

Modèles graphiques stochastiques et optimisation pour la gestion de systèmes agroécologiques

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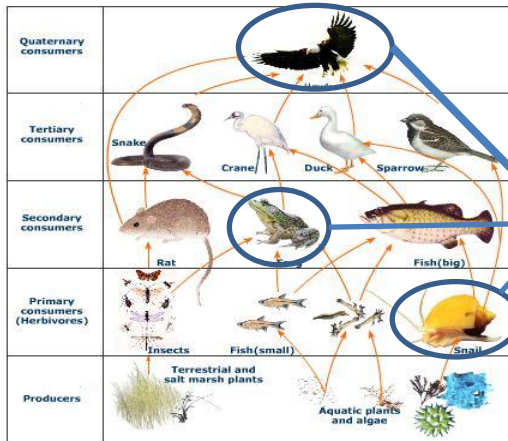
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Some AI tools for the management of stochastic processes on networks

- Tools 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
 - Continuous optimization
 - Heuristics
- Applications in **agroecological systems management**
 - Biodiversity conservation
 - Spatial sampling of weeds
 - Management of services / crop health at the landscape scale

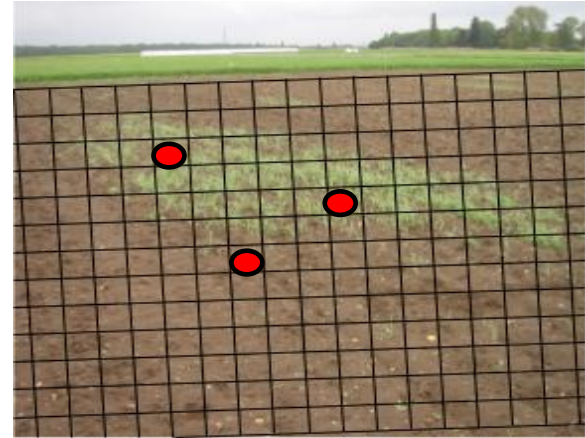
Three example case studies/models

Species conservation in food webs

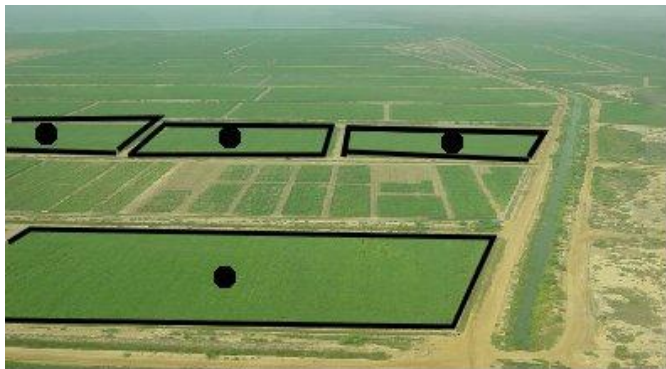


Conservation?

Weeds sampling for map reconstruction

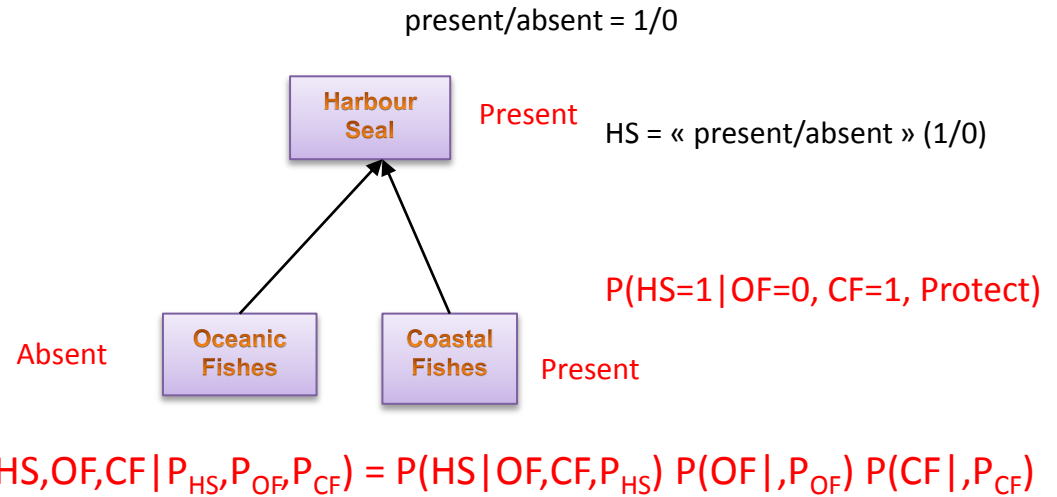
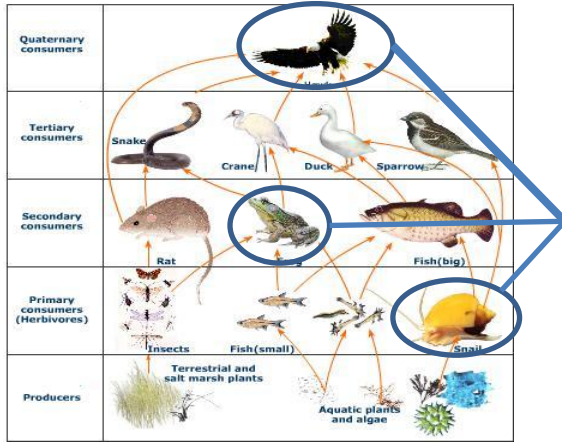


