INFORMATION CRITERIA AND APPROXIMATE BAYESIAN COMPUTING FOR AGENT-BASED MODELLING IN ECOLOGY

New tools to infer on Individual-level processes

Cyril Piou – Biomath 2015 – June 17

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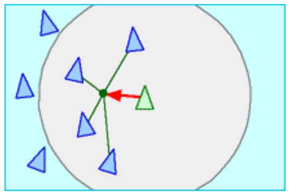
Plan

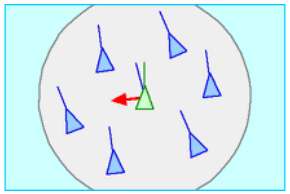
- Agent Based Modelling **ABM**
- Pattern-Oriented Modelling **POM**
- Information criteria in statistics **IC**
- POMIC **POMIC**
- Case study **CS**
- POMIC & ABC for ABM **ABC**

Agent-Based Modelling

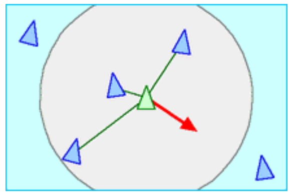
Reynolds, C. W. (1987) Flocks, herds and schools: a distributed behavioral model. *Computer Graphics*, **21,** 25-34.



Cohesion



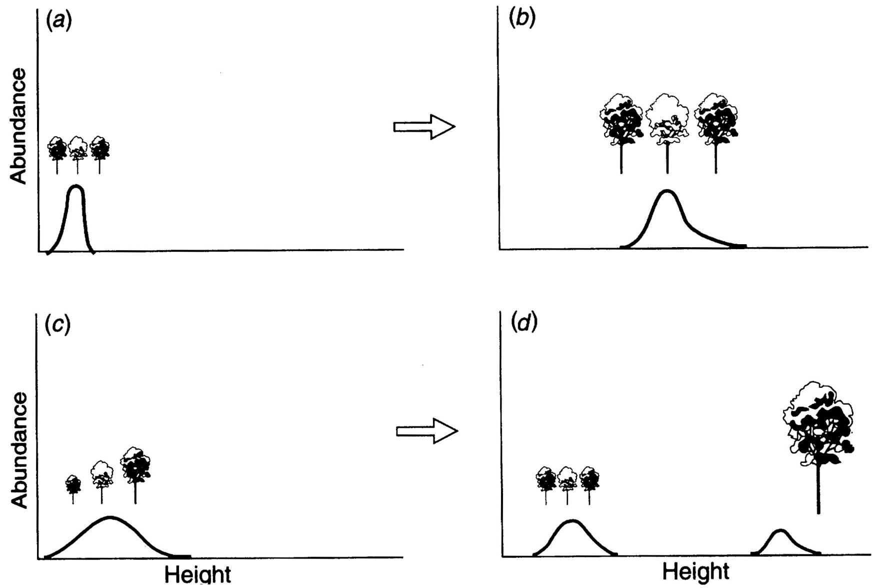
Direction



Separation

➔ How inter-individual **interactions** generate group or population emergent properties?

Agent-Based Modelling



➔ How individual **variability** influence population dynamics and structure?

Huston, M., D. DeAngelis, and W. Post. (1988). New computer models unify ecological theory. *BioScience* **38**:682-691.

Agent-Based Modelling

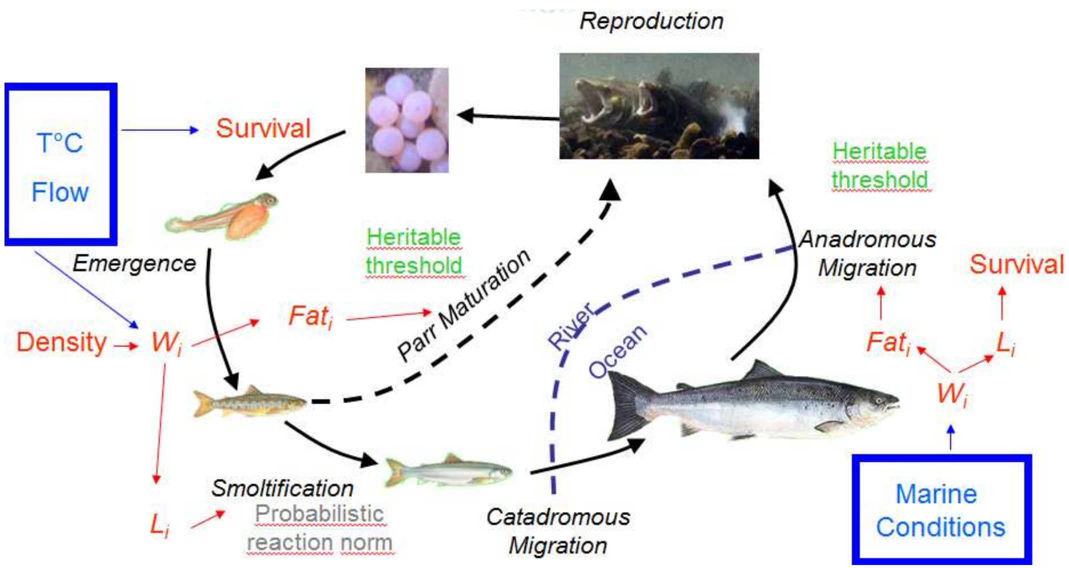
- Trout behavior model:
  - Use of shallow habitat when small; deep habitat when big
  - Shift in habitat when predators, larger competitors are introduced
  - Hierarchical feeding: big guys get the best spots
  - Movement to margins during floods
  - Use of slower, quieter habitat in high turbidity
  - Use of lower velocities at lower temperatures

➔ How individual **adaptations** regulate populations?

Railsback, S. F. & Harvey, B. C. (2002) Analysis of habitat-selection rules using an individual-based model. *Ecology*, ***83, 1817-1830.***

Agent-Based Modelling

- Salmon evolutionary model:



➔ How individual **genetics** allow populations to evolve in front of changes in environmental conditions?

Piou, C. & Prévost, E. (2012) *Ecological Modelling, **231, 37-52.***
Piou, C. & Prévost, E. (2013) *Global Change Biology*, 19, 711-723.
Piou, C. et al. in press *Journal of Applied Ecology*

Agent-Based Modelling

- 5 “branches” in ecology (DeAngelis & Mooij 2005):
  - Variation & phenotypic plasticity
  - Spatial interactions & movement
  - Life history and ontogenesis
  - Cognitive behavior
  - Genetic variability and evolution
- 3 main “reasons” to use the approach (Grimm & Railsback 2005):
  - Individual variability
  - Local interactions
  - Adaptive “behaviors”
- Problems of “realism” and “reproducibility”

Pattern-Oriented Modelling

- ABMs (and many other simulation models) were seen as too “theoretical” in the 1990s
- Their relation to real world system was often thin…
- ABMs used for management/real world advice purpose…

➔ Need of “sufficiently good” representations

➔ Need to continue learning from “patterns”

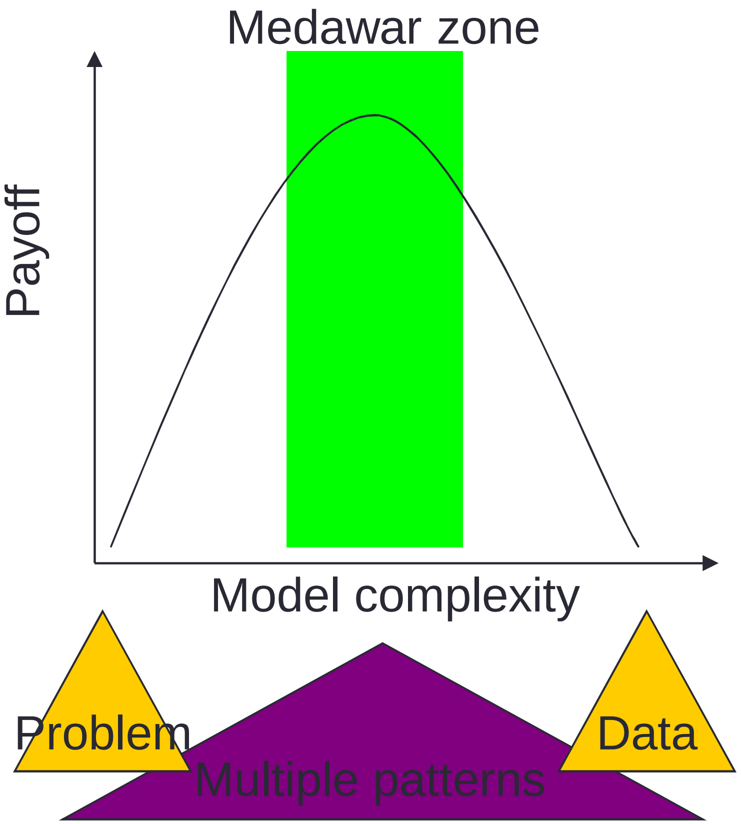
Pattern-Oriented Modelling

- POM was elaborated for complex system models (CA, ABMs …) :

