# **Theory-driven analysis of Ecological data - Day 1**

10:30-12:00 What types of theoretical models in ecology?

13:45-14:45 **How to build a model?** 

14:45-15:45 How to analyze a model?









Isabelle Gounand

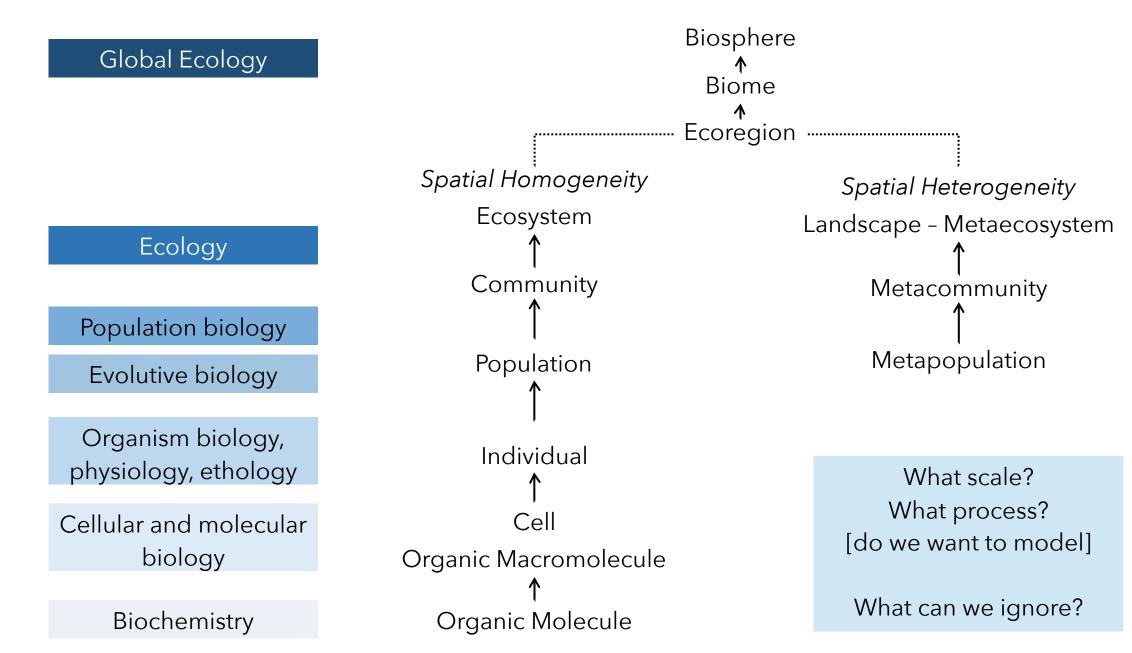


CESAB, Montpellier, March 11, 2024

# What types of theoretical models in ecology?

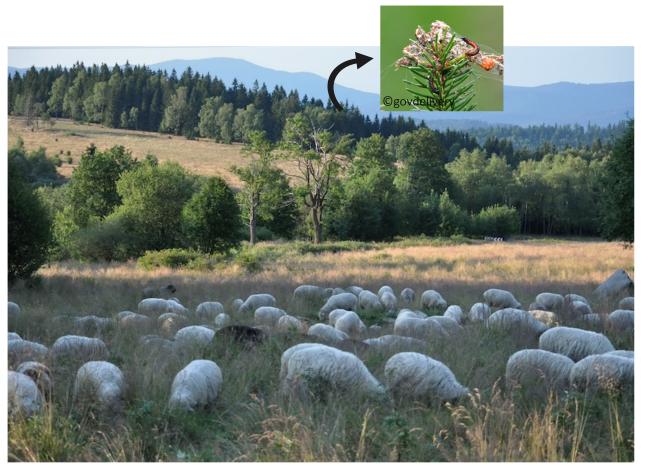
#### Content

- 1. What system? What question? What hypotheses? What model type?
- 2. What model formalism?
  - Deterministic stochastic processes
  - Time: discrete continuous
  - Accounting for space?
- 3. What technical choices?
  - Analytical vs Numerical
  - Agent Based Models vs Equations



#### System + Question

 $\rightarrow$  Scale  $\rightarrow$  Variable + Processes



Example: landscape with plants and herbivores

#### Individuals

*Which factors determine individuals development?* Physiology, morphology, behavior, life-cycle etc

#### Population

*How do resources regulate population growth?* Intra-specific competition, pop level rates, etc.

#### Community

How does grazing impact plant diversity?

 $\rightarrow$  What can we ignore?  $\rightarrow$  What assumptions do we make?

Herbivore preferences, plants relative growth, etc.

#### Ecosystem

*Can grazing increase primary production?* Ecosystem fluxes, recycling, etc.

#### Landscape

*Can spatial heterogeneity promote plant diversity?* Spatial connectivity, dispersal rates, etc.

System + Question

 $\rightarrow$  Scale

 $\rightarrow$  What can we ignore?  $\rightarrow$  What assumptions do we make?

 $\rightarrow$  Variable + Processes

This is neither the aim nor relevant to model all details.

Some processes are much faster or much slower than focal ones and can be considered constant.

Example: the upper level is often slower than those below and impose constraints



Physiology question => ignore tree dynamics



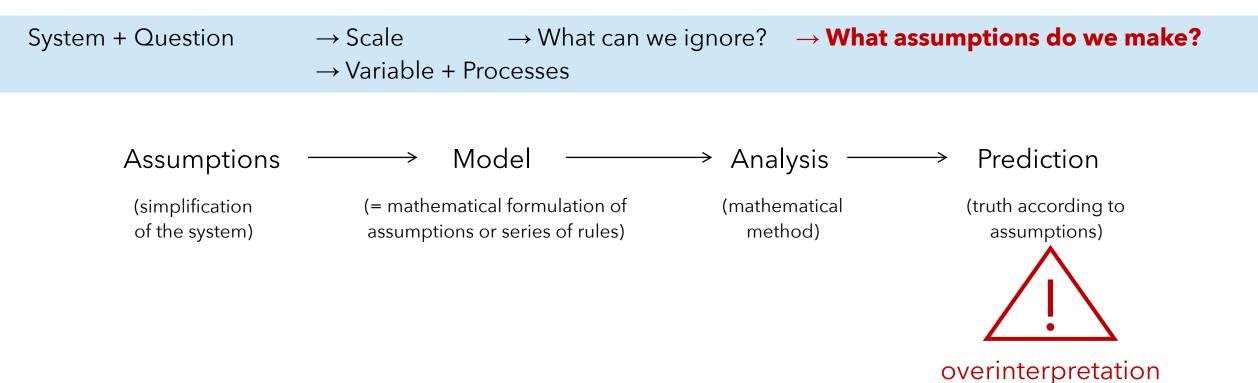
Long term population dynamics => include tree mortality dynamics



Year-scale fish population dynamics => ignore human demography



Century-scale fish population dynamics ⇒ include human demography (variation in catch effort)



#### **Types of assumptions**

- > critical: crucial to test the verbal hypothesis
- > exploratory: important to vary and test but not core to the verbal hypothesis
- > logistical: those important for tractability

(Servedio et al. 2014)

System + Question

 $\rightarrow$  What can we ignore?  $\rightarrow$  What assumptions do we make?

 $\rightarrow$  Variable + Processes

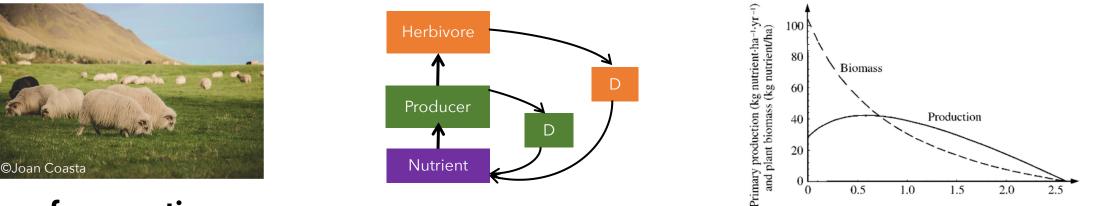
 $\rightarrow$  Scale

Question: Can grazing increase primary production?