Crop allocation to maximize ecosystem services Modelling/optimisation approaches

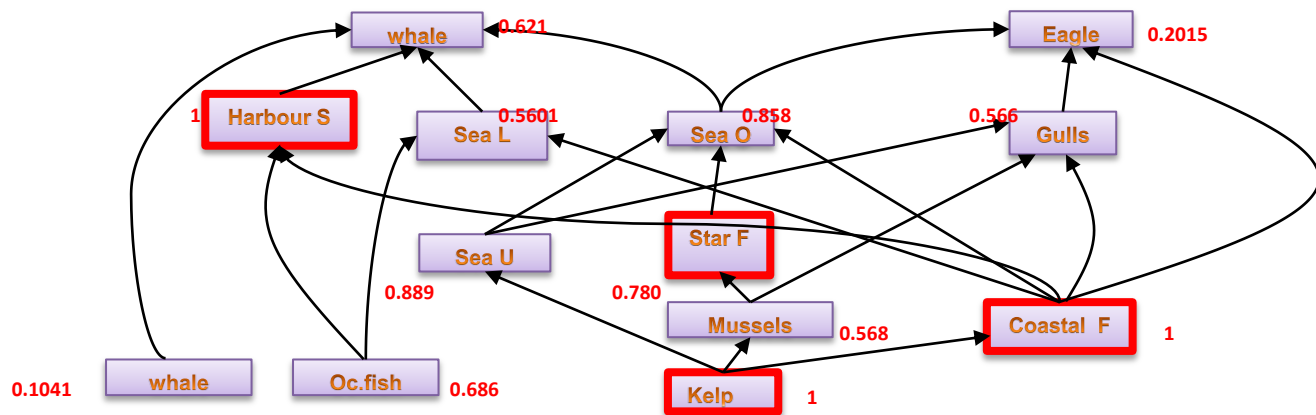


- « **static node selection** » to optimize expectation wrt a **Bayesian Network**
- « **adaptive node observation** » to optimize expected MAP in a **Markov Random Field**
- « **policy selection** » to maximize expectation wrt a **Dynamic Bayesian Network**

Problem I : Conservation of multiple species in food webs



« Which species to protect in a food web to optimize the expected number of present species? »



Problem I : Conservation of multiple species in food webs

Model: Bayesian Network = joint probability distribution over species occurrences.

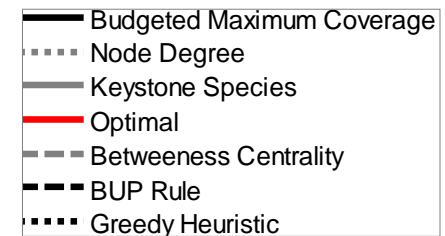
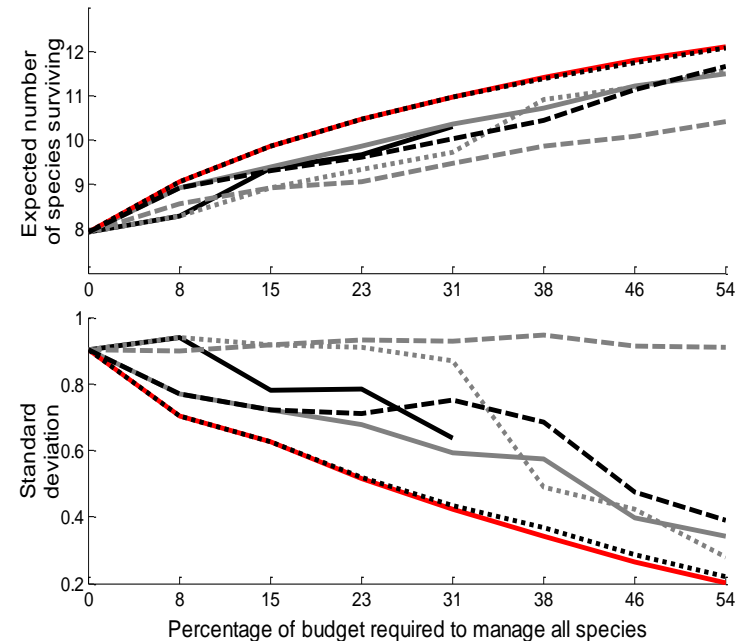
$$P(S_1, \dots, S_n) = \prod_{i=1..n} P_i(S_i | \text{Preys}(S_i), \text{Pr}_i)$$