Pattern or Emergent property = expression of underlying process

- POM evolved into 3 branches (reviewed in Grimm et al. 2005, Science) :
  1. Choose adapted model structure
  2. Analyze processes behind the pattern → Strong Inference
  3. Increment reliability of model & parameters → Inverse modelling

Use multiple patterns



Grimm et al. 2005

Payoff of a model = not only how useful for the problem, but also structural realism (reproduce nature).

Model complexity # nb of rules, parameters and state variables needed in the model.

Medawar zone = zone of model complexity when an increase in complexity of the model does not increase the payoff.

E.g. of Strong inference from multiple patterns

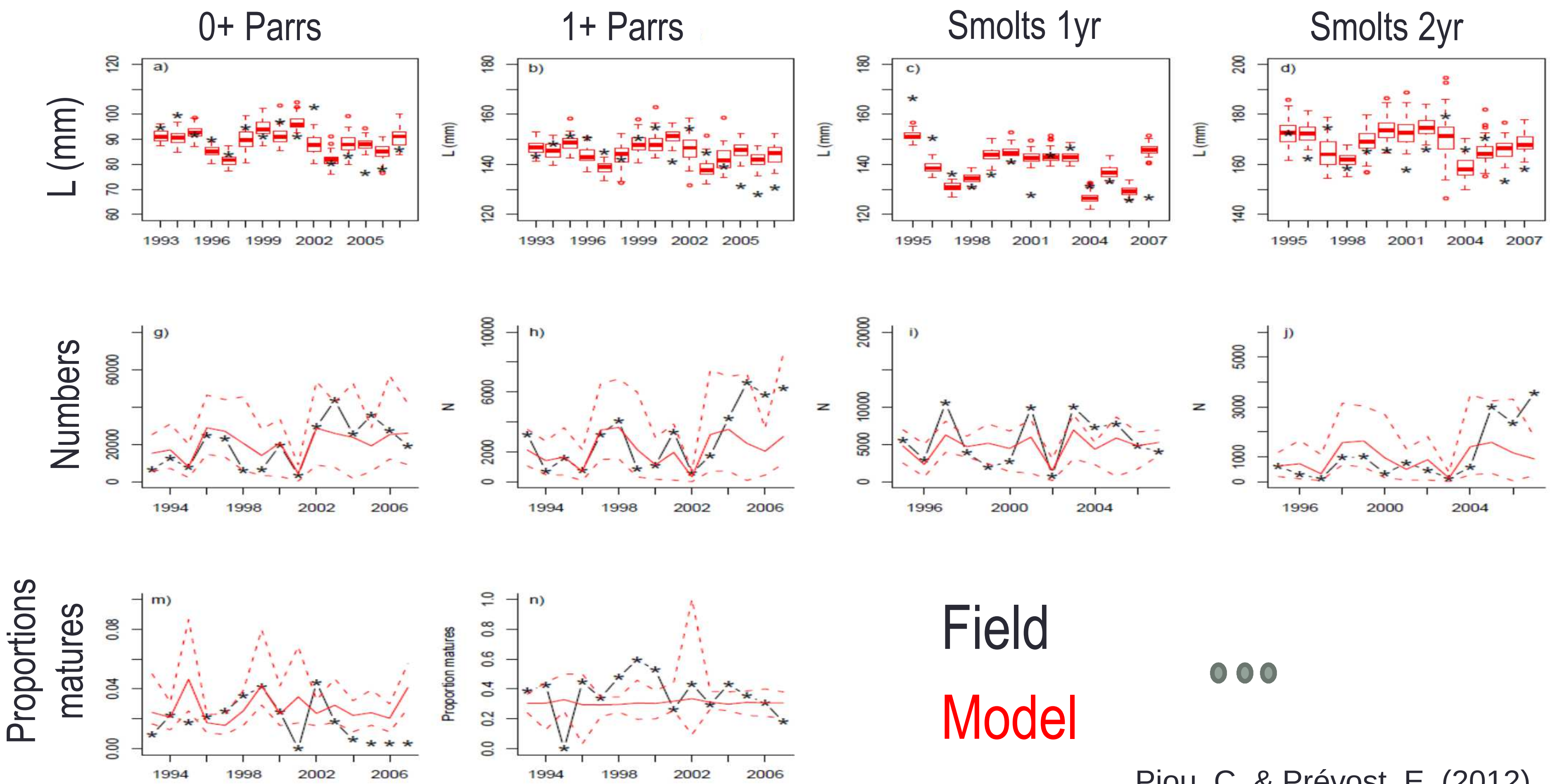
- Trout behavior model:

Pattern	Maximize growth	Maximize survival	State-based, predictive
Hierarchical feeding	✔		✔
Response to high flow	✔	✔	✔
Response to inter-specific competition	✔		✔
Response to predatory fish		✔	✔
Seasonal velocity preference			✔
Response to reduced food availability			✔

Railsback, S. F. & Harvey, B. C. (2002) *Ecology*, ***83, 1817-1830.***

E.g. of Inverse modelling from multiple patterns

- Salmon evolutionary model (16 time series):



Piou, C. & Prévost, E. (2012)

Akaike's Information Criterion

- Based on information theory (Akaike 1973)
- The best model is the one with smallest Kullback-Leibler distance

Akaike's Information Criterion

- Kullback-Leibler distance

$f(x)$

(probability of value in nature)

x

(variable considered)

$=$ "TRUTH" density distribution

With underlying unknown probability density function (*pdf*)

Akaike's Information Criterion

- Kullback-Leibler distance

$f(x)$

(probability of value in nature)

x

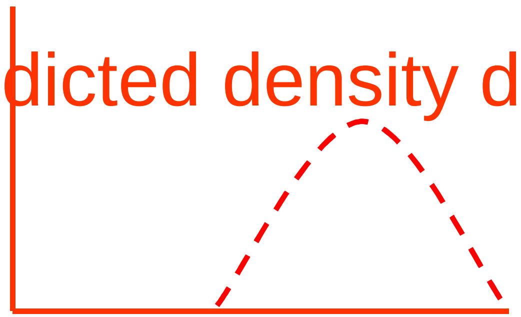
(variable considered)

$\overset{?}{=}$

$g(x)$

(probability of value with model)

Predicted density distribution



x

(variable to be predicted)

Akaike’s Information Criterion

- Kullback-Leibler distance

$$I\left(f\left(x\right);g\left(x\right)\right)=\int_{-\infty}^{+\infty}f\left(x\right)\log\frac{f\left(x\right)}{g\left(x\right)}dx$$

Akaike's Information Criterion

- AIC proposition:

$$AIC = -2\log L(\theta_k) + 2k$$

→ Model selection dependent on fit and parsimony

- Assumptions:
  - The *n* is large enough
  - Mean expected likelihood as estimator of K-L distance
  - Maximum likelihood ~ mean expected likelihood

Model selection in Bayesian statistics

- Proposition of Spiegelhalter et al. (2002 *Journal of the Royal Statistical Society B*, **64,** 583-639) for Bayesian models :

Deviance $$D(\theta) = -2\log(L(\theta))$$

Complexity of model

$$DIC = 2 \cdot \overline{D(\theta)} - D(\bar{\theta}) = \overline{D(\theta)} + pD$$

$$\overline{D(\theta)} - D(\bar{\theta}) = pD$$

Mean deviance on posterior distribution

Deviance of model with estimates of parameters from posterior distribution

- Prerequisite:
  - Convergence of a MCMC gives posterior distribution
  - Identification of likelihood function for parameters
- DIC was demonstrated as generalization of AIC

POMIC proposition

- Pseudo-likelihood➔ pseudo-deviance
- Posterior distribution estimation:

  Metropolis without likelihood (~ABC)
- Complexity: Adapting DIC proposition

Piou, C., Berger, U. & Grimm, V. (2009) Proposing an information criterion for individual-based models developed in a pattern-oriented modelling framework. *Ecological Modelling*, **220**, 1957-1967.