(de Mazancourt et al. 1998 Ecology)

Grazing intensity (yr<sup>-1</sup>)

Hypothesis: Herbivory can maximize primary production if herbivore recycling path is faster than plant ones

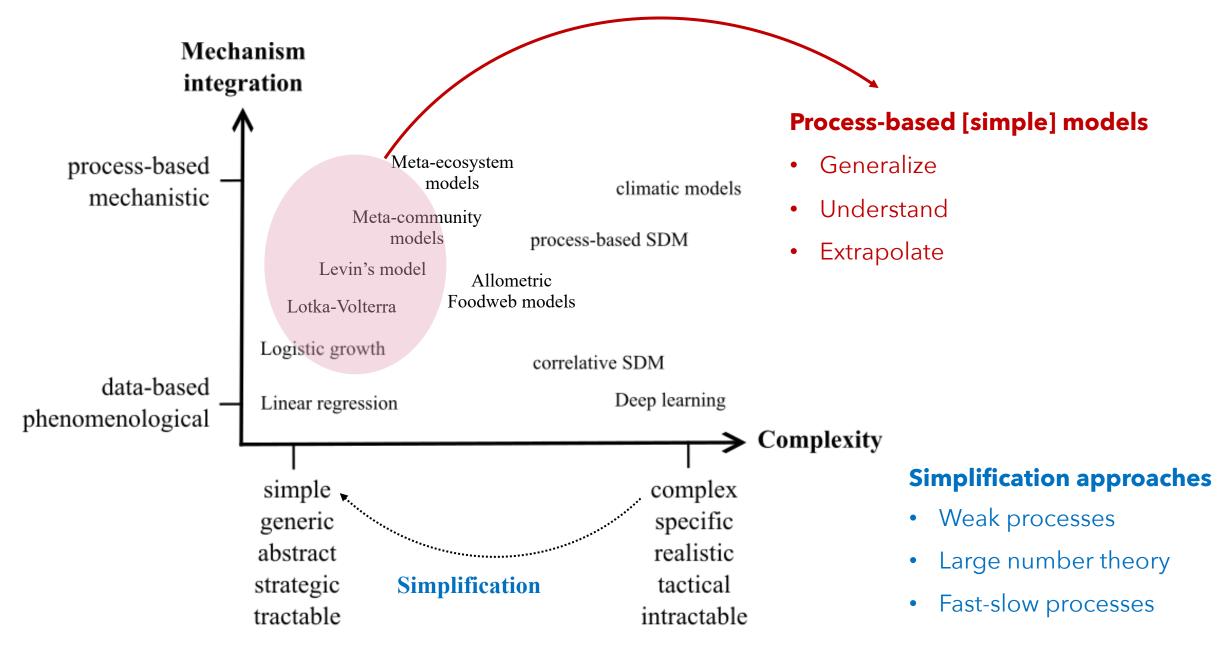


### Types of assumptions

- $\sim$  critical: crucial to test the verbal hypothesis => 2 paths of recycling
- > exploratory: important to vary and test but not core to the verbal hypothesis => functional
- logistical: those important for tractability => ODE deterministic
  (Servedio et al. 2014)

response (donor vs recipient controlled)

### 1. What model type?



# 2. What model formalism?

- 1. Do we need **deterministic or stochastic** dynamics?
- 2. Do you model time or not ? Are processes continuous or discrete in **time**?
- 3. Do we need to consider **space** explicitly?

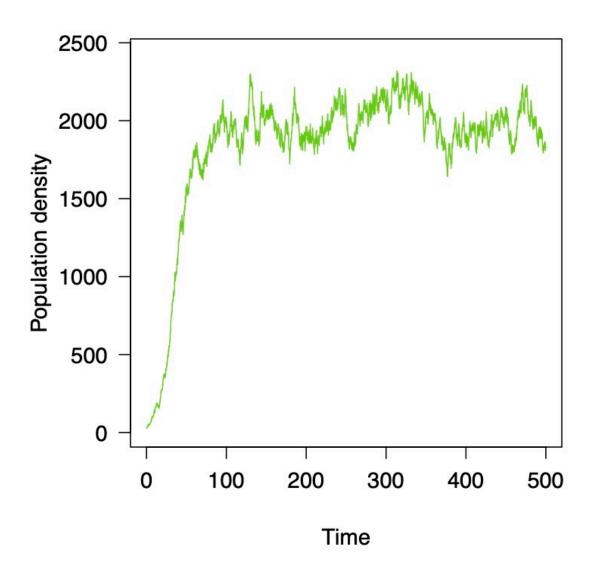
What is stochasticity? What sort of stochasticity counts in ecology?

- demographic stochasticity
- environmental stochasticity

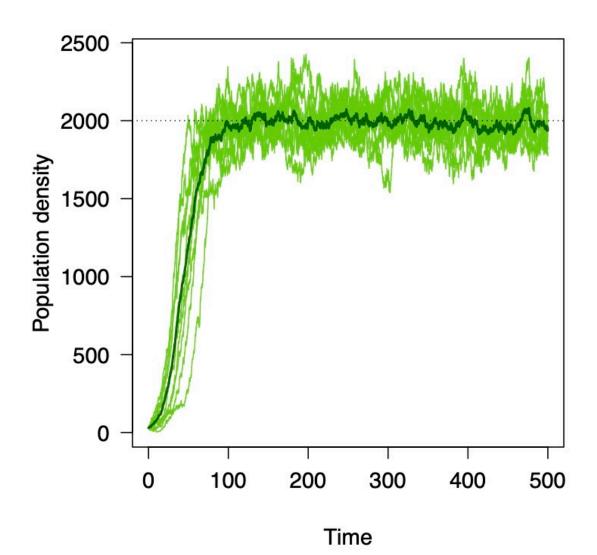


- trait variability

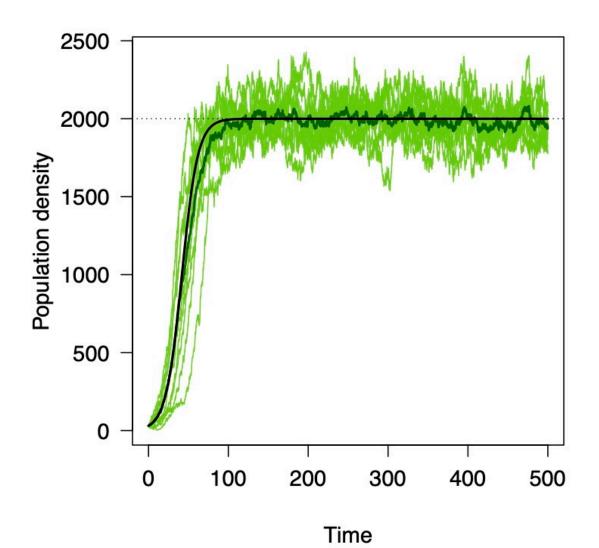
# When should we account for it?



