The Mathematics of Ecological Networks Management

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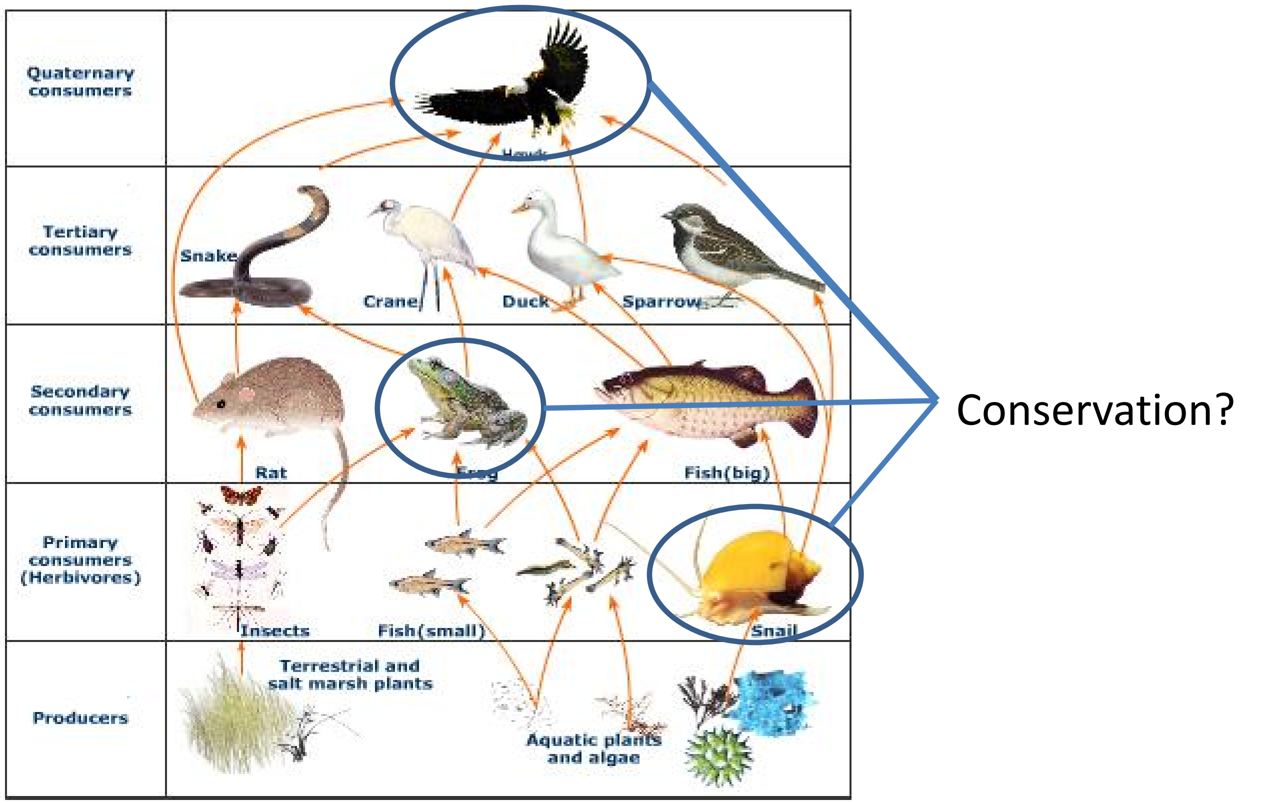
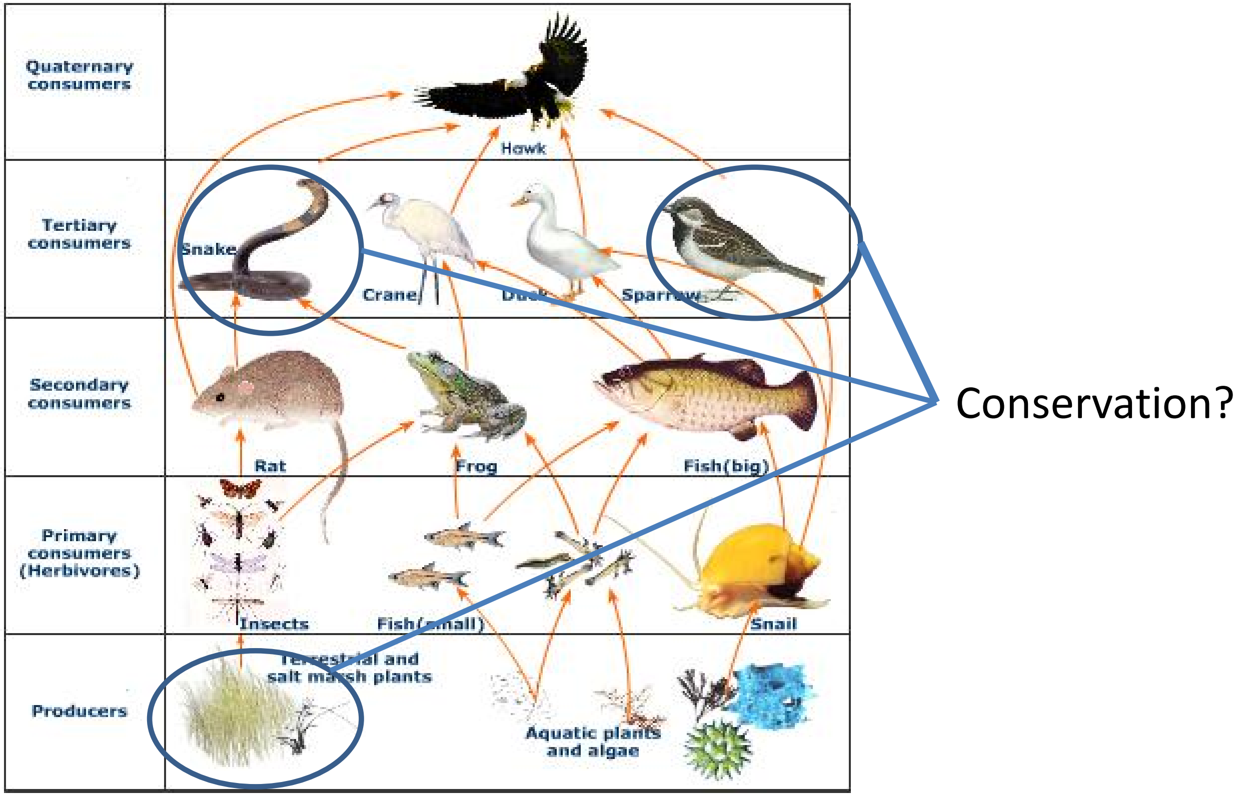
Conservation of multiple species in food webs



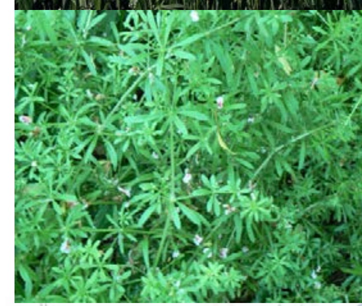
On which species should we spend our money if our goal is to preserve biodiversity?

Conservation of multiple species in food webs



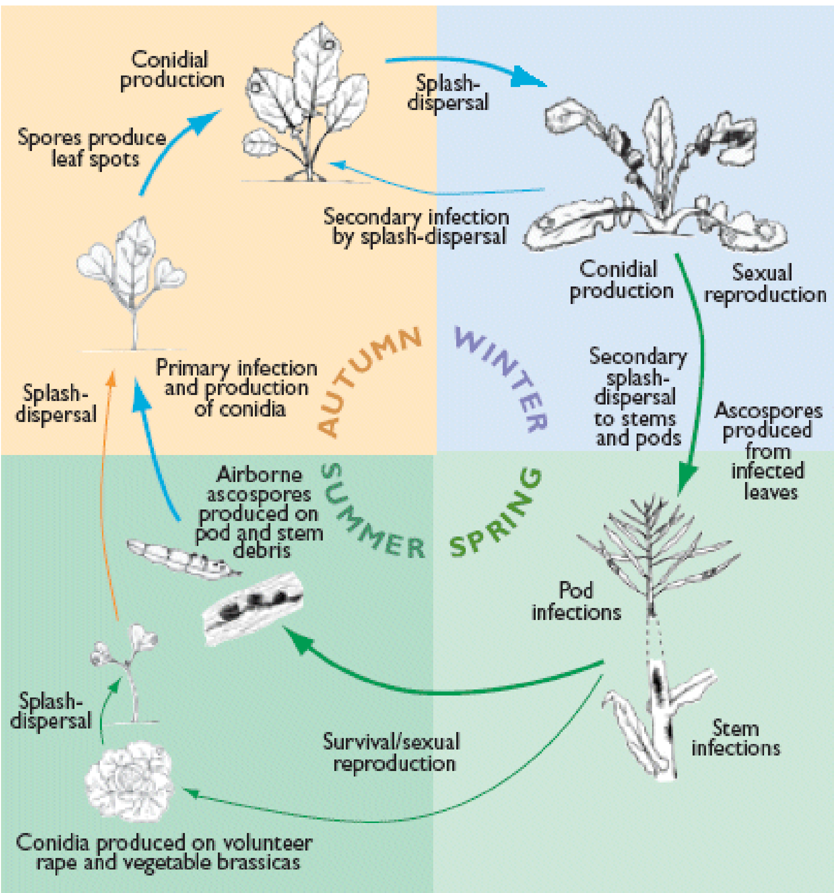
On which species should we spend our money if our goal is to preserve biodiversity?

