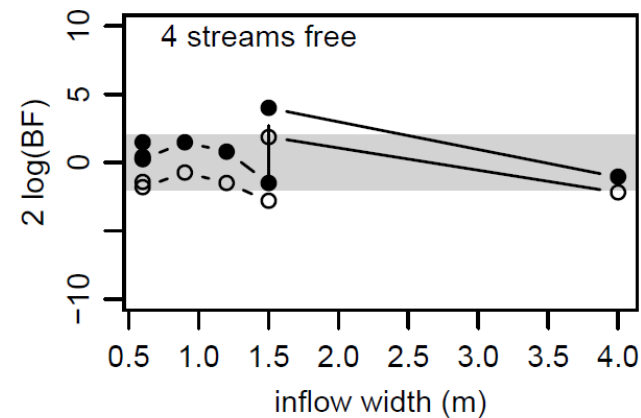
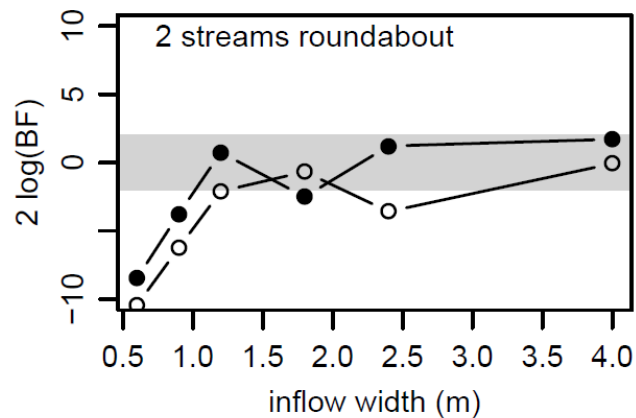
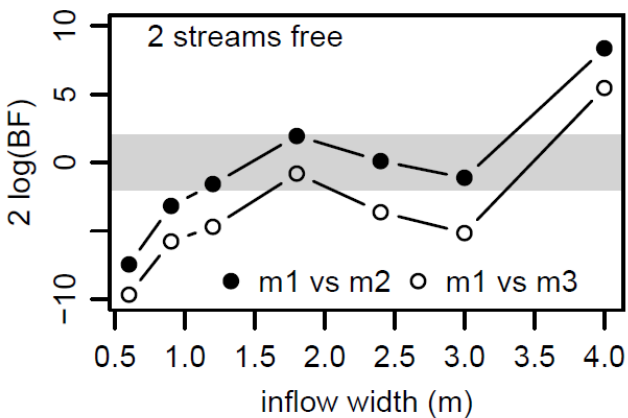
Using acceptance rate of priors for different models in ABC, we can approximate the Bayes factor,

$$BF = \frac{P(data|M_a)}{P(data|M_b)}$$

Model Selection using ABC



Model Selection using ABC



Pedestrian discussion

**Population dynamics
models for intersecting
pedestrian streams**

Macroscopic
analysis of
dynamics

Models pre-
dict different
dynamics

ABC allows
model fitting
and selection

Starting point
for general
insights?

Acknowledgements

Munich

Michael Seitz

Exeter

Darren Croft

Safi Darden

Jülich

Stefan Holl

Mohcine Chraibi



The Leverhulme Trust



AXA
Research Fund
Through Research, Protection

Thank you!