Example: random demographic events

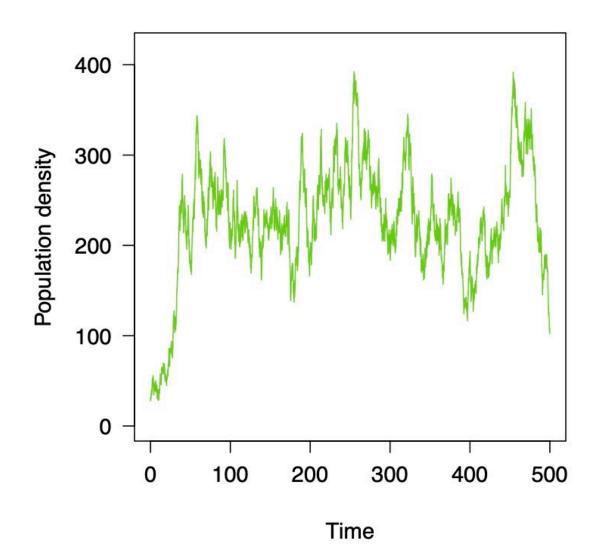


Example: random demographic events



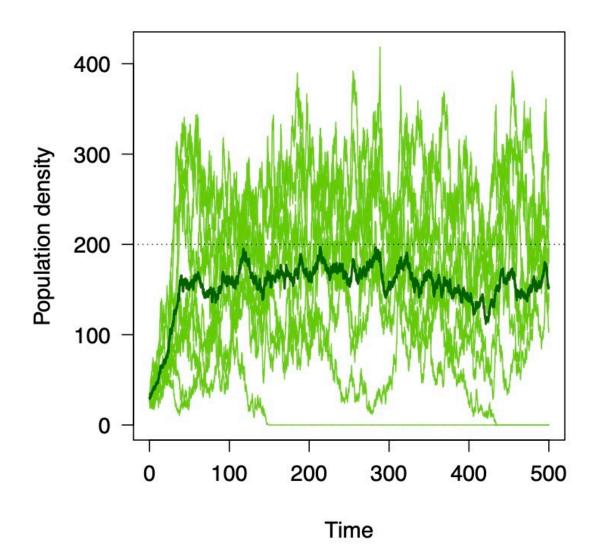
Example: random demographic events

- $\rightarrow$  care of the mean only
- $\rightarrow$  good approximation



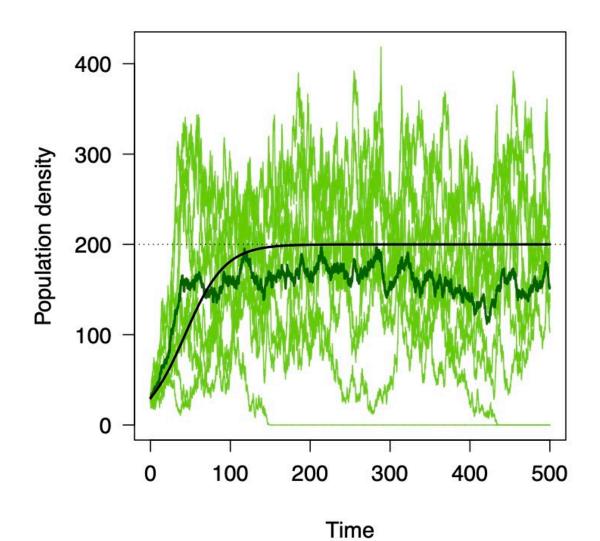
Example: random demographic events

Randomness large compared to population size (e.g., small populations)



Example: random demographic events

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Example: random demographic events

Randomness large compared to population size (e.g., small populations)

 $\rightarrow$  wrong prediction



#### Stochastic models

Randomness of processes is important

When we have small numbers (integers relevant), which makes stochastic processes important relative to mean

 $\rightarrow$  Ex: Questions of viability of small populations



 $\rightarrow$  Ex: IBM models or SDE See models in day 3 and 4 (Matthieu) Deterministic models

The noise can be ignored

When processes can be summarised with average parameters, variance is small compared to mean: mean growth rate, mass action law

#### $\rightarrow$ For large populations

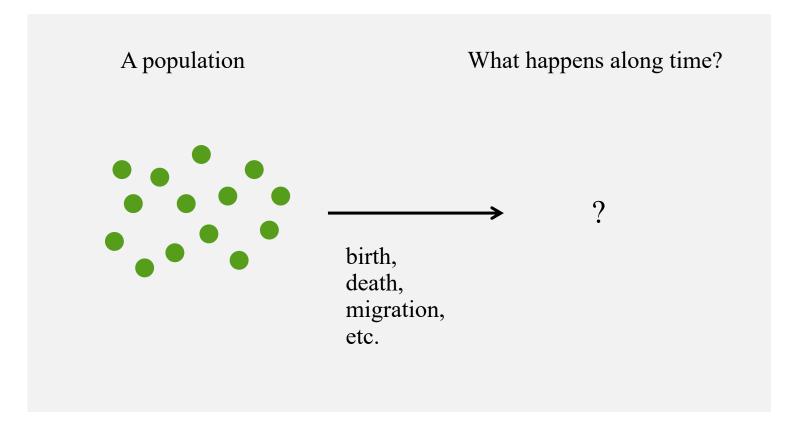


→ Ex: Deterministic ODE See models in day 2 and 4

# 2. What model formalism? (2) Time

We have static versus dynamic models: does our question require time?  $\rightarrow$  Ex: static trophic networks versus dynamic food web models (see day 4)

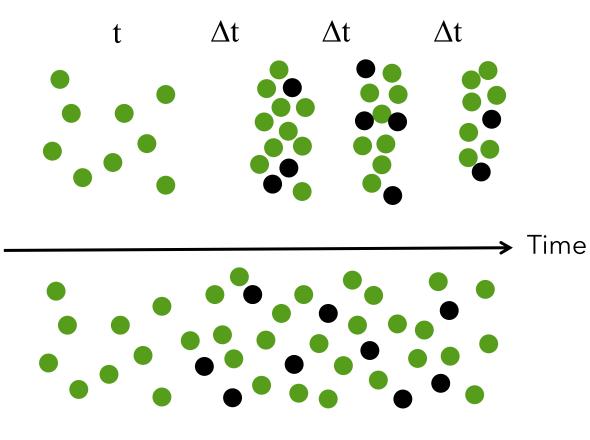
If dynamic, when might we use discrete or continuous-time formalism?



# 2. What model formalism? (2) Time

We have static versus dynamic models: does our question require time?  $\rightarrow$  Ex: static trophic networks versus dynamic food web models (see day 4)

If dynamic, when might we use discrete or continuous-time formalism?



# **Discrete time**

Synchronization of events

### **Continuous time**

Events happen at any time

# 2. What model formalism? (2) Time

#### Discrete time models

Events are synchronized

- Questions linked to the phenology
- Complex life cycles
- Synchronized generations
- Seasonal dynamics



### Continuous time models

Everything can happen at any time

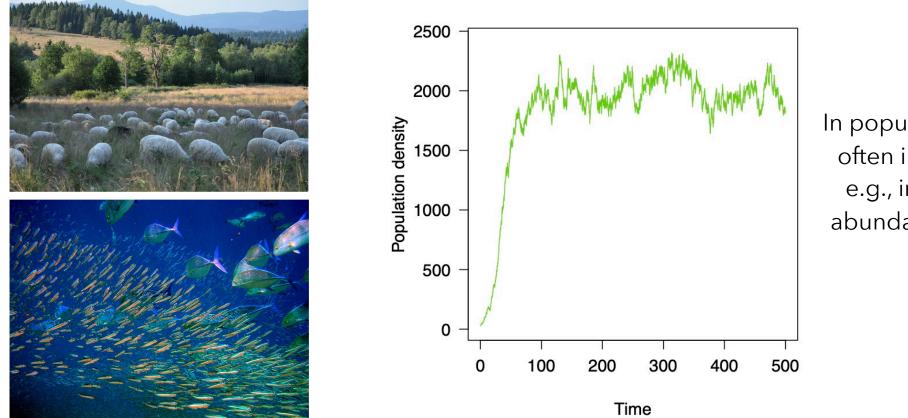
- Processes happen continuously
- Generations overlap



- $\rightarrow$  discrete time models where the time interval is very small boil down to continuous model
- $\rightarrow$  discrete or continuous time models can be either stochastic or deterministic
- $\rightarrow$  See models in day 2 (discrete), 3, 4 (continuous)

## 2. What model formalism? (3) Space

All ecological systems occur in space



In population models, space is often integrated in the unit, e.g., ind./km<sup>2</sup> or ind./m<sup>3</sup> or abundance in a given habitat of specific size

When is space important to describe your system and answer your question?

# 2. What model formalism? (3) Space

When interactions are localized, heterogeneously distributed in space.

Does diversity depend on spatial dynamics?



Does spatial patterns emerge from local dynamics?



When is space important to describe your system and answer your question?

# 2. What model formalism? (3) Space

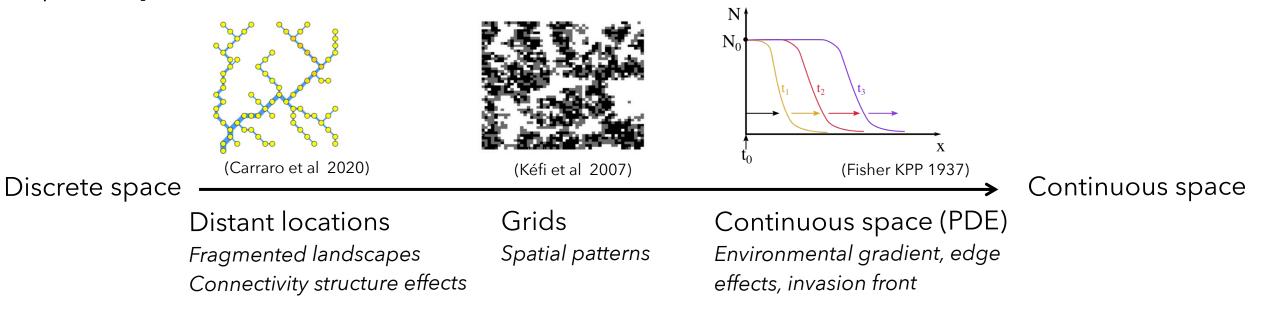
Does geographical position matter?