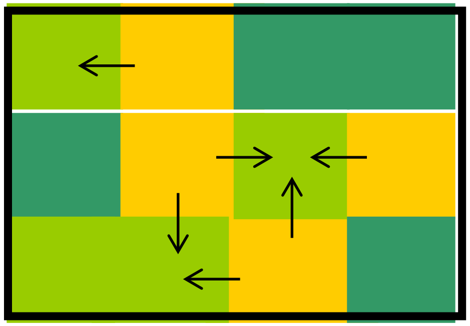
Spatial sampling of weeds for map reconstruction



How can we choose adaptively the locations to sample in order to reconstruct a “reliable” weed map?

Collective management of crop resistance to pathogens

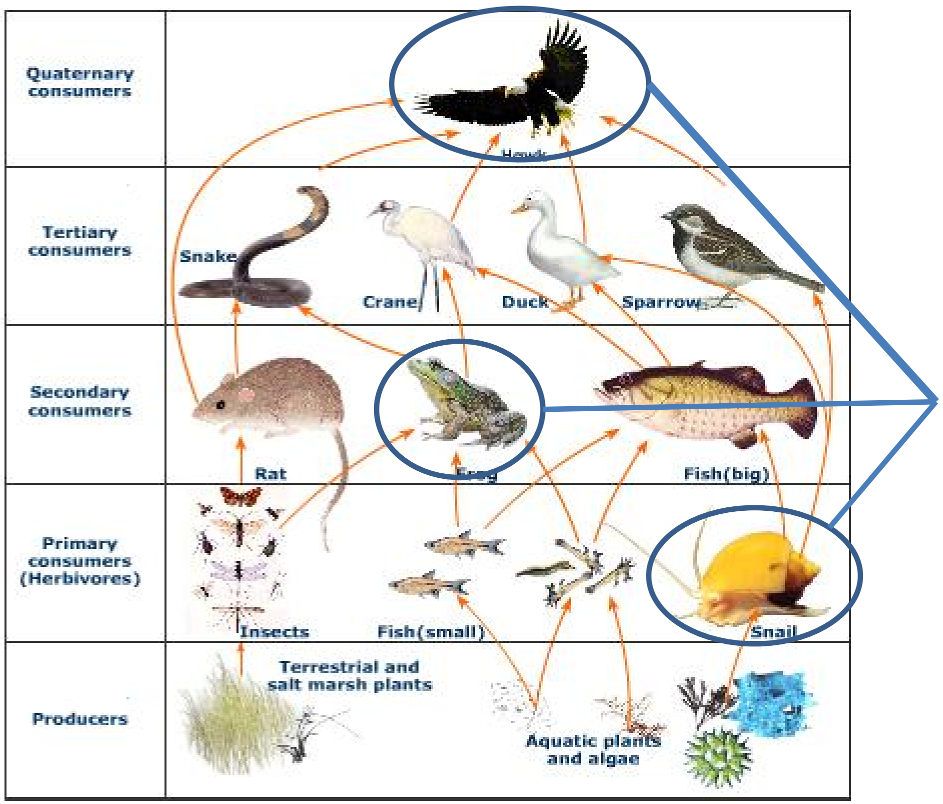




Where and when should we allocate Resistant crops/protection actions?

These problems are ecological management problems

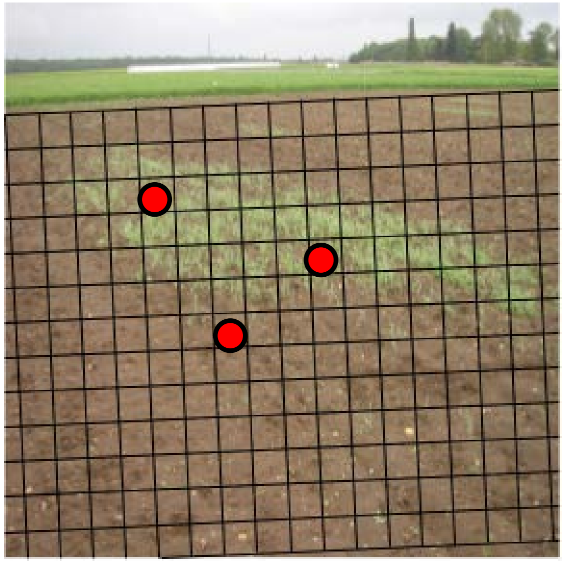
- Choosing and applying conservation actions!

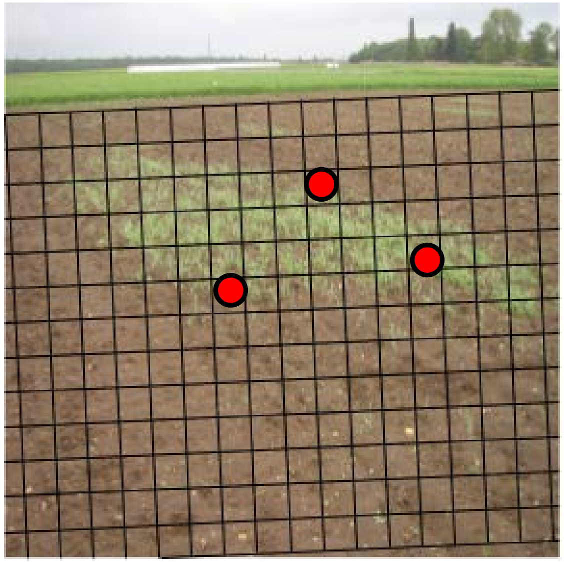


Conservation

These problems are ecological management problems

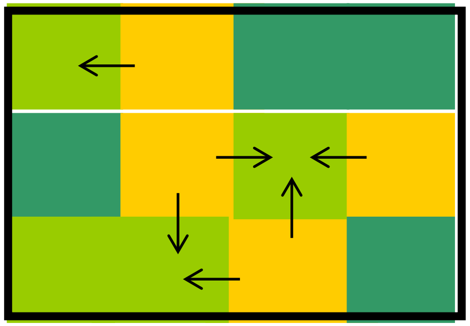
- Choosing and applying conservation actions!
- Choosing (adaptively) weed sample locations



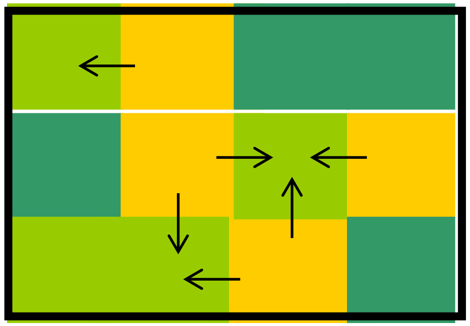


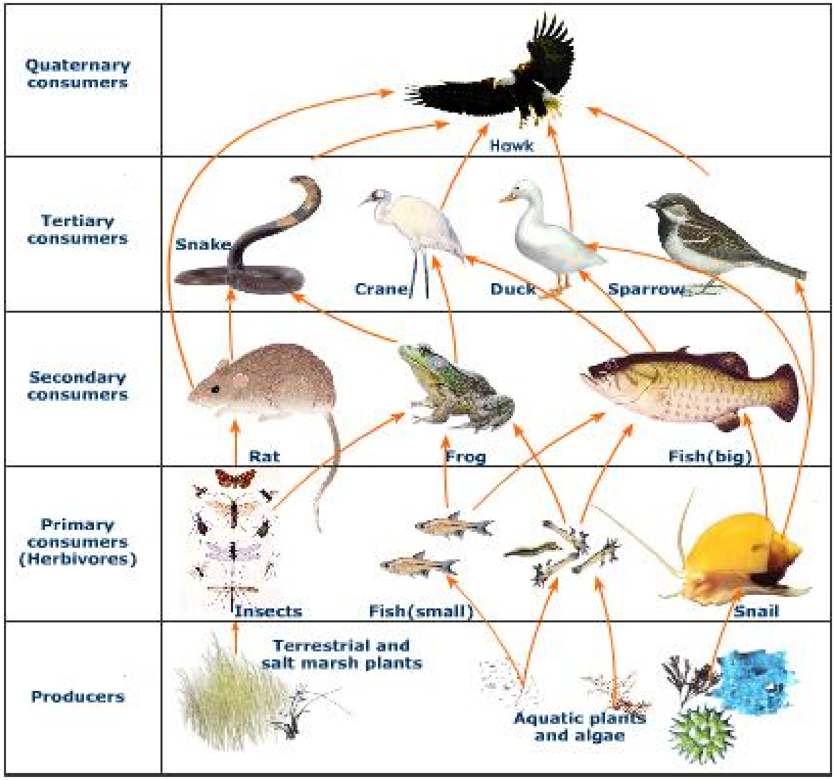
These problems are ecological management problems

- Choosing and applying conservation actions!
- Choosing (adaptively) weed sample locations
- Allocating crop systems in space/time



These problems involve networks





These problems involve uncertainty

- Threatened species persistence is uncertain!