Pseudo-likelihood

- For (most) ABMs we do not have likelihood functions of the parameters
- The likelihood of a parameter set given the data = Goodness of fit indicator

Pseudo-likelihood

- For (most) ABMs we do not have likelihood functions of the parameters
- One way to bypass this is approximating a likelihood-type function

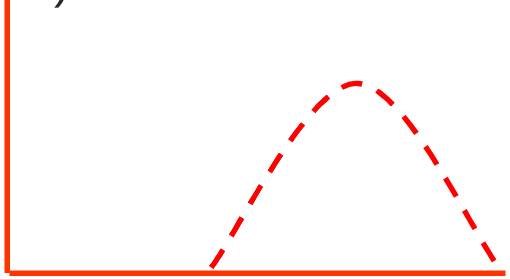
$g(x|\theta)$

(probability in model)

with Z included in θ

$b(x) = b(x|(\theta^* + Z))$

(probability in sample)



x

(predicted variable)

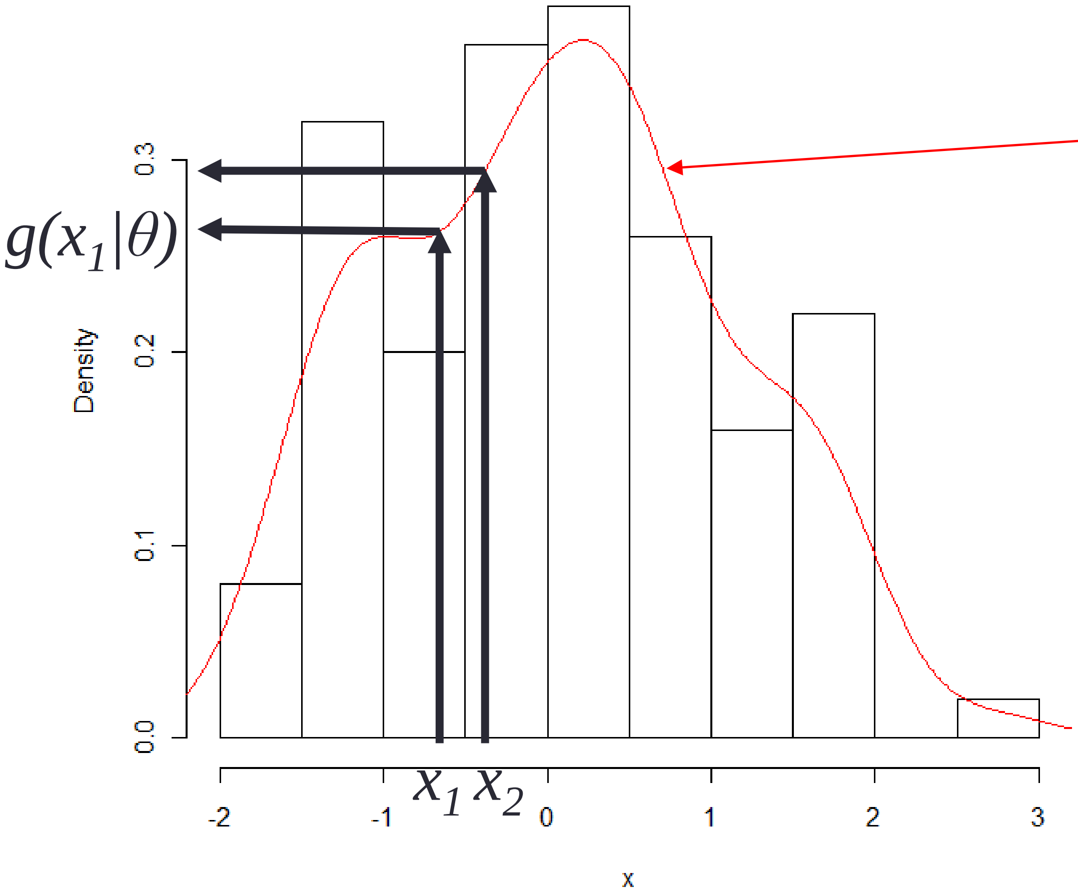
$$\stackrel{?}{=}$$

x

(sampled variable)

Pseudo-likelihood

- An estimate of likelihood:

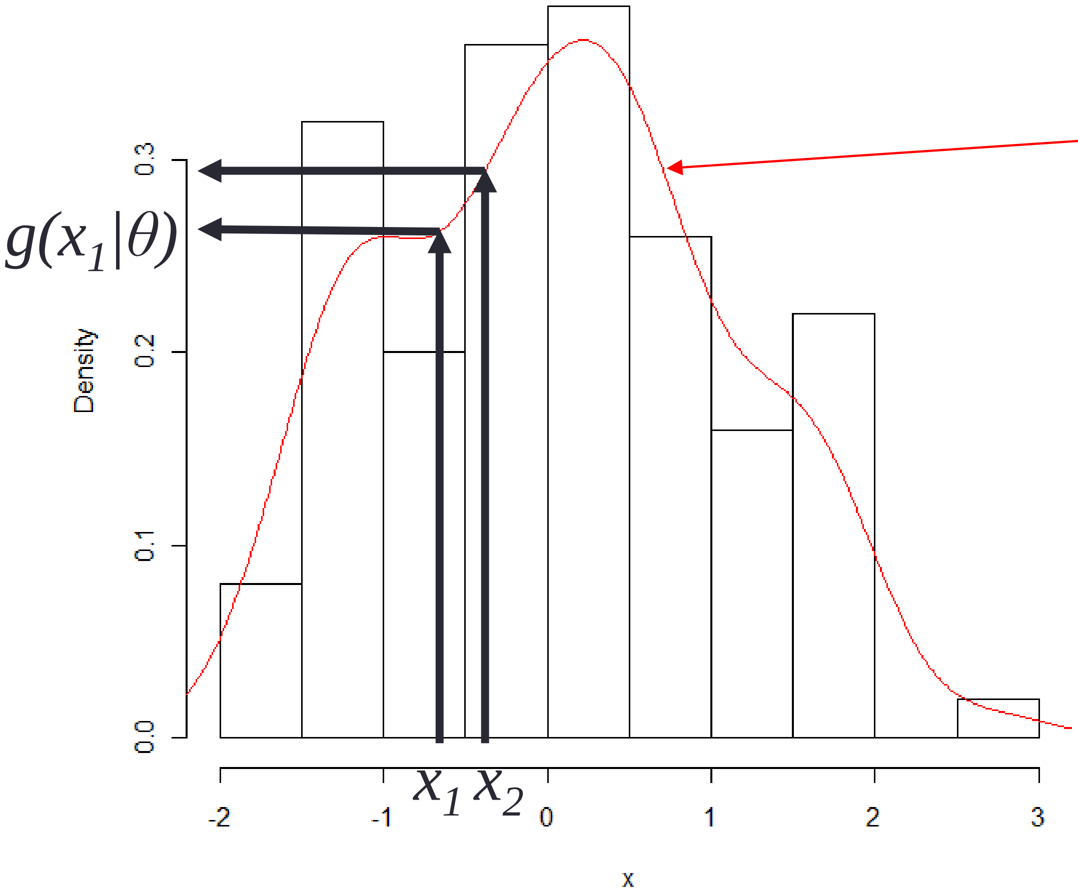


-Mesure of x in model
-Adjust estimation of density on range of real x
-« reading » of pseudo-likelihood of real x from this adjusted density

$$L(\theta|data) = \prod_{i}^{n} \left(g\left(x_i \mid \theta\right)\right)$$

Pseudo-likelihood

- An estimate of Deviance:



-Mesure of *x* in model
-Adjust estimation of density on range of real *x*
-« reading » of pseudo-likelihood of real *x* from this adjusted density

$$L(\theta|data)=\prod_{i}^{n}\left(g(x_i\mid\theta)\right)$$

$$POMDEV=-2\sum_{i=1}^{n}\log\left(g(x_i\mid\theta)\right)$$

Metropolis without likelihood

- Metropolis – Thanks Marjoram et al. (2003, PNAS)
  - Idea 1: estimator of likelihood ratios

$$P(accept\ \theta') = Estimate\ \ of\ \ LR\left(\frac{\theta'}{\theta_t}\right) \bullet \frac{Q(\theta_t \to \theta')}{Q(\theta' \to \theta_t)} \bullet \frac{P(\theta')}{P(\theta_t)}$$

  - Idea 2: production of data D' and reject parameters if $D' \neq D$ (±error)

$$P(accept\ \theta') = \begin{pmatrix} 1 \Leftrightarrow D = D' \\ 0\ \text{otherwise} \end{pmatrix} \bullet \frac{Q(\theta_t \to \theta')}{Q(\theta' \to \theta_t)} \bullet \frac{P(\theta')}{P(\theta_t)}$$

Metropolis without likelihood

- Metropolis + POMDEV: $$POMDEV' = -2\sum_{i=1}^{n} \log\left(g\left(x_i \mid \theta'\right)\right)$$
  - Idea 1: estimator of likelihood ratios

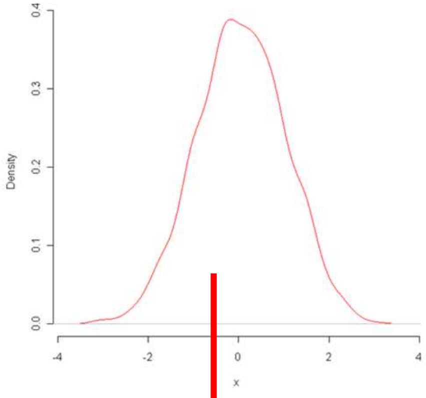
$$P\left(accept\ \theta', POMDEV'\right) = \frac{\exp\left(POMDEV_t - POMDEV'\right)}{2} \bullet \frac{Q\left(\theta_t \rightarrow \theta'\right)}{Q\left(\theta' \rightarrow \theta_t\right)} \bullet \frac{P\left(\theta'\right)}{P\left(\theta_t\right)}$$

  - Idea 2: production of data D' and reject parameters if $D' \neq D$ (±error)

$$P\left(accept\ \theta'\right) = \begin{pmatrix} 1 \Leftrightarrow POMDEV' \leq POMDEV acceptance \\ 0 \text{ otherwise} \end{pmatrix} \bullet \frac{Q\left(\theta_t \rightarrow \theta'\right)}{Q\left(\theta' \rightarrow \theta_t\right)} \bullet \frac{P\left(\theta'\right)}{P\left(\theta_t\right)}$$

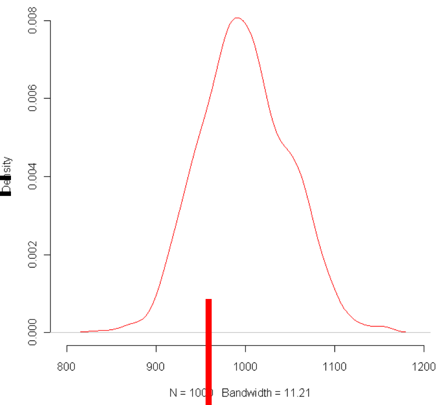
POMIC

$$P(\theta|D) =$$



$$POMDEV\left(\hat{\theta}\right)$$

$$POMDEV =$$

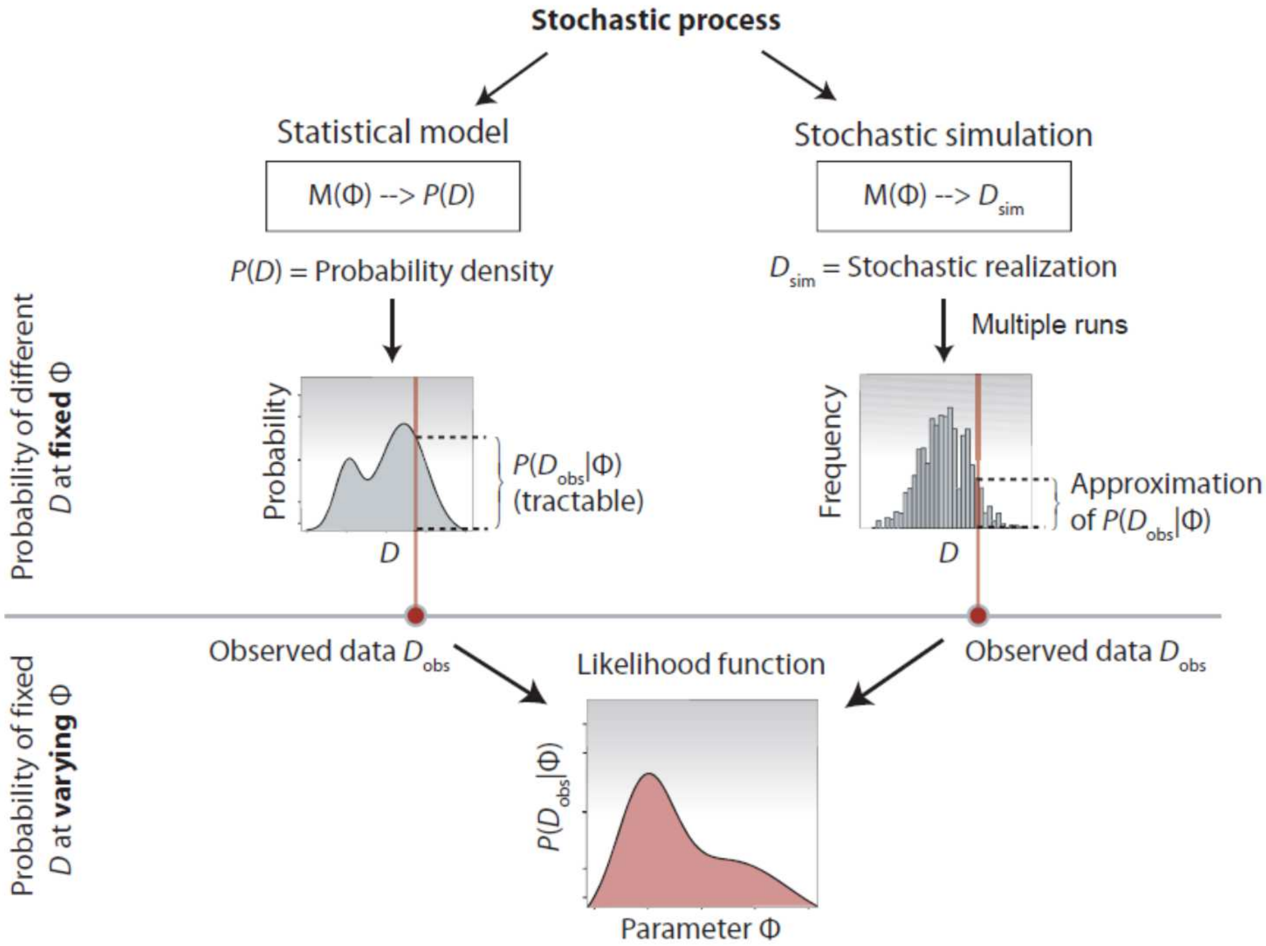


$$\overline{POMDEV} = \frac{1}{L}\sum_{l=1}^{L} POMDEV(\theta_l)$$

$$POMIC = 2 \cdot \overline{POMDEV} - POMDEV\left(\hat{\theta}\right) = \overline{POMDEV} + pD$$

$$pD = \overline{POMDEV} - POMDEV\left(\hat{\theta}\right)$$

POMIC ~ ABC



Hartig, F., Calabrese, J. M., Reineking, B., Wiegand, T. & Huth, A. (2011) Statistical inference for stochastic simulation models - theory and application. *Ecology Letters*, **14**, 816-827.