Space **implicit**: topology only

 $\rightarrow$  See models in day 3

(Levins 1969, Leibold et al. 2004)

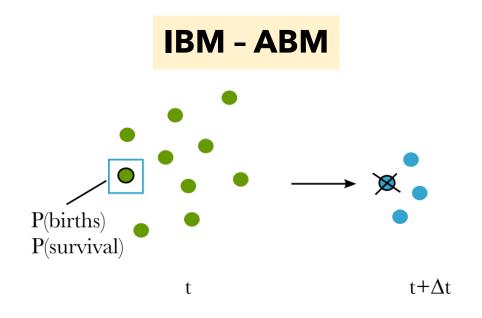
Space **explicit**: distances, geographical location



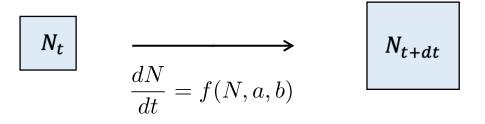
# 3. What technical choices?

Agent Based Models vs Equations
 Analytical vs Numerical

### 3. What technical choices? (1) rules vs maths



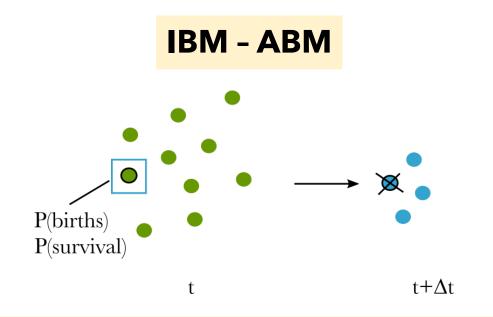
# **Dynamical equations**



- Variables are individuals or agents (integers)
- Processes (birth, death, dispersal) are formulated as a series of rules involving probabilities, applied to each agent.

- Variables are population densities / biomasses (decimals)
- We use maths
- Processes are embedded into parameters

### 3. What technical choices? (1) rules vs maths



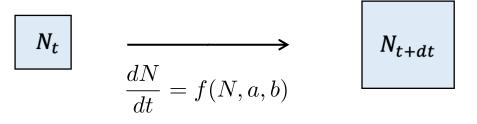
Modelled objects & relations = assumptions
 (without approximations) → complex

behavior easier to represent



- No need for math skills
- Computation time & resources
- Coding skills required

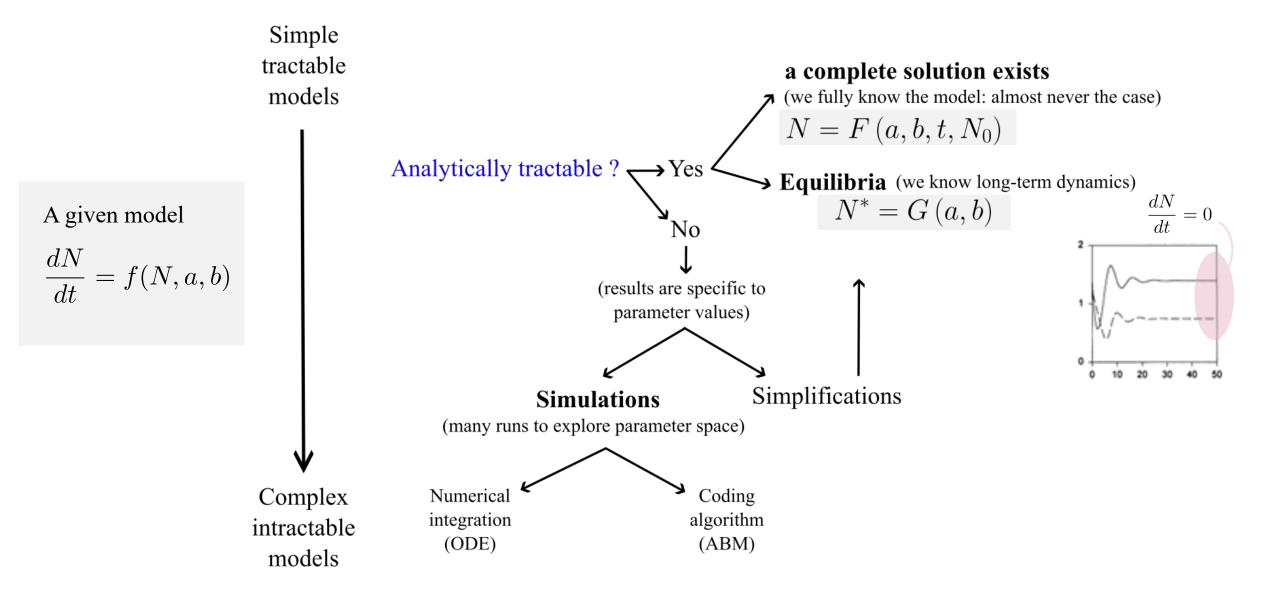
# **Dynamical equations**



- Simplification with math approximations
- Large analysis power for extreme case
- Fast computation: lower C footprint
- Easier to fit to data
- Imposed relations between variables
- Math skills required

### 3. What technical choices? (2) Analytical vs simulations

**Analytical versus simulation models** → Parsimony provides analytical power



# How to build a model?

#### Content

you 1. Sketch your system and choose your formalism

2. Identify the assumptions in a classical theoretical model

3. Code the model in R: principle of numerical integration

4. Explore the model

### **0. What is your question?**

# **1. Sketch your system**

What are your variables?

How are they connected? Which processes do you integrate?

# And Choose your formalism

What formalisms in terms of stochasticity, time, space?

What assumptions on modelled processes?

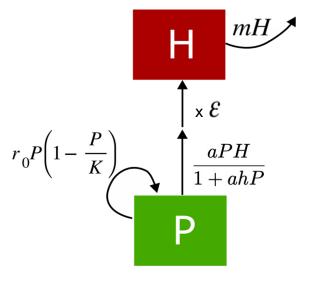


### 2. Identify assumptions in theoretical models

#### **Rosenzweig-MacArthur model (1963)**

$$\begin{cases} \frac{dP}{dt} = r_0 P (1 - \frac{P}{K}) - \frac{aPH}{1 + ahP} \\ \frac{dH}{dt} = \varepsilon \frac{aPH}{1 + ahP} - mH \end{cases}$$

#### $r_{\theta}$ growth rate K carrying capacity a attack rate h handling time m mortality rate $\varepsilon$ conversion efficiency



#### General assumptions from formalism

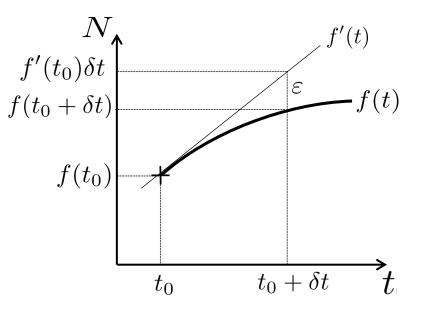
- Populations are sufficiently large for their biological rates to be approximated with averaged parameters: within a population, all individuals identical
- Generations overlaps in time
- Space is homogeneous

#### Assumptions from mathematical formulations

- Resources for producers are limited and resource dynamics are much faster than population dynamics
- There is no recycling feedback
- Mass action law: encounter rates are proportional to densities
- Herbivore consumption saturates through time needed to manipulate food
- Herbivores dies without producers (metabolic needs)
- Only a part of herbivore consumption is converted into new biomass