- Weeds (especially the seed bank) are barely detectable!

- Pathogens dynamics/spread are uncertain!

Mathematics of ecological networks management

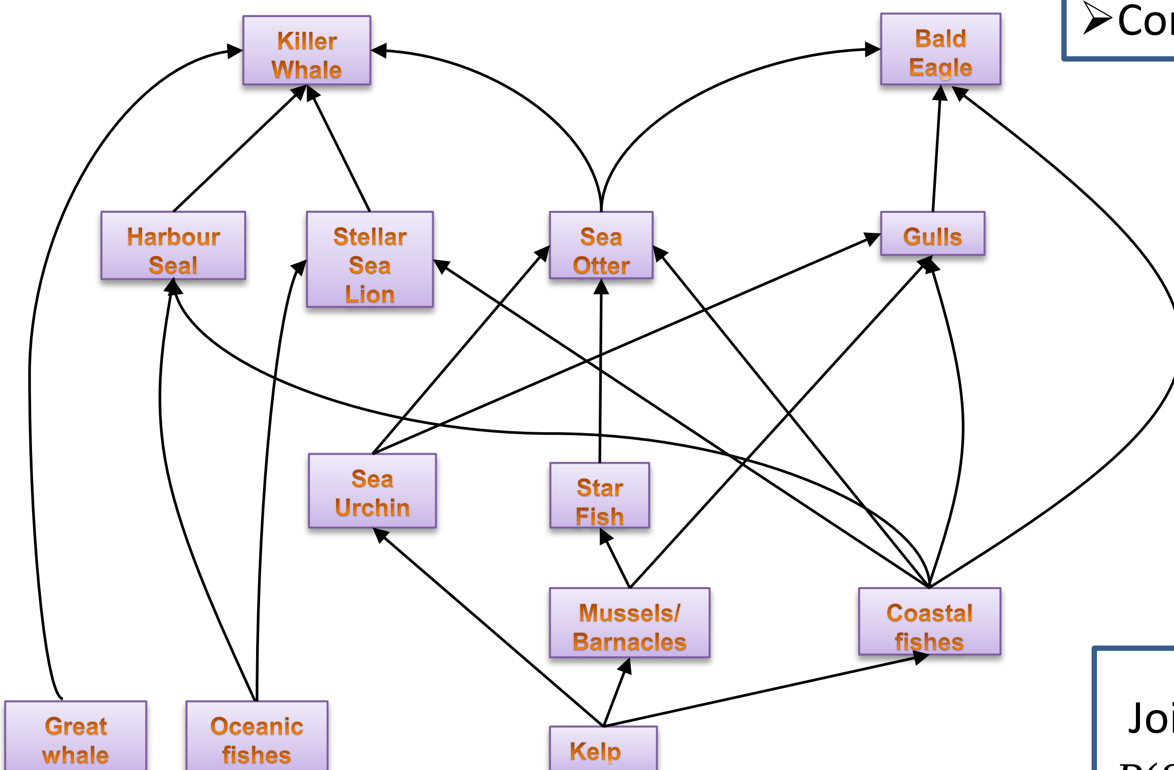
- Mathematical tools for the
  Management of stochastic processes on networks

- These mathematical tools are based on Stochastic graphical models
  - Bayesian networks
  - Markov Random Fields
  - Factored Markov Decision Processes

- Plus the use of optimization/approximation methods
  - Dynamic programming
  - Reinforcement learning
  - Heuristics

Bayesian networks

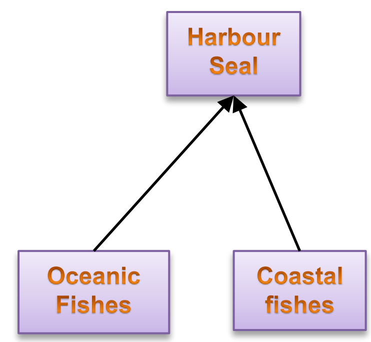
Concisely express joint probability distributions over sets of variables



- A directed acyclic graph over variables
- Conditional probability tables

Conditional probabilities

P(HS|OF,CF)



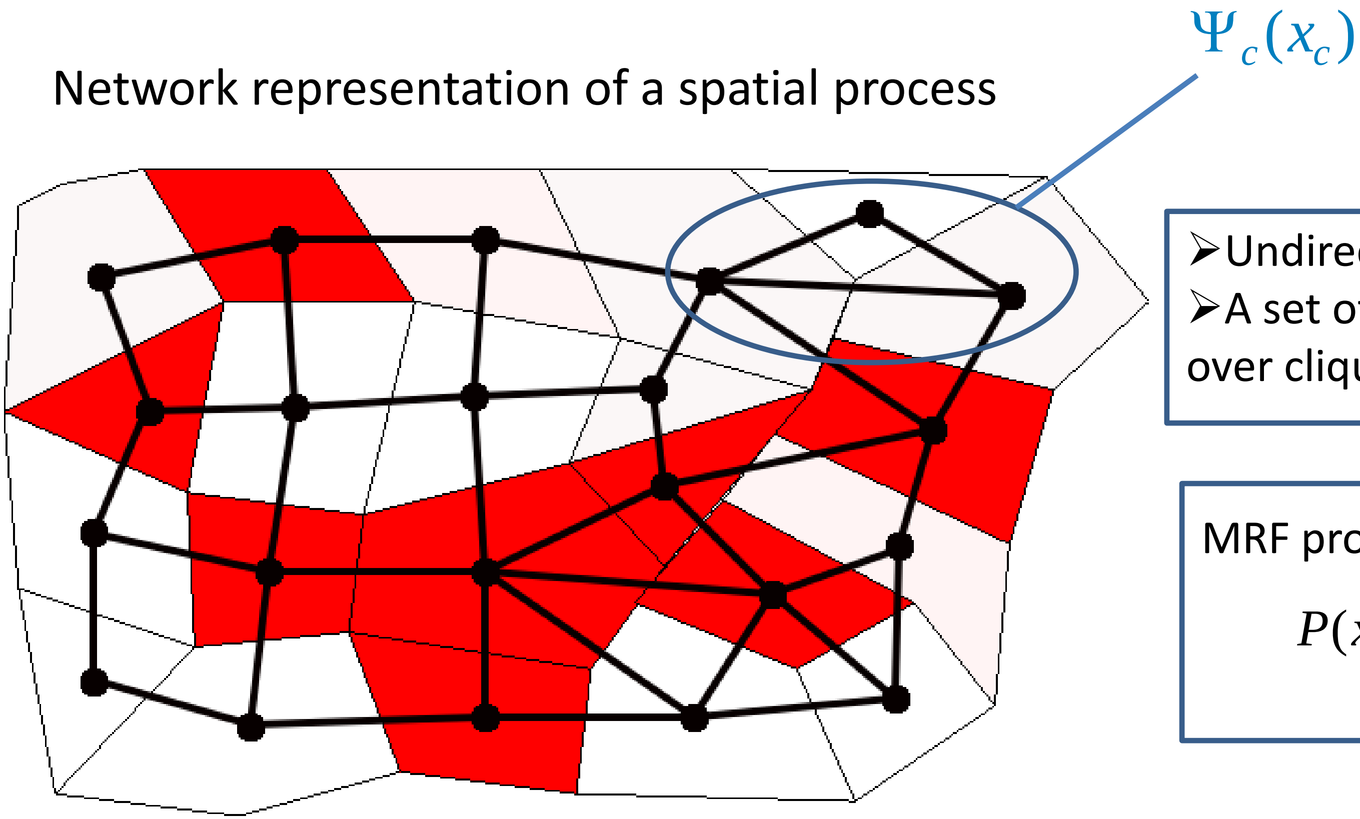
Joint probability model:

$$P(S_1,\ldots,S_n)=\prod_{i=1..n} P_i(S_i\,|\,\mathrm{Pr}eys(S_i))$$

Markov random fields

A framework for representing uncertain knowledge about spatial processes

Network representation of a spatial process



- Undirected graph with cycles
- A set of potential functions over cliques: $\Psi_c(x_c) > 0, \forall x_c$