Case study

- Inferring on innate locust behavior with individual based models and an information criteria

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Centre National de Lutte Antiacridienne

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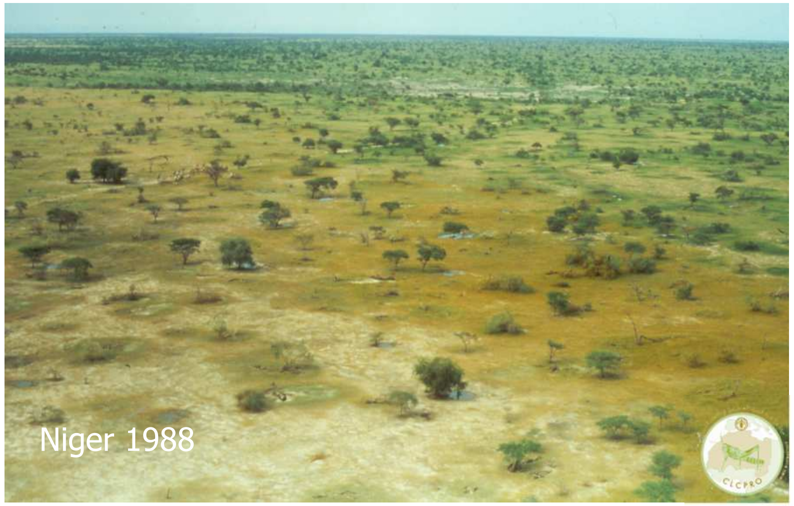
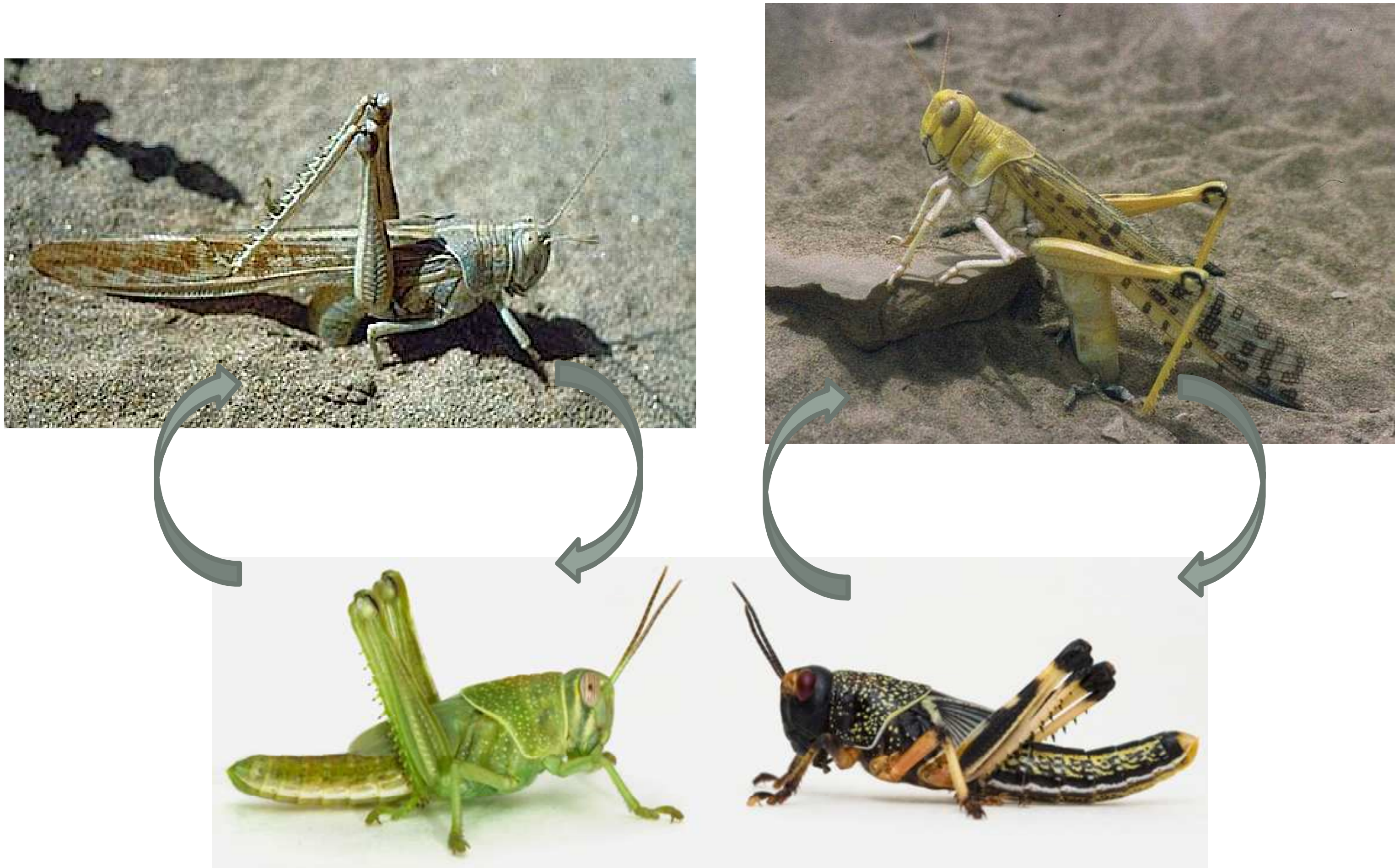
Solitarious