Optimization problem:

$$\underset{\substack{\Delta \subseteq \{1..n\} \\ \text{Cost}(\Delta) \leq B}}{\text{max}} \mathbf{E} \left[\sum_{i=1}^n S_i \mid \Delta \right]$$

Solution:

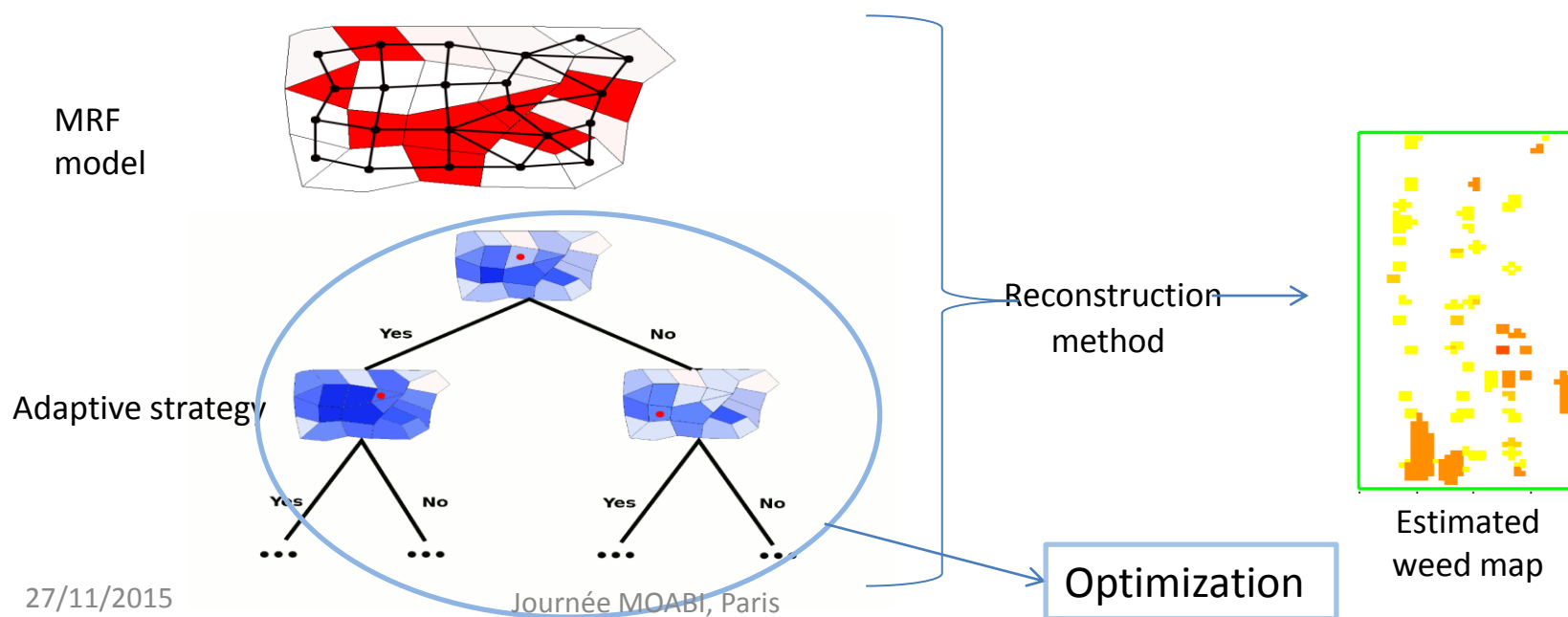
- Exact (naïve) for small problems
- Heuristics for large problems



Problem II: Optimal static/adaptive sampling for weeds map reconstruction



« Where to sample to optimize the expected quality of the returned map? »