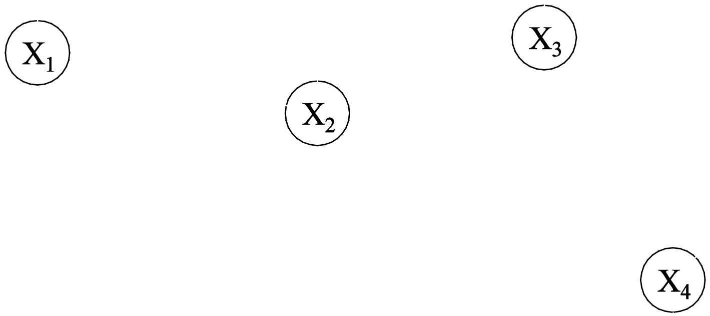
MRF probability distribution:

$$P(x) \propto \prod_{c \in C} \Psi_c(x_c)$$

Graph-based Markov Decision Processes

Structured problems of sequential decision under uncertainty

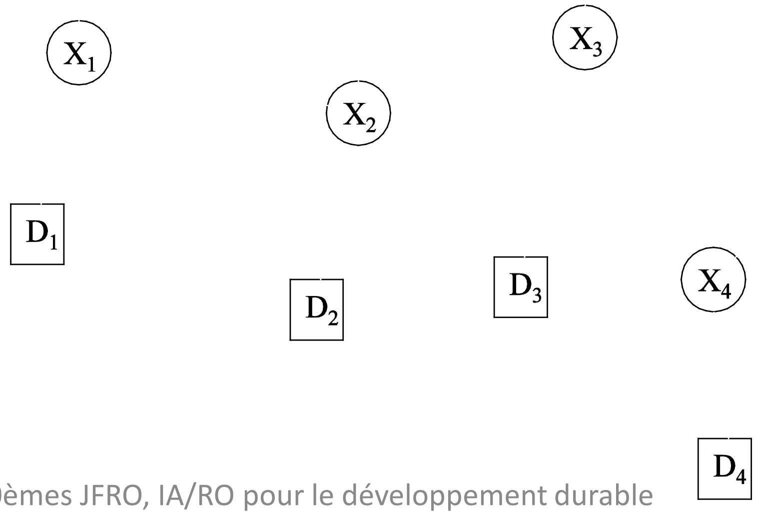
- Several state variables $\{X_i\}$



Graph-based Markov Decision Processes

Structured problems of sequential decision under uncertainty

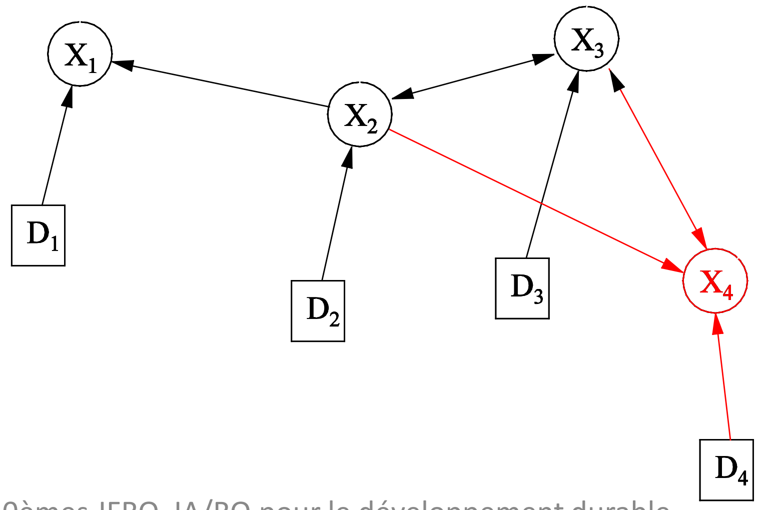
- Several state variables $\{X_i\}_{i \in V}$ and decision variables $\{A_i\}_{i \in V}$



Graph-based Markov Decision Processes

Structured problems of sequential decision under uncertainty

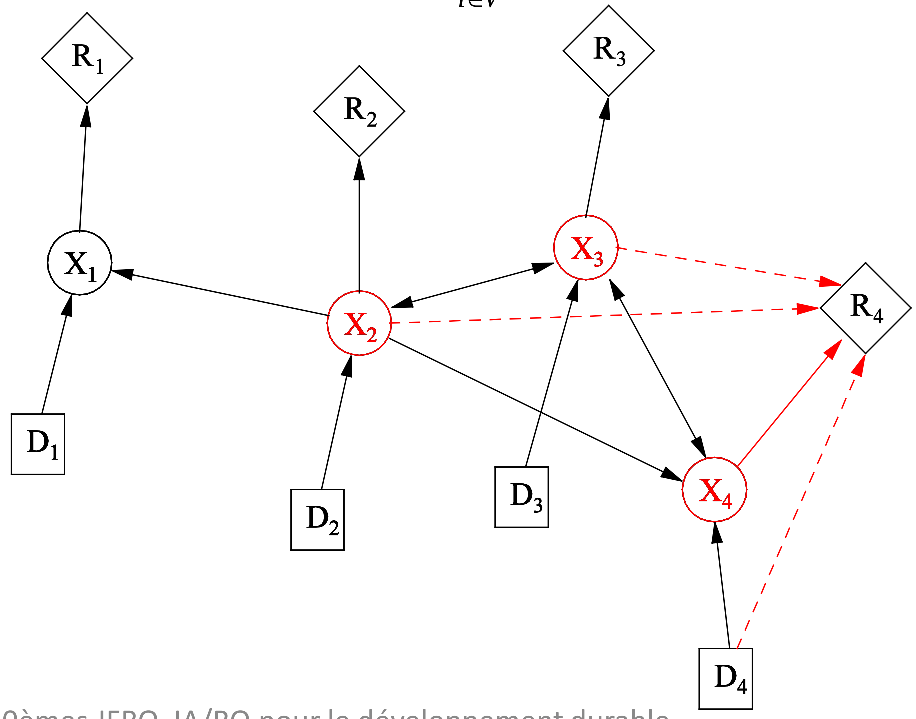
- Several state variables $\{X_i\}_{i \in V}$ and decision variables $\{A_i\}_{i \in V}$
- A factored stochastic transitions model: $p\left(x^{t+1} \middle| x^t, a^t\right) = \prod_{i \in V} p_i\left(x_i^{t+1} \middle| x_{N(i)}^t, a_i^t\right)$



Graph-based Markov Decision Processes

Structured problems of sequential decision under uncertainty

- Several state variables $\{X_i\}_{i\in V}$ and decision variables $\{A_i\}_{i\in V}$
- A factored stochastic transitions model
- A local reward model $r\left(x^t, a^t, x^{t+1}\right) = \sum_{i\in V} r_i\left(x_i^t, a_i^t, x_i^{t+1}\right)$



Graph-based Markov Decision Processes

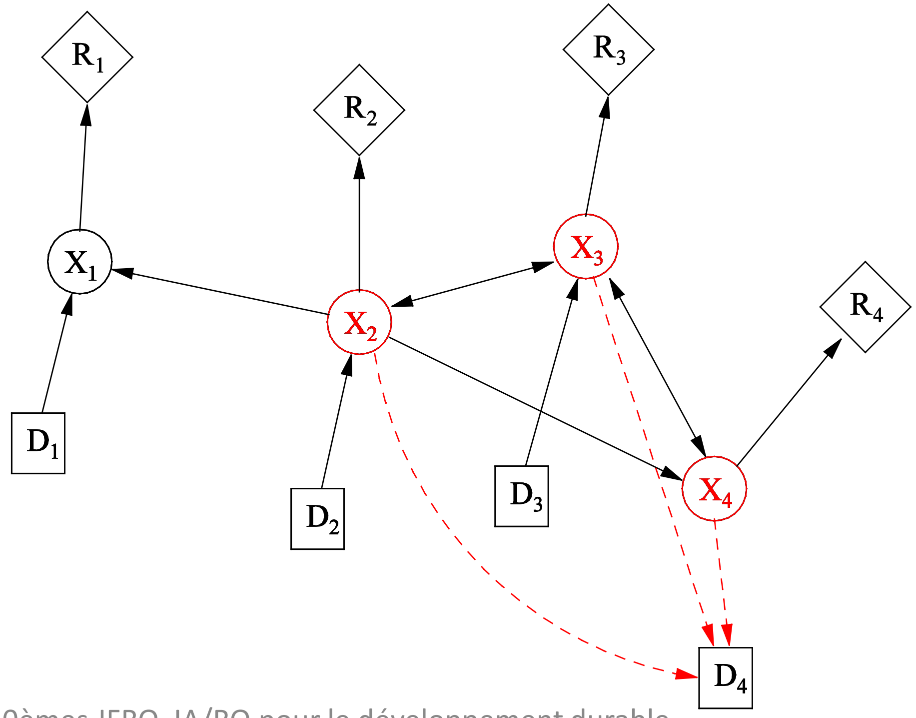
Structured problems of sequential decision under uncertainty

- Optimization problem:

Find a policy $\delta : X \rightarrow A$ assigning an action $\delta(x)$ to every possible states of the system, maximizing the expected discounted sum of future rewards

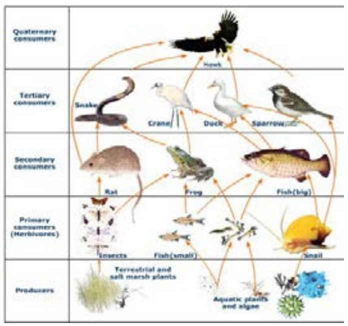
- Local policies (approximate):

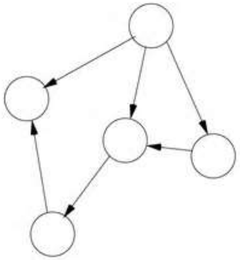
$$\left\{\delta_i\left(x_{N(i)}\right)\right\}_{i\in V}$$



Conservation of multiple species in food webs

Eve MacDonald-Madden & Iadine Chadès *(CSIRO and University of Queensland)*
Peter Baxter, William Probert & Hugh Possingham *(University of Queensland)*
Edward Game *(The Nature Conservancy)*
Nathalie Peyrard *&* ***Régis Sabbadin*** *(INRA-MIAT)*





- **Problem** : Multiple species protection, within a network of trophic relations

- **Management decision** : which species should we protect (and when) , in order to make the network the most resilient?