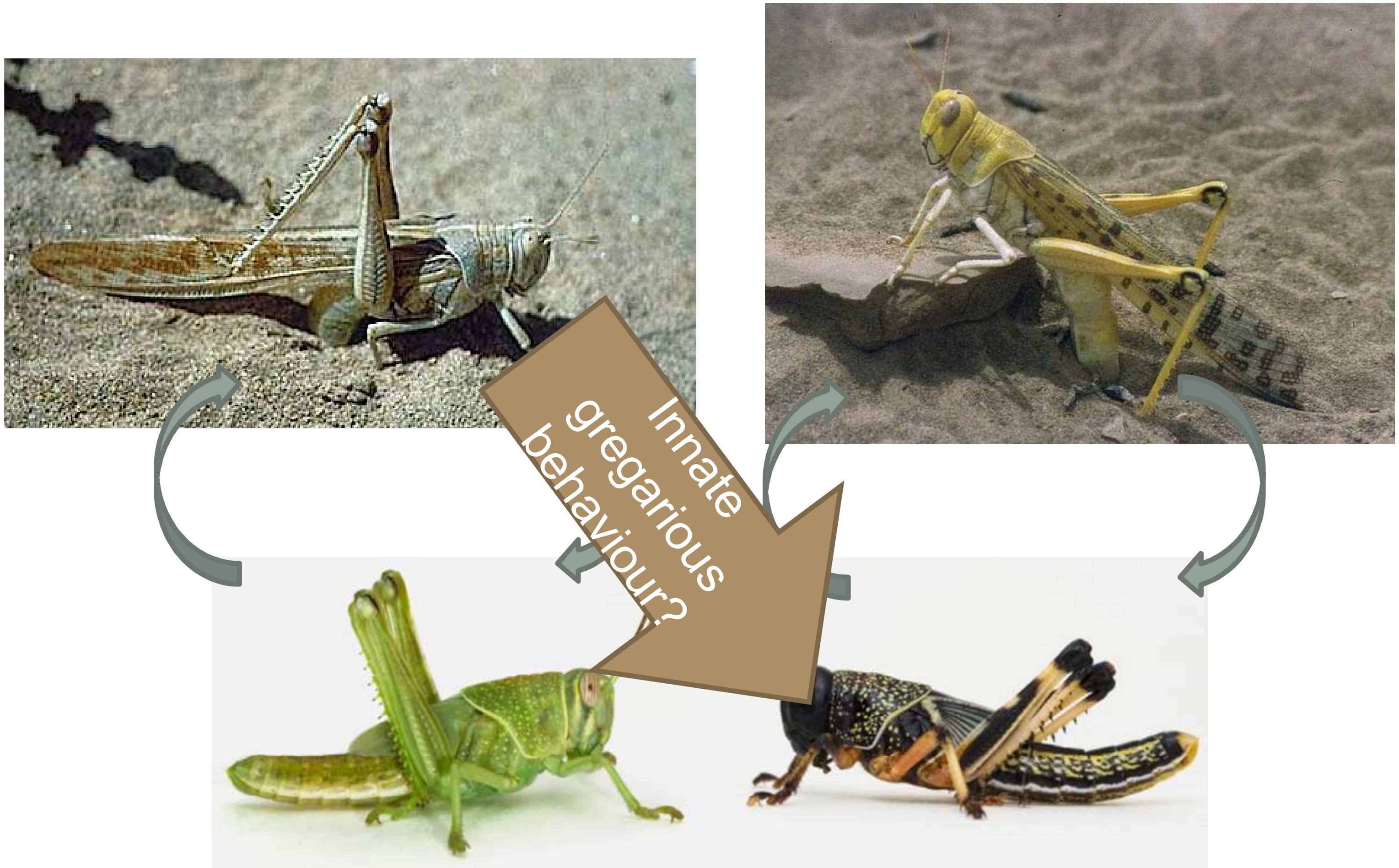
Density

Gregarization



Gregarious




Innate
gregarious
behaviour?

Innate gregarious behavior?

- Ellis (1956) found a random distribution of hatchlings in cages

- Simpson et al. (Islam et al. 1994, Bouaïchi et al. 1995, Simpson et al. 1999…) ➔ individual measurements ➔ difference of behavior among solitarious and gregarious hatchlings
  (but mixing activity and attractivity and
  isolating individuals at hatching time)

- Guershon & Ayali (2012) ➔ group measurements ➔ behaving identically: grouping together on sticks
  (but discarded egg pods producing few individuals, first 2h after hatching and wrong statistical method)

Innate gregarious behavior?

- Group measure to keep interactions
- But problem of mixing of processes/behaviors (level of activity, aggregation, food search, resting…)

Laboratory experiments

- 17 experiments:
  - 11 from grouped mothers
  - 6 from isolated mothers
- 30 eggs positioned on a wet petri-dish ~24h before hatching time in a center of an arena
- Photo recording every 15min during at least 7h (up to 16h) after first hatching

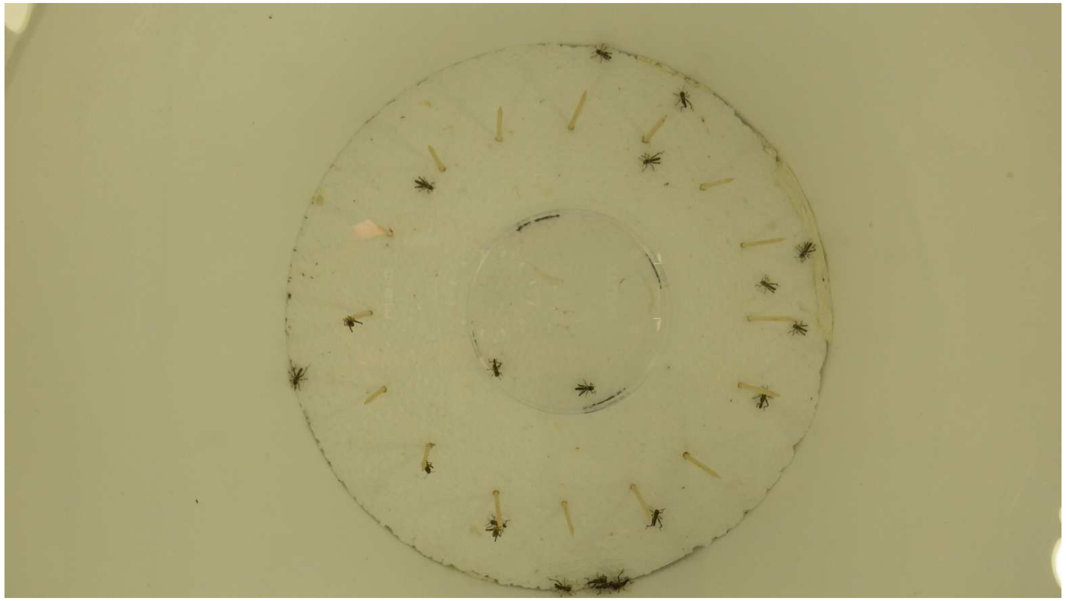
Laboratory experiments

- Photo analysis:
  - Count of individuals per stick
  - Count of individuals on other parts of the arena

➔NND (on sticks)

➔Activity (change of nb per sticks)

➔Proportions of individuals on sticks



ABM analysis

OVERVIEW

- Model description
  - Objective: Simulate our experiments
  - Entities & state variables:

  - Scales: 101 time steps (time step = 15min), 16 sticks, N eggs = hatched eggs in experiments

ABM analysis

- Model description
  - Process overview:

OVERVIEW

```
to go
  if ticks = timeMax [stop]
  ask sticks [update-attractivity]
  SetvectorAttractivity
  ask locusts with [shape = "egg"][hatching]
  ask locusts with [shape = "locust"][update]
  prepareData
  tick
end
```

Update locusts:

$$P(climb) = \text{invlogit}(a \times age + b)$$

$$choice = i\,?$$

$$P(walk) = 1 - P(climb)$$

$$P(changeStick) = pC$$

Update-attractivity:

$$\text{attractiveness}_i = 1 + \frac{d \times n_i}{\sum_j n_j} + \frac{f \times \sum_{\text{k neighbors of i}} n_k}{\sum_j n_j}$$

SetvectorAttractivity:

$$P(choice = i) = \frac{attractiveness_i}{\sum_j attractiveness_j}$$

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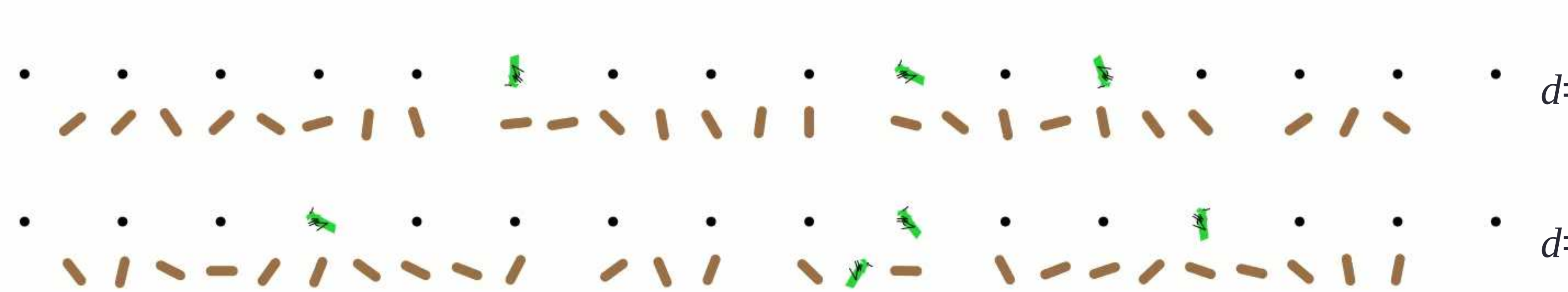
ABM analysis