A given dynamics 
$$N = f(t)$$
  $\frac{dN}{dt} = f'(t)$ 

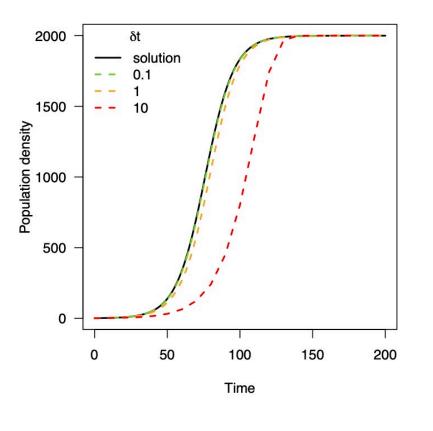
- Numerical integration is a recursive process:
  approximate the system from the previous time step
- A simple algorithm for ODEs: the Euler method  $f(t_0 + \delta t) = f(t_0) + f'(t_0)\delta t + \varepsilon$



• The error depends on time interval and the type of dynamics

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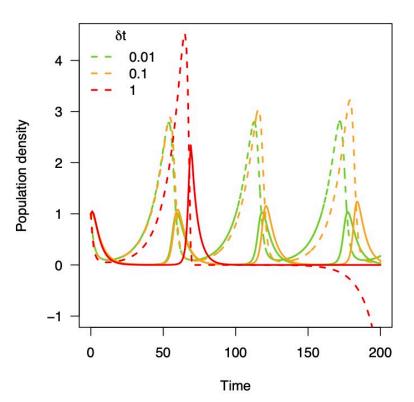
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**Example 1, Logistic growth** 

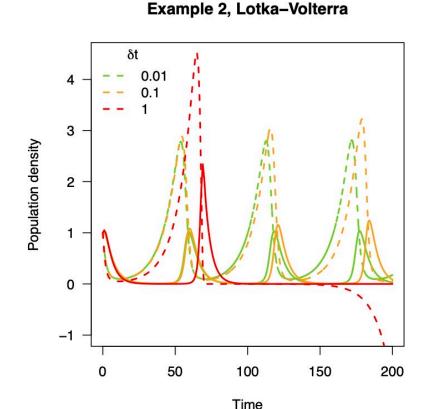
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- The error depends on time interval and the type of dynamics

Example 2, Lotka–Volterra



A given dynamics 
$$N = f(t)$$
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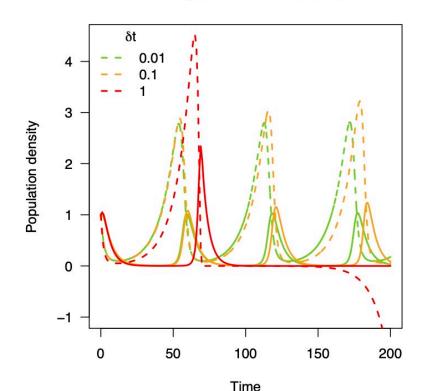
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- The error depends on time interval and the type of dynamics
- Mathematicians proposed different algorithms to minimize the error depending on the problem.
- These algorithms are implemented into solvers. Some have adaptive time steps with error tolerance.



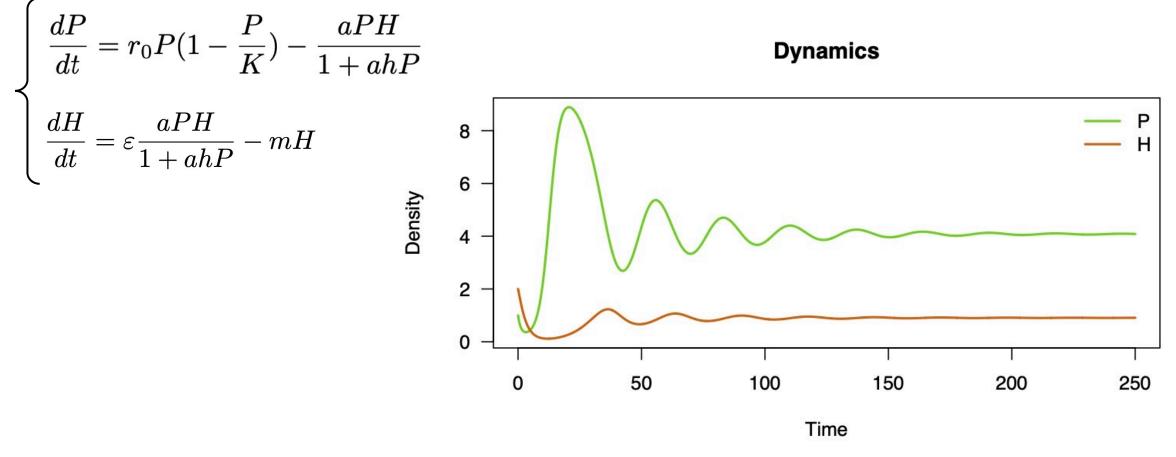
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- These algorithms are implemented into solvers. Some have adaptive time steps with error tolerance.
- In R we can use the function ode of the package deSolve



Example 2, Lotka–Volterra



#### **Rosenzweig-MacArthur model (1963)**



In R we can use the function ode of the package deSolve



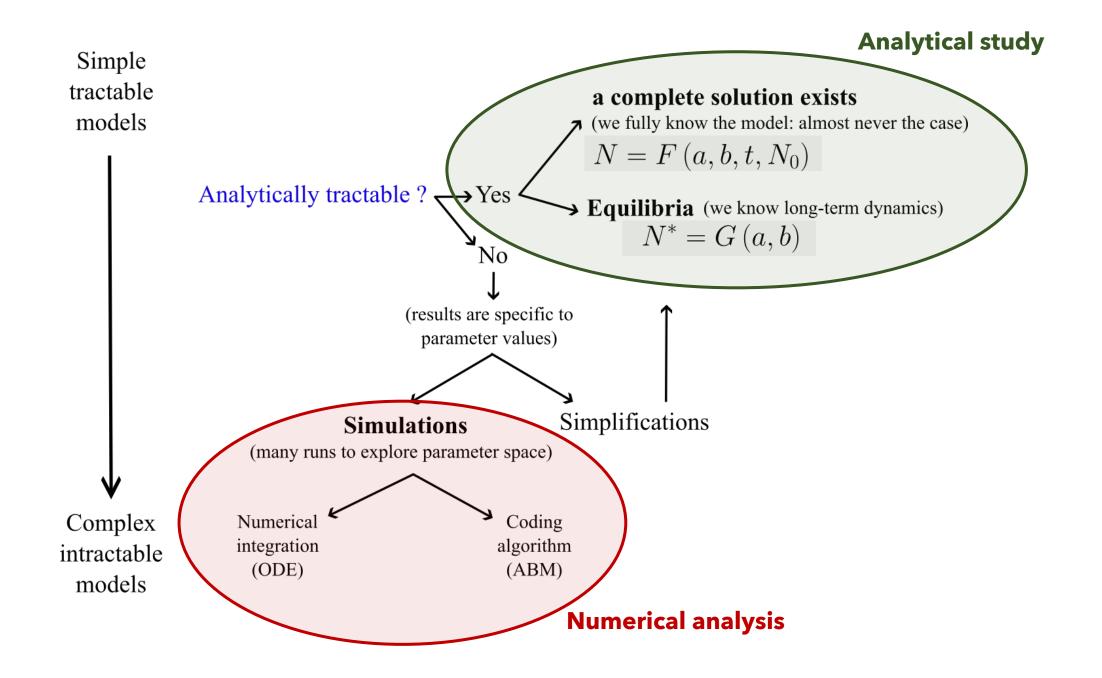
#### **4. Explore the model**

- Modify the initial conditions. Is the long term result changing?
- Modify the parameters
- Which strategy to explore the model and answer our question?