Food webs and bayesian networks

- Classically, trophic relations in food webs are:
  - deterministic, qualitative or quantified by mass flows (dynamical systems)

- The Bayesian network approach is:
  - stochastic and quantified by conditional probabilities of presence

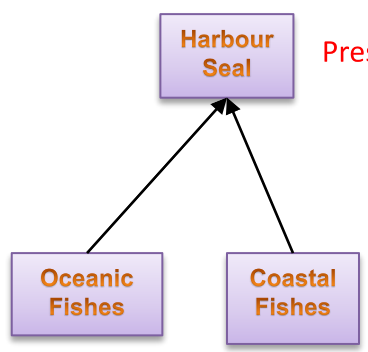
Joint probability distribution over species occurrences:

$$P(S_1,\ldots,S_n) = \prod_{i=1..n} P_i(S_i \mid \mathrm{Preys}(S_i))$$

present/absent = 1/0

Present

HS = « present/absent » (1/0)



P(HS=1|OF=0, CF=1)

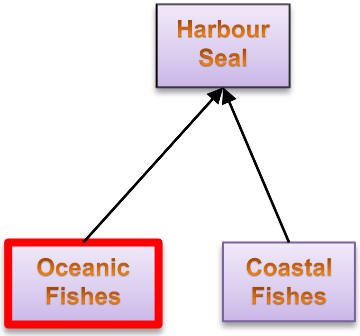
Absent

Present

P(HS,OF,CF) = P(HS|OF,CF) P(OF) P(CF)

Food webs, bayesian networks and « optimal » conservation

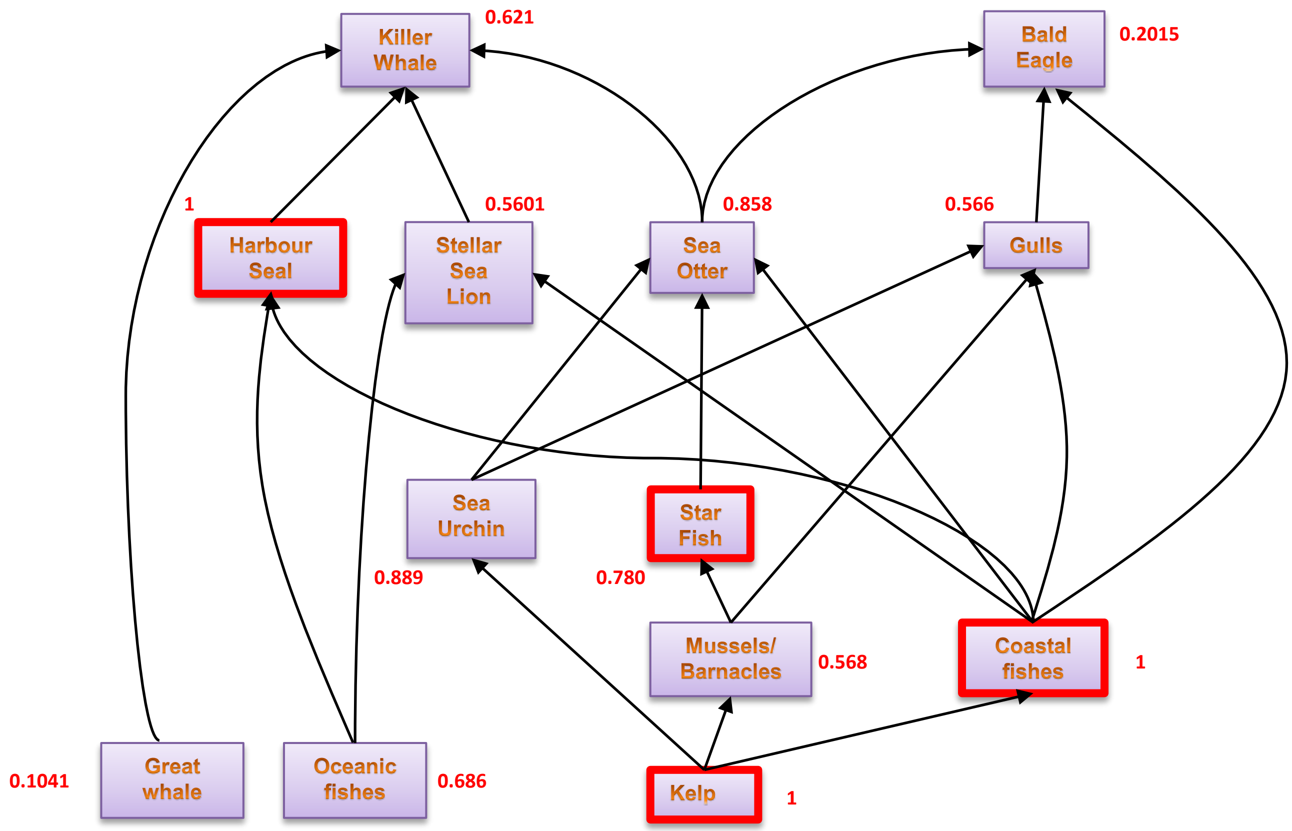
- « Conserving » a species increases its survival probability
- And the survival probability of its predators



- And thus, the species richness of the food web!

- Find the « optimal » feasible set of species to conserve, given
  - A conservation budget B
  - Species conservation costs C_i
  - A global criterion (expectation of the number of surviving species)

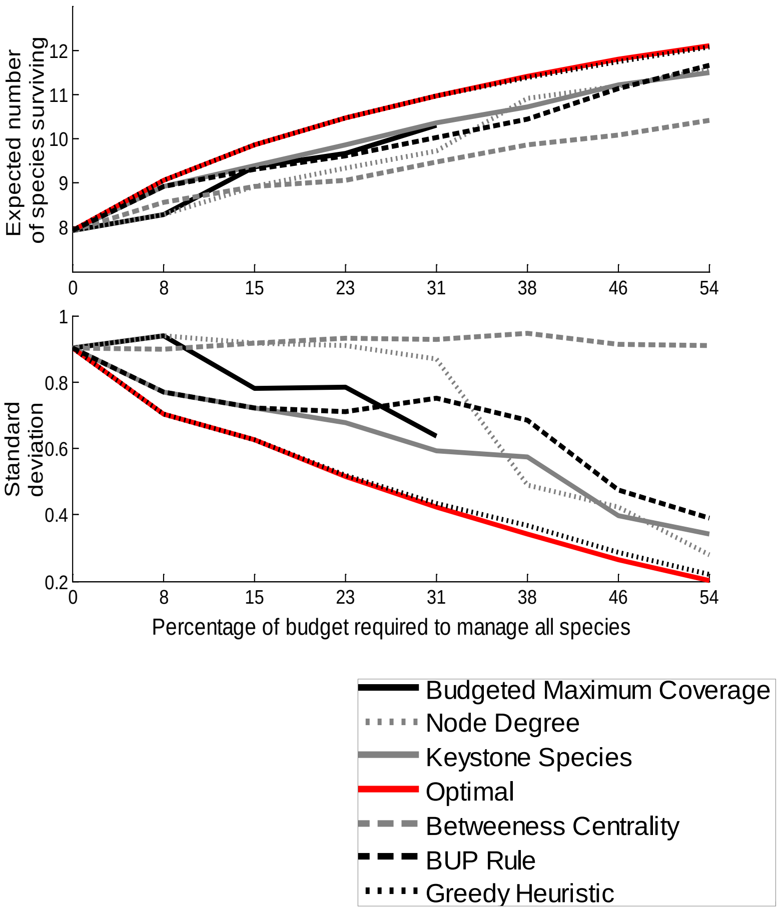
Food webs, bayesian networks and « optimal » conservation

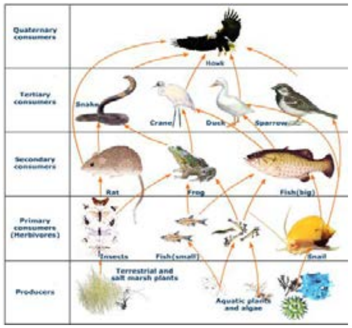


Problem: Optimal conservation is too difficult in general!