OVERVIEW

- Model description
  - Parameters: a, b, d, f, pC
    (to be adjusted with MCMC per experiment)
  - Forced dynamics: hatching time of eggs (as in experiments)



d=0

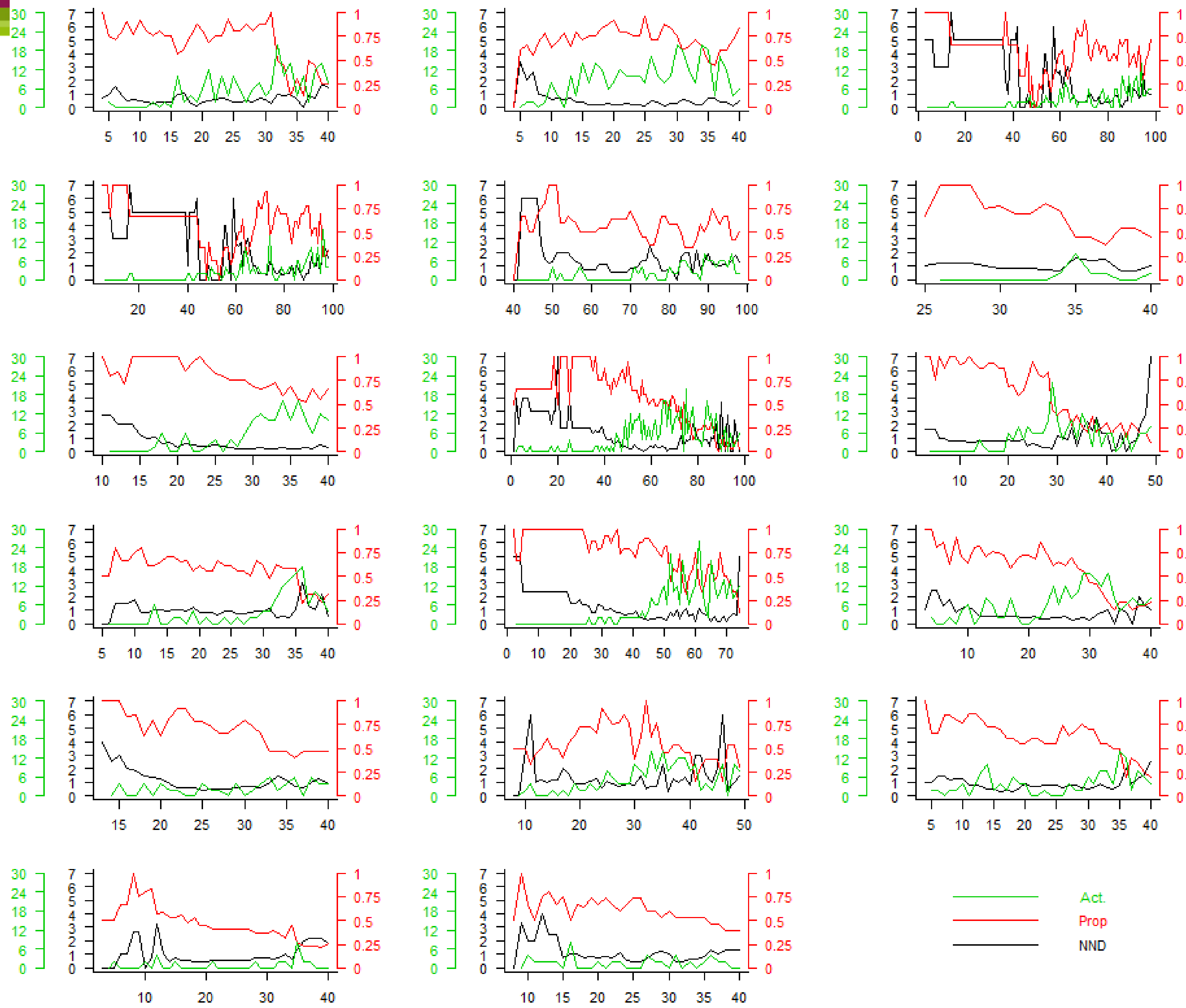
d=50

ABM analysis

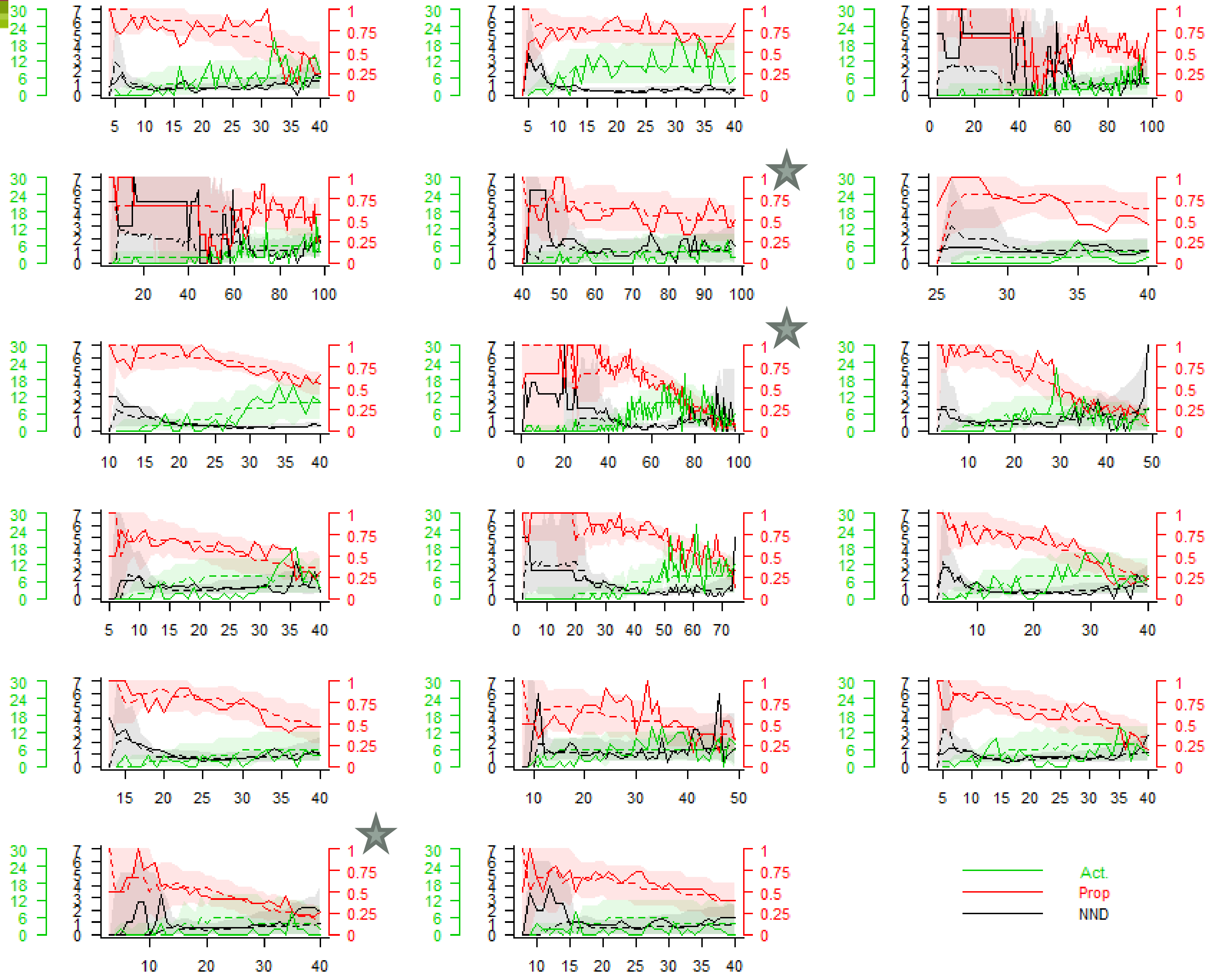
- Searching for behavior explaining the lab results
  - 3 model versions :
    - ModelO → $d=f=0$ $pC=?$ $a=?$ $b=?$
    - ModelA → $d=?$ $f=0$ $pC=?$ $a=?$ $b=?$
    - ModelB → $d=?$ $f=?$ $pC=?$ $a=?$ $b=?$