### How to analyse a theoretical model?

#### Content

- 1. General analysis
  - Equilibria
  - Local stability analysis (Jacobian matrix)
  - Bifurcation diagrams
  - Dependence to initial conditions
- 2. Simulation strategies
  - Parameter exploration
  - Model comparison
  - Experiments with synthetic data
  - Robustness of conclusions



#### The Rosenzweig-MacArthur model (1963)

$$\frac{dP}{dt} = r_0 P \left(1 - \frac{P}{K}\right) - \frac{aPH}{1 + ahP}$$

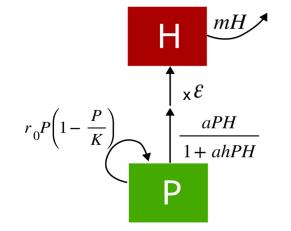
$$\frac{dH}{dt} = \varepsilon \frac{aPH}{1 + ahP} - mH$$

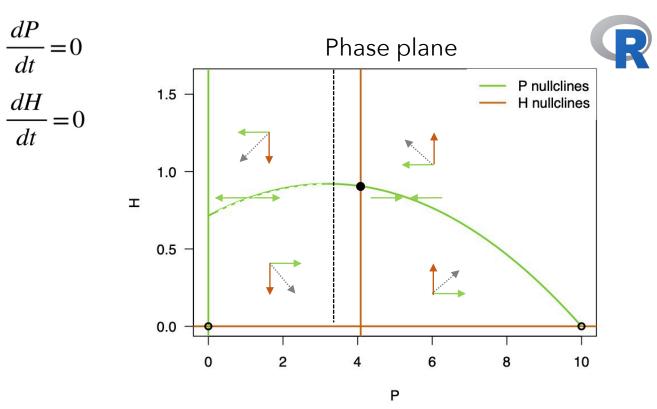
- First Step : Determine the Equilibria, solve:
- Graphically it's nullclines intersections:
  - for P growth P=0

$$H = r_0 \left(\frac{1 + ahP}{a}\right) \left(1 - \frac{P}{K}\right)$$

• for H growth H=0

$$P = \frac{m}{a(\varepsilon - hm)}$$





#### The Rosenzweig-MacArthur model (1963)

$$\frac{dP}{dt} = r_0 P \left(1 - \frac{P}{K}\right) - \frac{aPH}{1 + ahP}$$

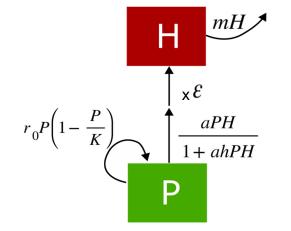
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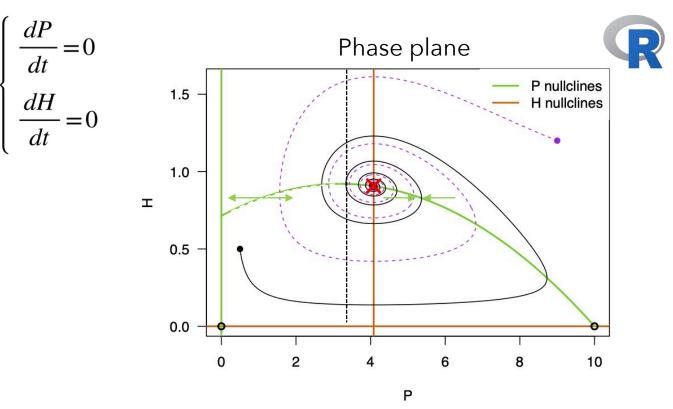
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$$\frac{dH}{dt} = \varepsilon \frac{aPH}{1 + ahP} - mH$$

- First Step : Determine the Equilibria, solve:  $\begin{cases} \frac{dP}{dt} = 0\\ \frac{dH}{dt} = 0 \end{cases}$
- Symbolic calculus (Maxima, Mathematica, Matlab)
- In R we can get the numerical calculation of equilibria with

the function stode of the package rootSolve or with the

function searchZeros of the package nleqslv

When tractable, expresses  $P^*$  and  $H^*$  with the

parameters (symbols)  $\rightarrow$  general expression

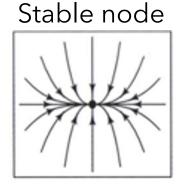
$$\begin{cases} P^* = 0, H^* = 0 \\ P^* = K, H^* = 0 \\ \end{cases}$$
$$\begin{cases} P^* = \frac{m}{a(\varepsilon - hm)} \\ H^* = \frac{\varepsilon r_0 (aK(\varepsilon - hm) - m)}{a^2 K(\varepsilon - hm)^2} \end{cases}$$

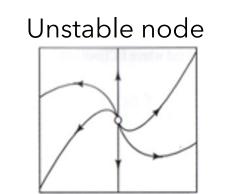
- Feasibility criteria
- Interpretation on parameters

For a 2-equation system in continuous time

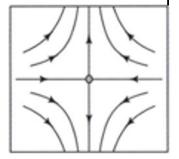
Phase portraits, typology of trajectories and stability for 2-equations models, some examples:

#### Monotonous trajectories





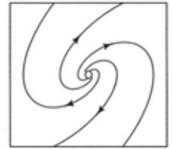
Unstable saddle point



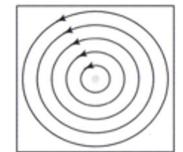
# Oscillatory trajectories

Stable spiral

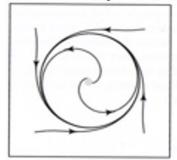
Unstable spiral



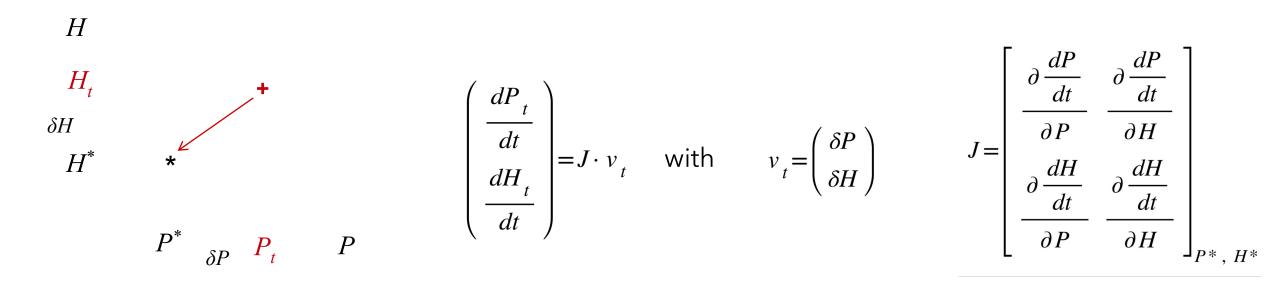
#### Neutral center



Limit cycle



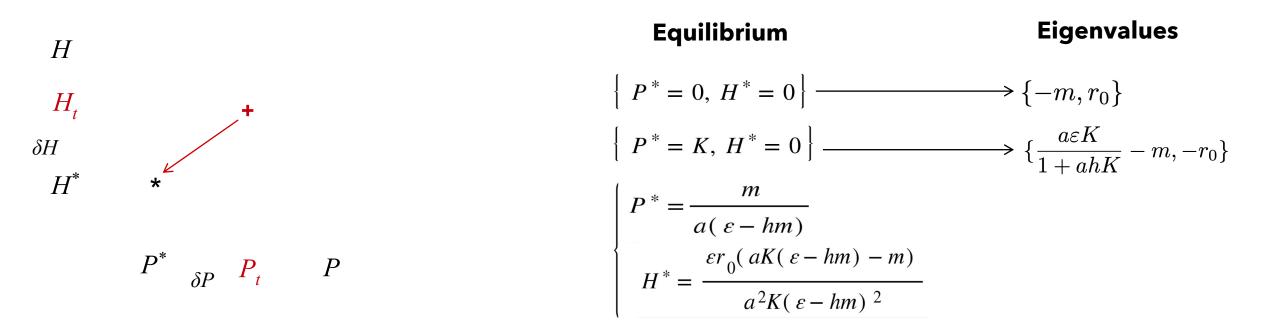
Determine the stability of each equilibrium by analyzing the Jacobian matrix at the equilibrium



Stability analysis = examining eigenvalues of J (real or complex numbers)

Stability criterium: Stable when the real parts of eigenvalues are negative

Determine the stability of each equilibrium by analyzing the Jacobian matrix at the equilibrium



Stability analysis = examining eigenvalues of J (real or complex numbers)

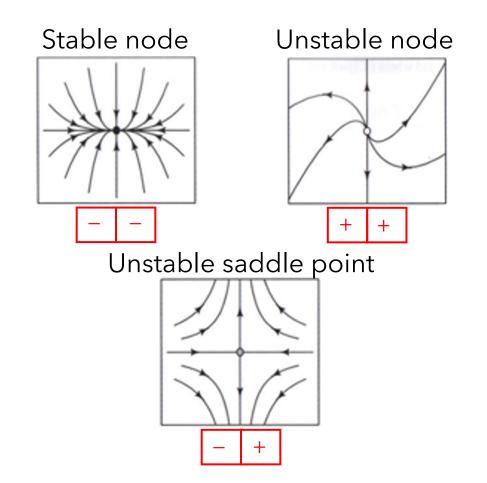
#### Stability criterium: Stable when the real parts of eigenvalues are negative