Food webs, bayesian networks and conservation heuristics

- Structure : Alaskan Network
- 20 sets of randomly generated probability tables
- Comparison of the expectation and variance of the number of surviving species





Conclusions

- A Bayesian network and combinatorial optimization model for species conservation within food webs

- Efficient heuristics for approximating optimal conservation

- No theoretical guarantee about the heuristics' performance

- Even more difficult in the "dynamic" case (work in progress)

Spatial weeds sampling for map reconstruction

Sabrina Gaba *(INRA- UMR Agroécologie)*

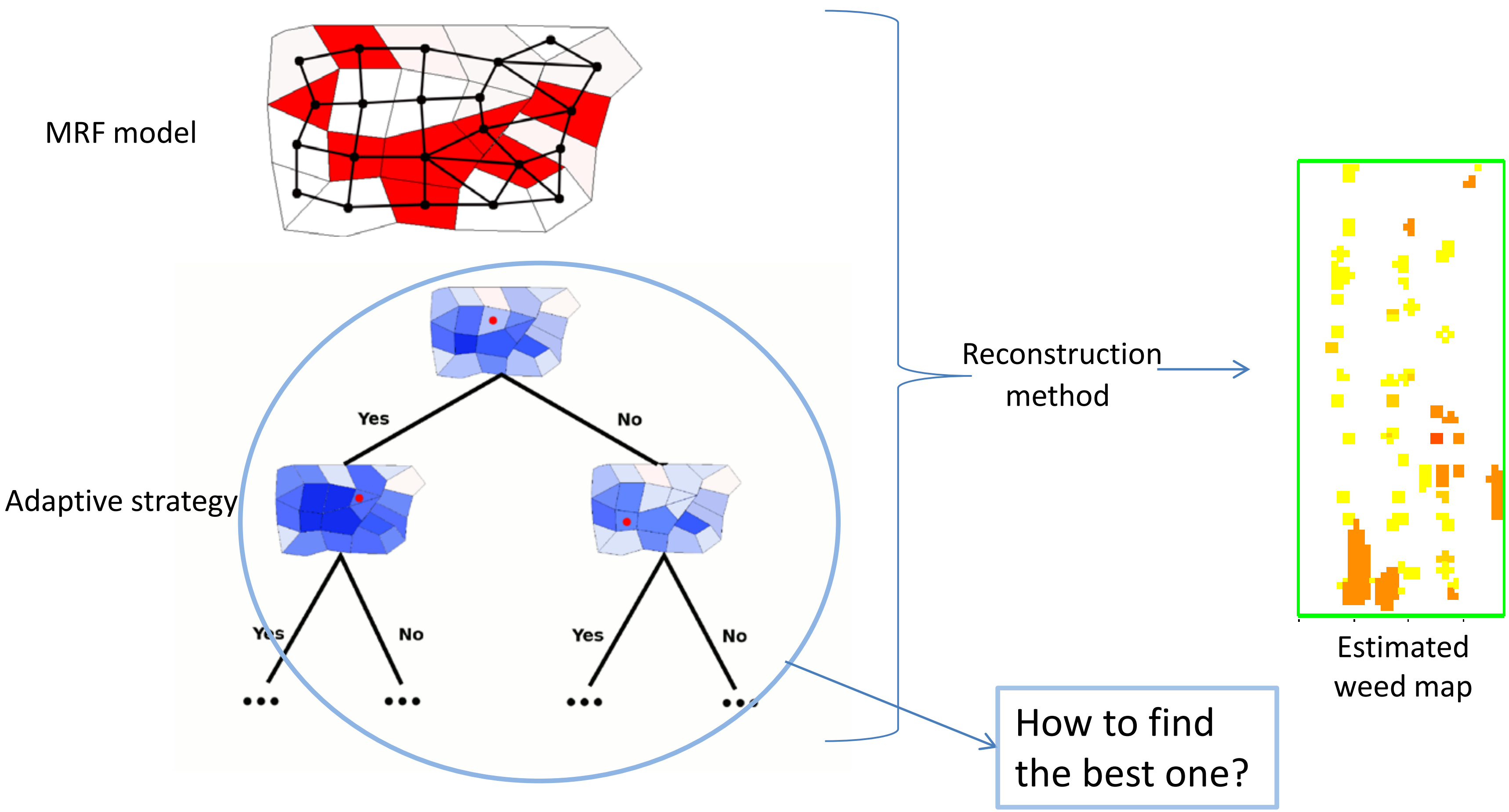
Mathieu Bonneau, Nathalie Peyrard *&* ***Régis Sabbadin*** *(INRA-MIAT)*

- **Problem:** an accurate map of weed repartition in the crop field
  - is a useful tool for studying weeds populations
  - but observations are costly

- **« Management » decision :** where to get sample observations in order to achieve a good compromise between map accuracy and sampling cost?

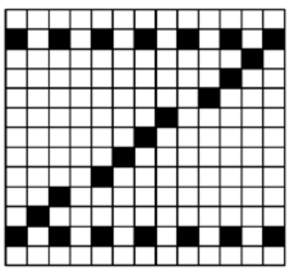
Optimal adaptive sampling strategy

We combine MRF and MDP to model the problem of designing an adaptive strategy by optimization and we propose two heuristic solutions



Performance of adaptive sampling heuristics

Comparison with 8 static sampling strategies



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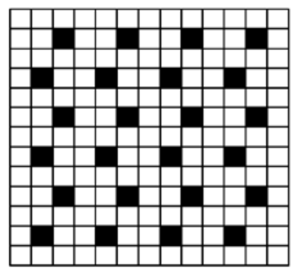
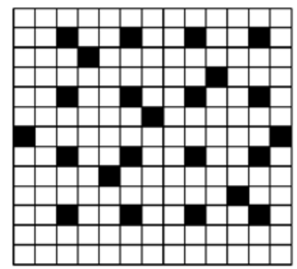
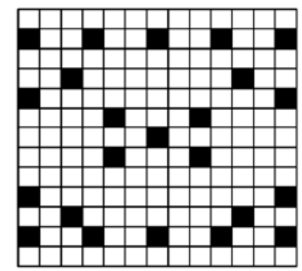


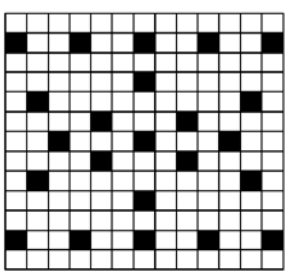
Reg1



Reg2



Reg3



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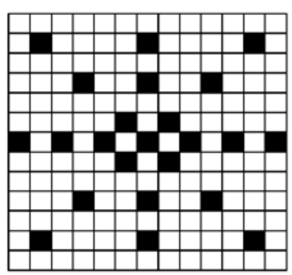
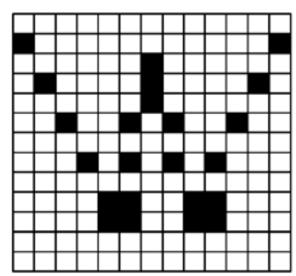
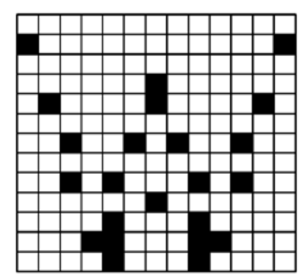


Star



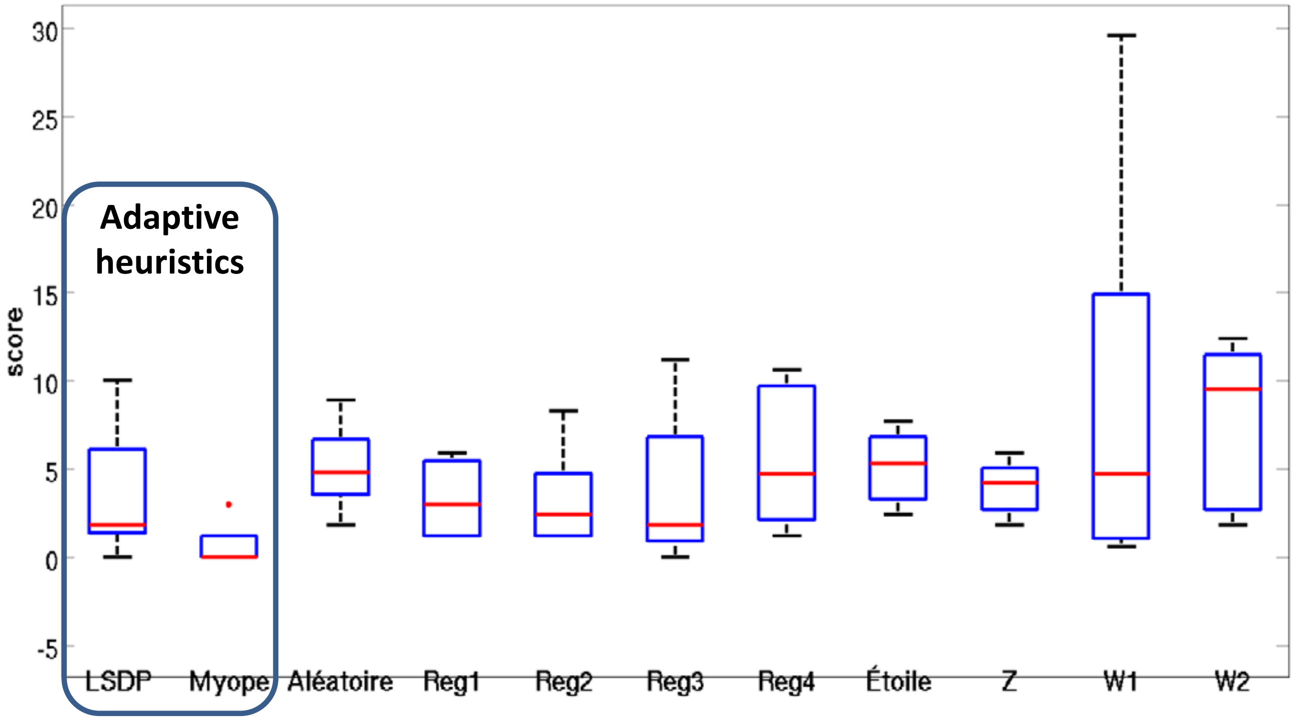
W1



W2

Performances of adaptive sampling heuristics

- Benchmark of 6 real weed maps
- Field of 13 by 13 quadrats, sample size = 13,5 % of total
- **NWC** = number of well classified quadrats
- **Score** = NWC(best strat) – NWC (strat)