ABM analysis

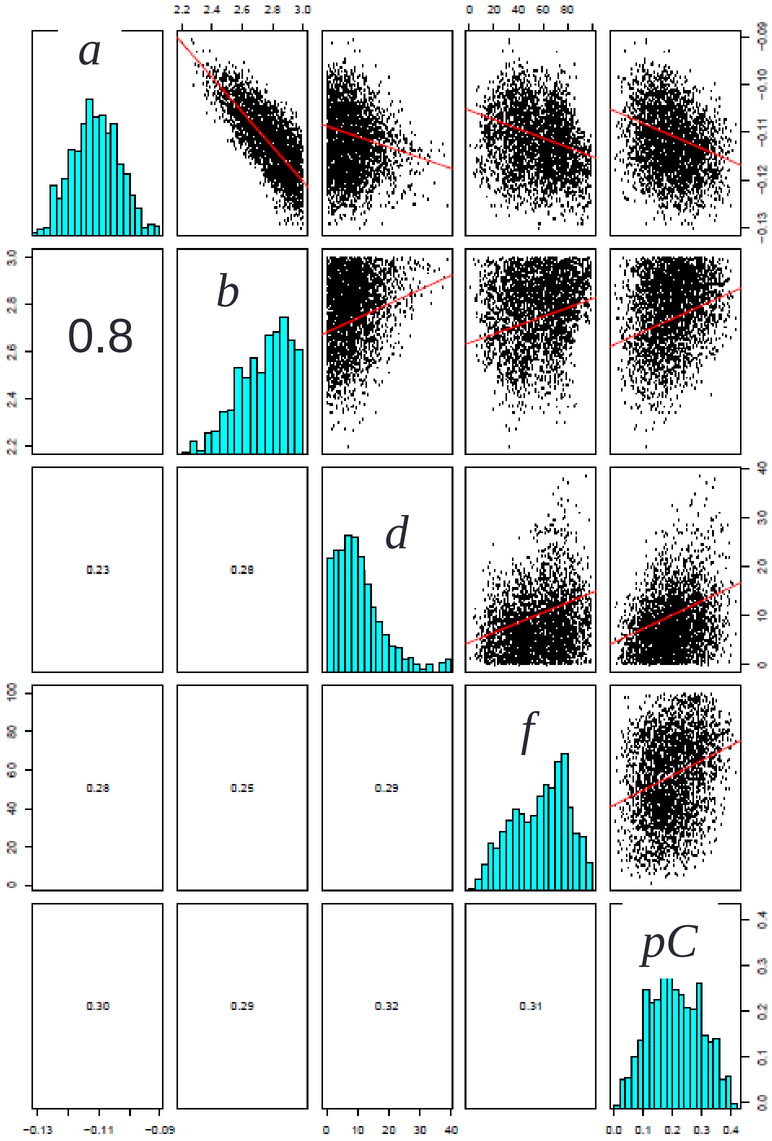
- Searching for behavior explaining the lab results
  - 3 model versions :
    - ModelO → d=f=0 pC=? a=? b=?
    - ModelA → d=? f=0 pC=? a=? b=?
    - ModelB → d=? f=? pC=? a=? b=?
  - With each model and for each experiment (17) parameterization and posterior creation with MCMC (following Piou et al. 2009)
  - POMIC measure to infer on likely behavior that lead to the 3 temporal patterns of:
    - Mean NND through time
    - Proportion of individuals on sticks through time
    - Activity through time



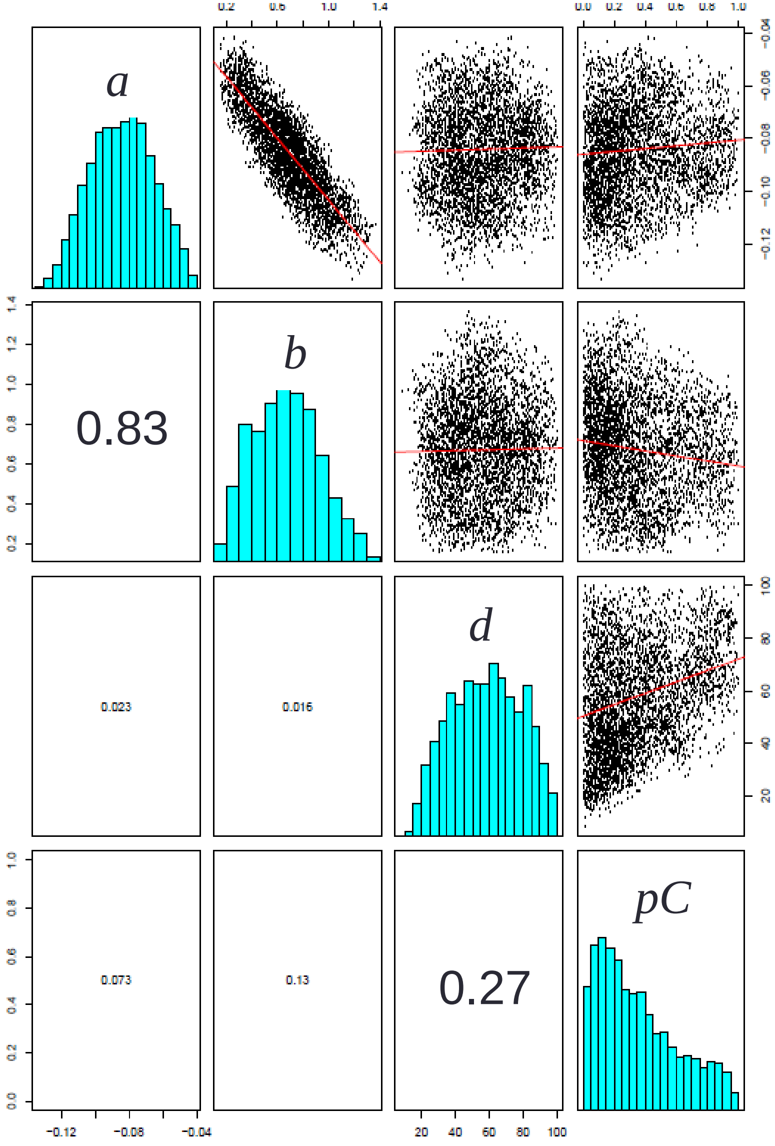
Act.
Prop
NND


Act.
Prop
NND

ModelB for experiment 8 …



ModelA for experiment 16 …



ABM analysis

	Gregarious											Solitarious					
Experiments	1	2	3	4	**5**	6	7	**8**	9	10	11	12	13	14	15	**16**	17
Best Model	O	O	B	O	**A**	O	B	**B**	A	O	O	O	O	O	O	**A**	A
Second Model	B	A	O	A	**B**	B	O	**O**	O	A	B	A	B	A	A	**B**	O
Third Model	A	B	A	B	**O**	A	A	**A**	B	B	A	B	A	B	B	**O**	B
$\hat{d}$ of best model	-	-	2.5	-	**14**	-	2	**9**	7	-	-	-	-	-	-	**57**	37
ΔPOMIC 1st-2nd	1	1	1.6	32	**2**	.2	.0	**4**	0	4	12	.8	.9	14	.6	**5**	1
ΔPOMIC 1st-3rd	1	4	4	42	**4**	.6	.2	**6**	3	13	13	2	1.5	26	1	**59**	5

Gregarious innate behavior *sometimes* significantly happening

…but from both treatments…

Conclusions of case study

- Innate gregarious behavior might exist in Desert Locust
  - Small *n* of lab experiments…
  - ABM integration of different processes
- POMIC approach applicable to behavioral analyses

POMIC & ABC

- Potential in behavioral ecology to infer on complex systems dynamics
- Problem of chain convergence for complex models ➔ trade-off of case complexity and inference possibility…
- Other techniques of ABC could be applied (summary statistics, regression…)

- Study of group behavior of hopper bands to come…


THANK YOU!
БЛАГОДАРЯ !