J from the function fully.jacobian and  $\lambda$  from the function eigen (package <code>rootSolve</code>)



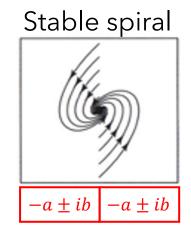
#### **Monotonous trajectories**

eigenvalues are real ( $\lambda \in \mathbb{R}$ ,)

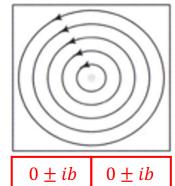


#### **Oscillatory trajectories**

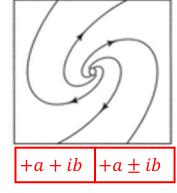
eigenvalues are complex ( $\lambda \in \mathbb{C}$ )



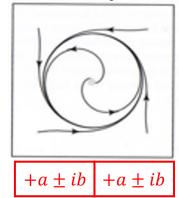
Neutral center



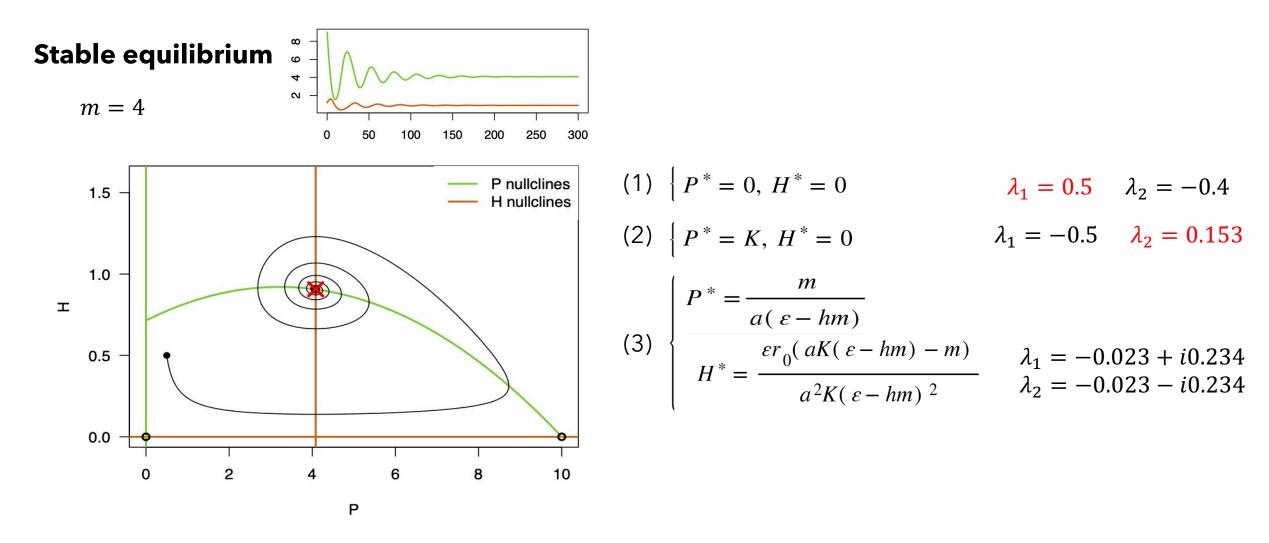
Unstable spiral







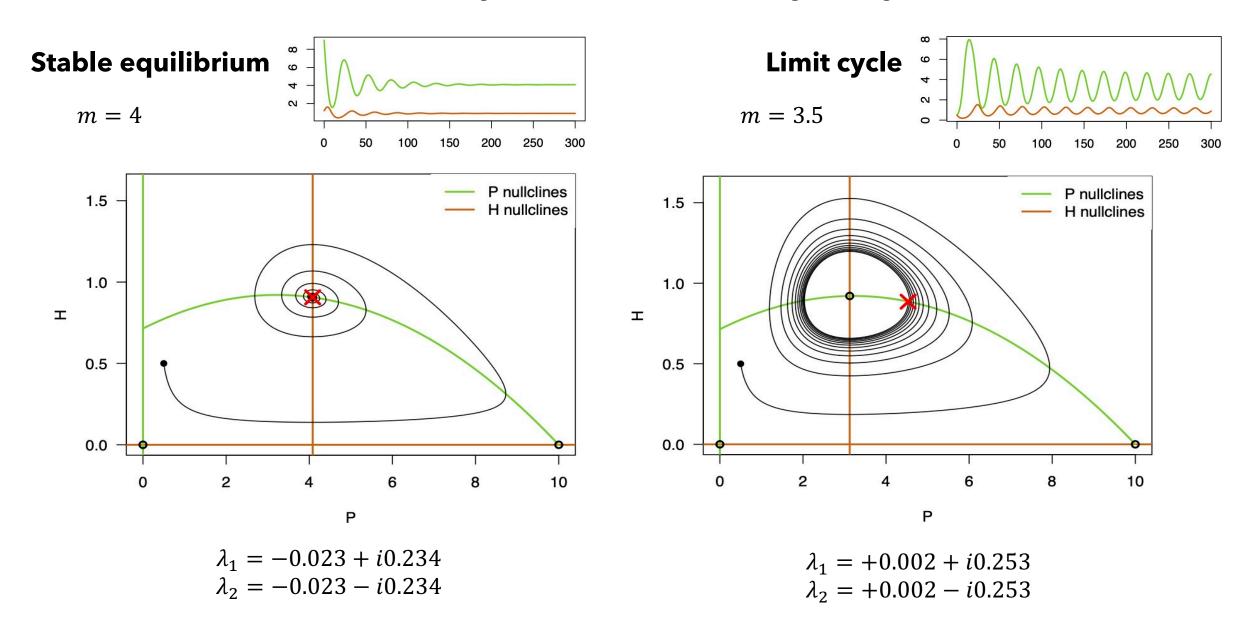
For a 2-equation system in continuous time

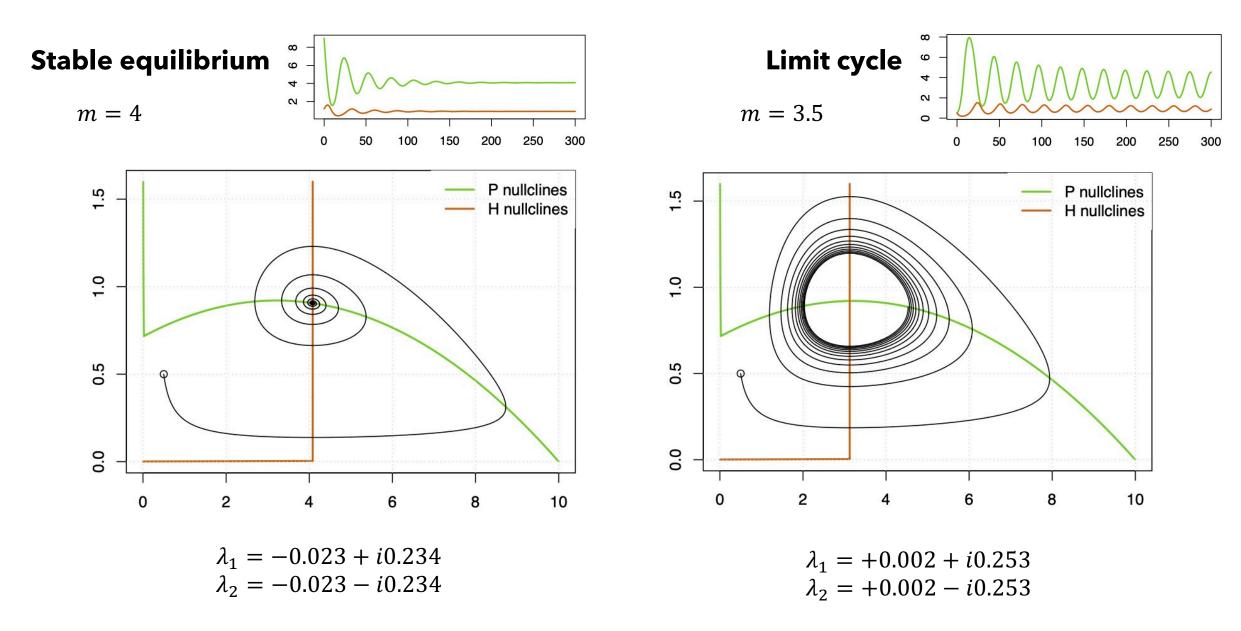




# R

#### 1. General analysis (2) Local stability analysis





### 1. General analysis (3) Bifurcation diagrams

How does long-term (asymptotic) behaviour of the system vary with one parameter?