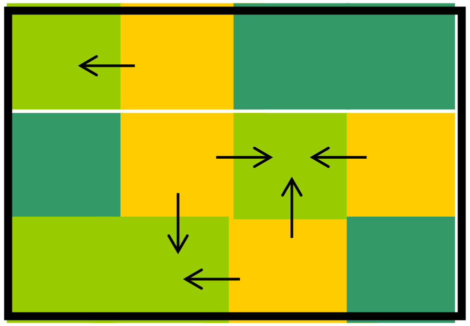
Adaptive sampling is more efficient

Conclusions

- A framework and two heuristics for adaptive sampling under cost constraints
- Adaptive sampling gives more accurate maps for the same cost
- Method also applied on a problem of fire ants sampling
- The sampled system is assumed static

Collective management of crop resistance to pathogens

Benjamin Borgy *(ex INRA-AGIR- MIAT)*
Jean-Noël Aubertot *(INRA-AGIR)*
Nathalie Peyrard *&* ***Régis Sabbadin*** *(INRA-MIAT)*



➢ **Problem** : Cultivar resistance enables to avoid fungicides but can be broken down

➢ **Management decision** : Where and when should we allocate resistant crops to maintain both resistance and yield?

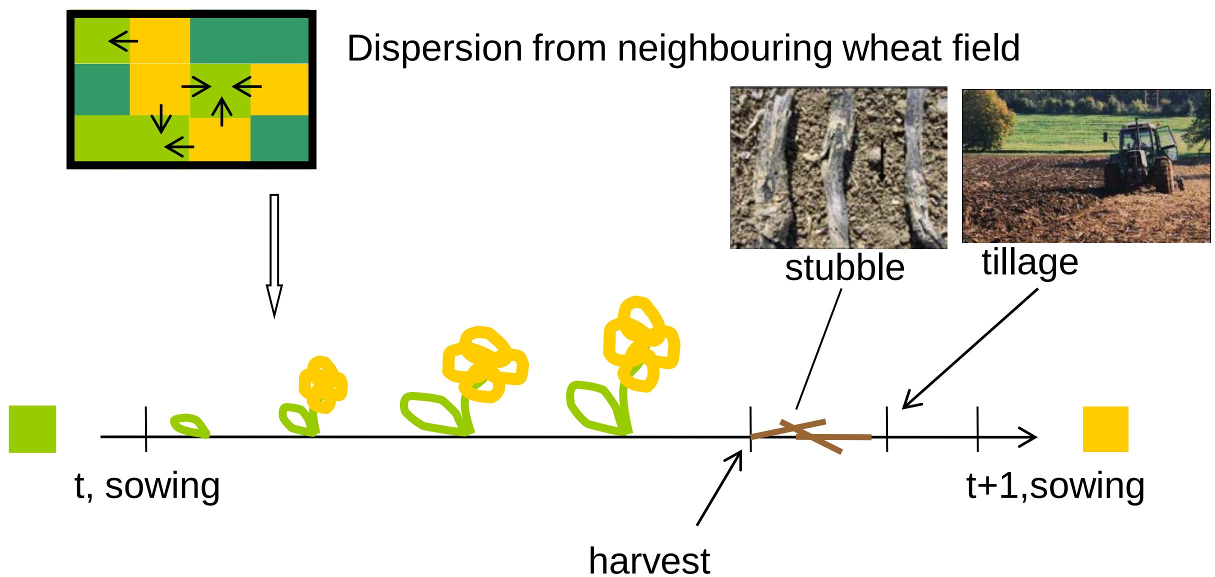
Case study: blackleg on canola

Crop rotation

- canola
- wheat
- barley

Host-pathogen interaction

	resistant	susceptible
virulent	+	+
avirulent	-	+



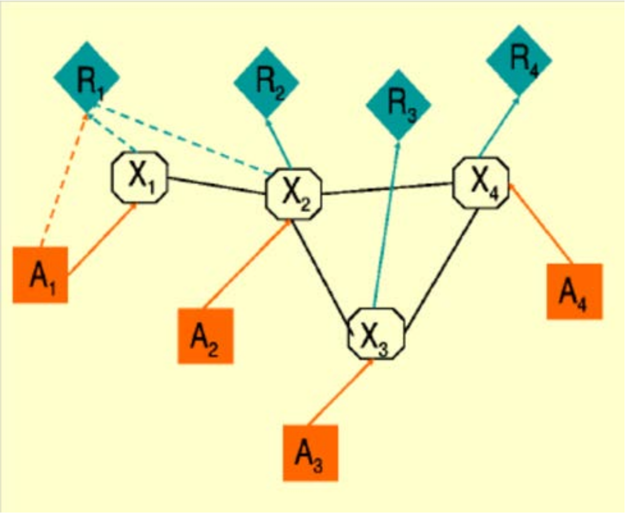
A GMDP model for the control of blackleg on canola

- **State variables in each field**
  - crop
  - infection intensity
  - composition of pathogen population

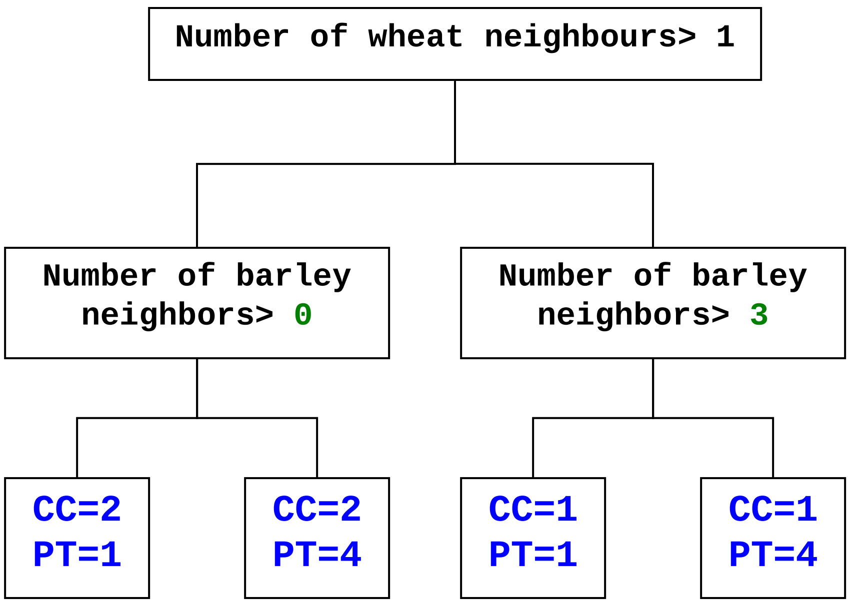
- **Actions (on canola fields)**
  - cultivar choice (CC)
  - ploughing threshold (PT)

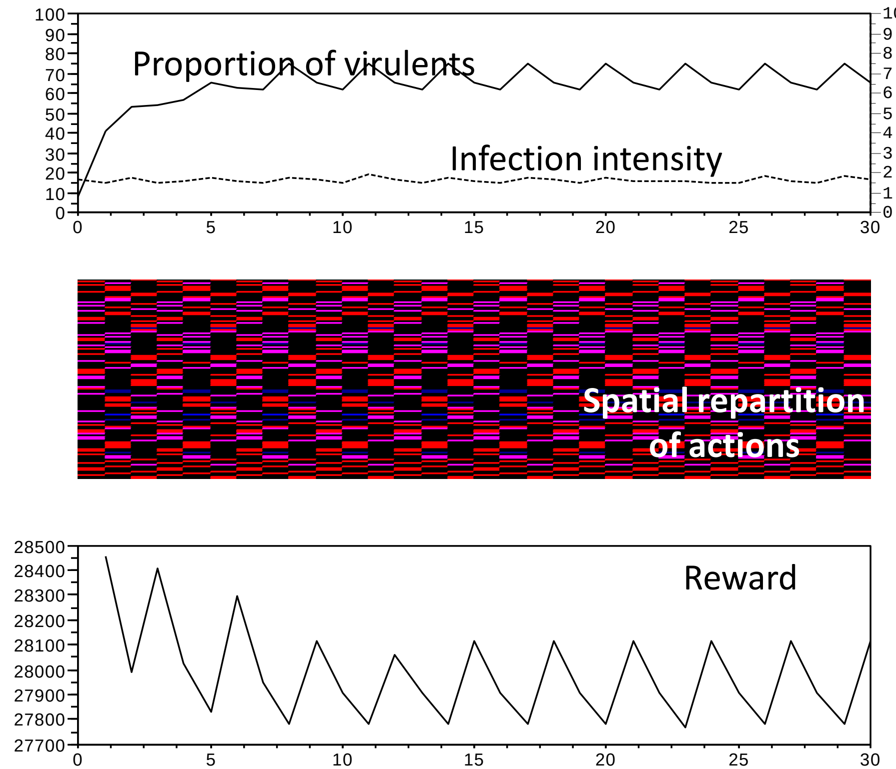
- **Transition functions:**
  - learned from simulations (SIPPOM)

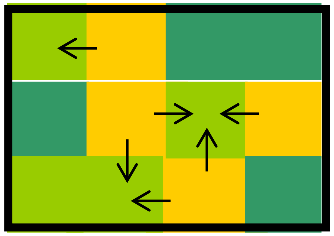
- **Reward:**
  - sum of local gross margins



A tool for strategies simulation



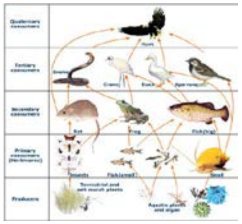


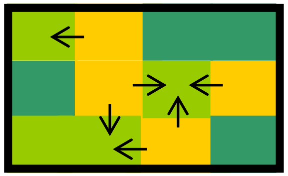


Conclusions

- A framework for designing collective strategies by optimization
- A model for comparing and simulating management strategies

- BUT no satisfying solution to the problem of design by optimization





General conclusions

- **Managing ecological networks**
  - **Networks can be**: spatial, causal, …
  - **Management can be**: control, conservation, sampling ..
  - **Ecosystems and agricultural systems** : management share similarities
- **Common tools for all these problems**
  - graphical models, simulation, optimization
  - **Computing exactly** the optimal strategy is out of reach

Current research focuses on approximate resolution

Still some challenges!

Design by optimization of strategies for managing ecological networks

- How to improve solutions of problems with large factored state and action spaces?
  - We have heuristic solutions but there is still room for improvement

- How to manage a network when observations are costly?
  - Combine sampling and control/conservation actions

- Dynamics
  - How to control a system where the network changes through time?

- …

References

Food webs management

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Adaptive spatial sampling

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GMDP, collective management of crop fields, forests or reserves

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Summary

- Ecological networks management:
  - Ecology: From agricultural systems, in interaction with communities of pathogens to ecological management (food webs)
  - Network: Spatial correlations (fields, sites) and species correlations (food web, weeds communities…)
  - Management: Control (eradication), conservation or sampling for map construction
- Methodological tools:
  - Stochastic models of interactions: Bayesian Networks, Markov Random Fields, Dynamic Bayesian Networks
  - Control : MDP, Combinatorial optimization…

Management should be

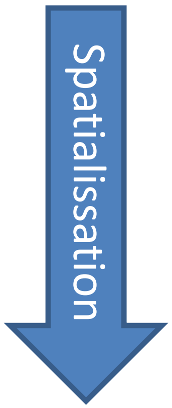
- **Spatially explicit :** long-distance pathogen dispersion
- **Collective:** decisions are taken in each field but are interdependent
- **Long term:** we want to minimize yield losses now and in the future

- *Collective strategy design is difficult because of spatial and temporal dependences*

Message

- Justifier l'utilisation de MGS et de l'opti pour ecological management
  - Why networks: Importance of interactions (spatial, species…) in Ecology.
  - Why stochastic models: Obviously processes are uncertain
  - Why optimization: management implies policy conception and optimization is useful for this. One step beyond comparison or simulation of management strategies.

Gestion de la santé des cultures : Importance de la composante « spatiale »



- Parcelles gérées « indépendamment » (hormis rotations)
- Prise en compte de relations « globales » (travail, biodiversité, « stocks » de pathogènes/adventices...)
- Prise en compte des dispersions (adventices, pathogènes...)

Une gestion « explicitement spatiale » des cultures permet la prise en compte de :

- La dispersion de pathogènes/adventices
- Les interactions culture/adventices/pathogènes

Dans la conception de modes de gestion des cultures

Management should be

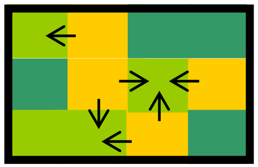
Contrôle des bioagresseurs des cultures :

- **Global**
  Stratégies collectives plus efficaces que des stratégies individuelles
  - **Échelle pluri-parcellaire + Échelle pluri-annuelle + Multiples interactions**
    Conception de stratégies collectives efficaces difficile

- **Durable**
  - Cultivars possédant des résistances spécifiques et/ou quantitatives
  - Contournement de la résistance si cultivar surexploité

Comment concevoir des stratégies collectives exploitant durablement les résistances variétales ?

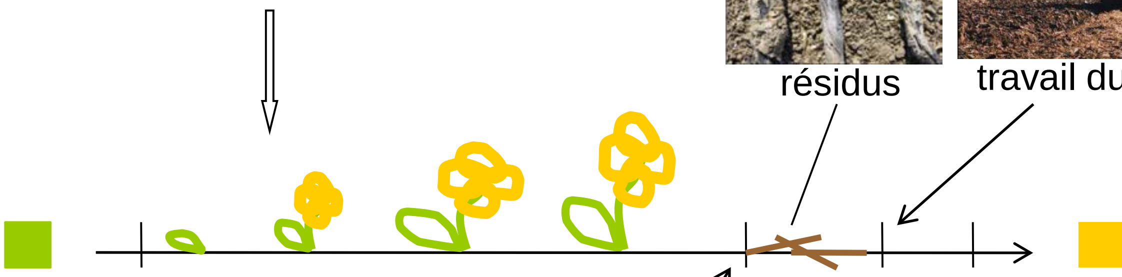
Le Modèle



propagation depuis les parcelles de blé voisines

résidus

travail du sol



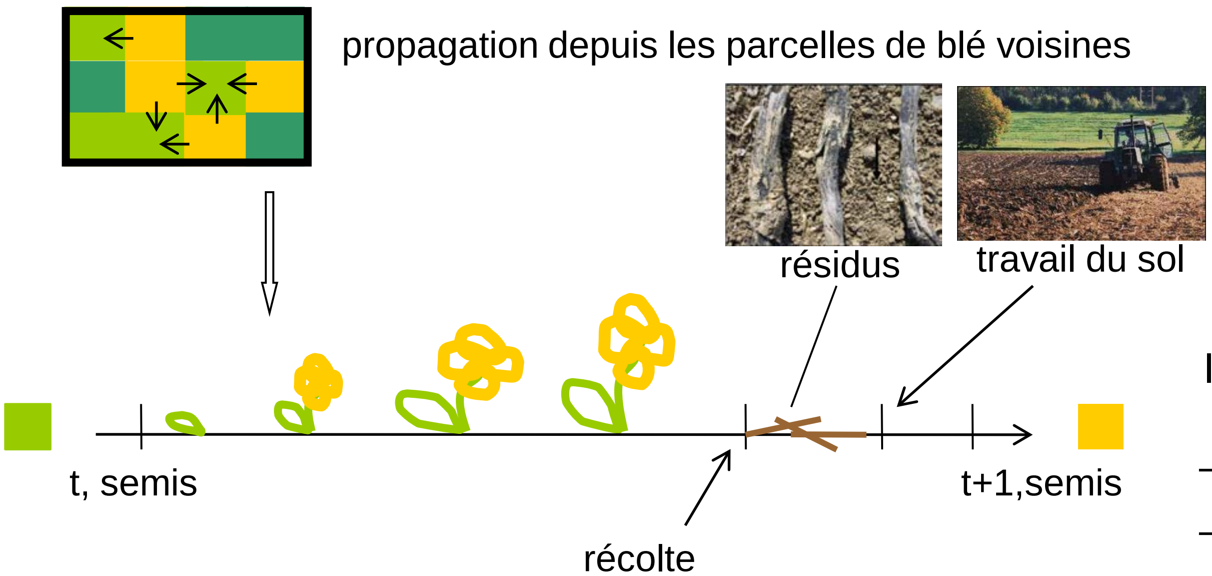
Rotation des cultures

- colza
- blé
- orge

Interactions hôte-patho

	résistant	sensible
virulent	+	+
avirulent	-	+

Le Modèle



Rotation des cultures

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Interactions hôte-patho

	résistant	sensible
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Variables d'état d'une parcelle

- Culture en cours (C → B → O)
- Sévérité d'infection des résidus (G2)
- % Pathotypes virulents (SG)

Actions

- Choix variétal (S ou R)
- Seuil de travail du sol avec labour

(labour si G2> τ)

Graph-based Markov Decision Processes

Structured problems of sequential decision under uncertainty

- Several state variables $\{X_i\}_{i \in V}$ and decision variables $\{A_i\}_{i \in V}$
- A factored stochastic transitions model
- A local reward model
- Local policies

$$\left\{\delta_i\left(x_{N(i)}\right)\right\}_{i \in V}$$