real part of dominant eigenvalue Ρ Hopf bifurcation 0.2 Н Extremum densities • 15 stable limit 0.1 node cycle Eq (2) Eq (3) 0.0 10 000000 stable -0.1 unstable 5 -0.2 • Eq (2) • Eq (3) -0.3 0 0 5 10 15 0 20 15 5 10 20 0 Κ κ

Variables

Stability



### 1. General analysis (3) Bifurcation diagrams

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real part of dominant eigenvalue Ρ Hopf bifurcation 0.2 Н Extremum densities • 15 stable limit 0.1 node cycle Eq (2) Eq (3) 0.0 10 -0.1 5 -0.2 -0.3 0 5 10 15 0 20 15 5 10 20 0 Κ κ

Variables

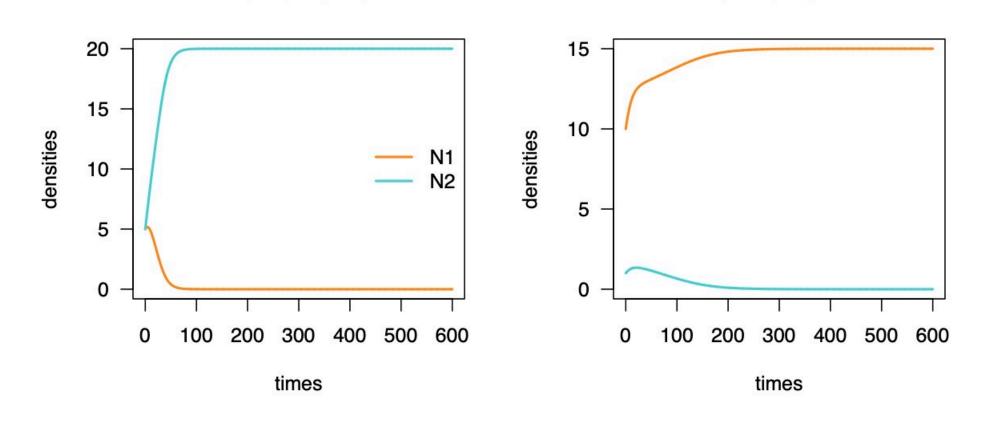
Stability



### **1. General analysis (4) Dependance to initial conditions**

- > We can observe several equilibrium points for the same parameters (historical effects)
- > Example of Lotka-Volterra competition only initial densities differing:

P0 = 5 H0 = 5



P0 = 10 H0 = 1

> Screen series of initial densities to find all the equilibria using searchZeros in nleqslv

# 2. What simulation strategy?

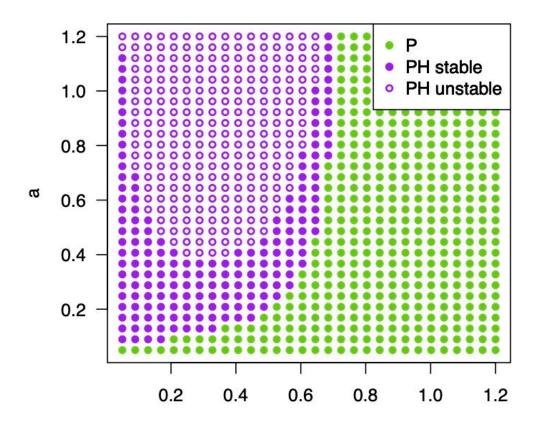
- 1. Parameter exploration
- 2. Model comparison
- 3. Robustness of conclusions
- 4. *in sillico* experiment on synthetic data

### 2. Simulation strategy (1) Parameter exploration

- Generalisation of bifurcation diagrams with 2-D parameter space exploration.
- The aim is to identify all the possible behaviors of the model within 'reasonable' parameter ranges

Here we vary *h* the handling time and *a* the grazing rate

- *h* should be sufficiently small, for H to persist
- Increasing *a* allows to compensate high *h*
- Increasing *a* destabilizes the system



coexistence and stability

### 2. Simulation strategy (1) Parameter exploration

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- Generalisation of bifurcation diagrams with 2-D parameter space exploration.
- The aim is to identify all the possible behaviors of the model within 'reasonable' parameter ranges

20

15

10

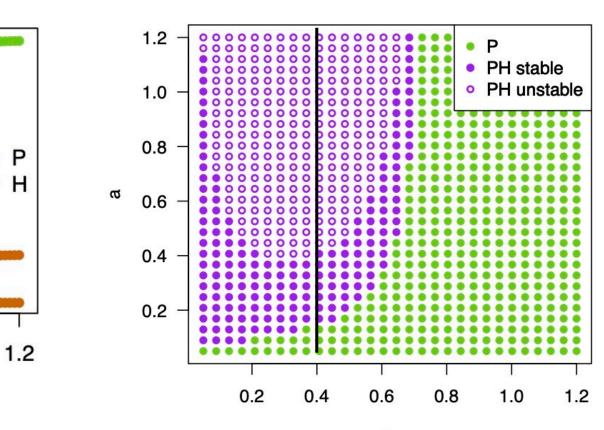
5

0

0.2

0.4

Extremum densities





0.6

0.8

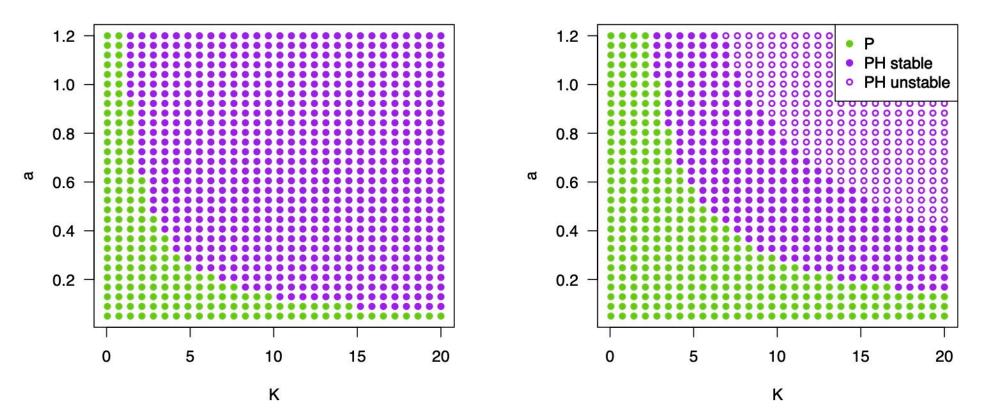
1.0

### 2. Simulation strategy (2) Model comparison

Here we compare models with different functional responses for the herbivore

Holling type I

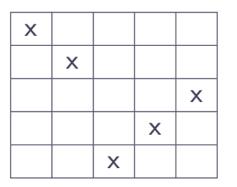
Holling type II



In our system a type I (linear) increases persistence and stability compared to a type II (saturating) functional response because it creates a lag between P and H growths.

### 2. Simulation strategy (3) Robustness of conclusions

- Sampling strategies (coverage / interpretability / cost):
  - One factor at a time; empirical data fix some parameters or restrain ranges.
  - Complete plan
  - Latin Hypercube sampling / Sobol
- Sensitivity analysis:

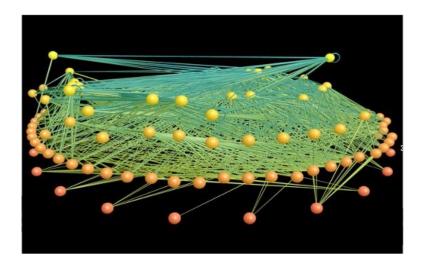


- Check the sensitivity of the results to variation in parameters ± 10%
- Methods to discard factors for further experiments (Morris / Saltelli)

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### **2. Simulation strategy (4) Experiments with synthetic data**

Complex system experiments not feasible in nature  $\rightarrow$  create realistic virtual data, for example food webs having the same general properties as natural food webs, to do perturbation experiments and observe how this would modify food we structure.





# Some useful references

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