Problem II: Optimal static/adaptive sampling for weeds map reconstruction

Model: Markov Random Field

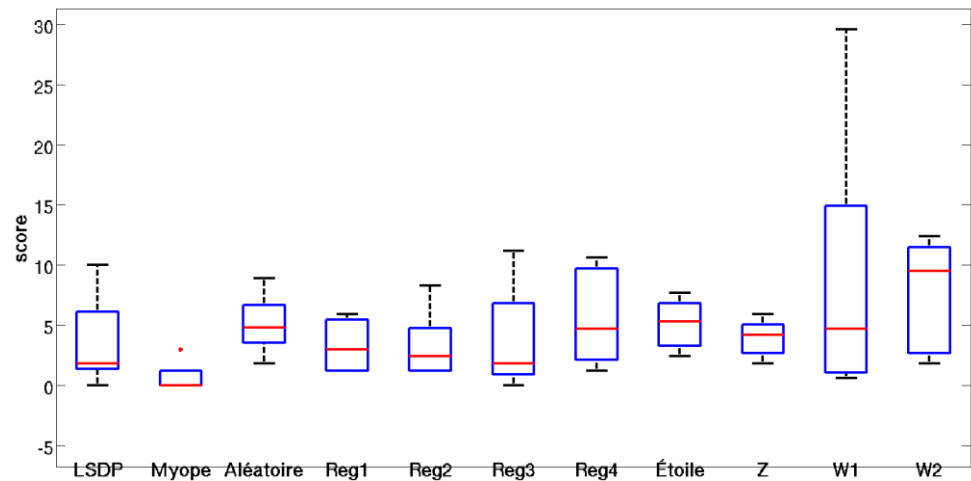
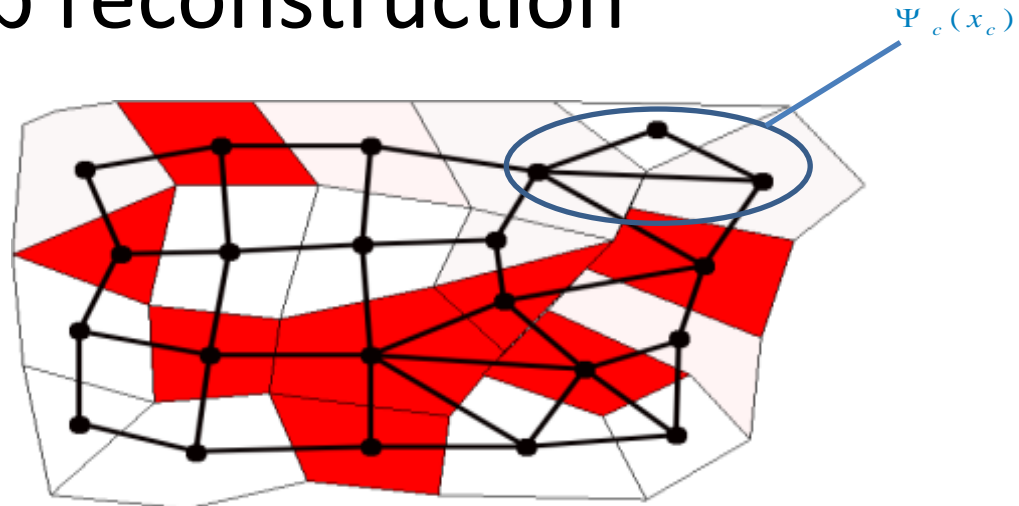
$$P(x) \propto \prod_{c \in C} \Psi_c(x_c)$$

Optimization problem (static):

$$\max_{\substack{\Delta \subseteq \{1..n\} \\ Cost(\Delta) \leq B}} \mathbf{E}_{x_\Delta} \left[\sum_{i=1}^n \max_{x_i} P(x_i | x_\Delta) \right]$$

Solutions:

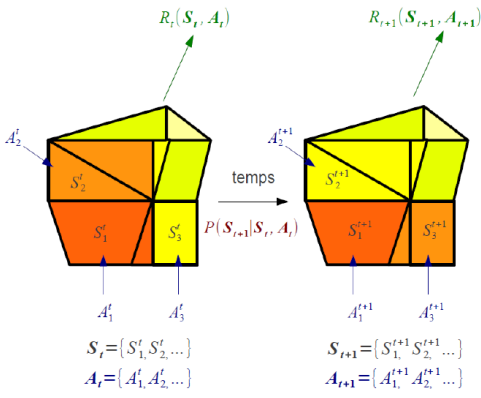
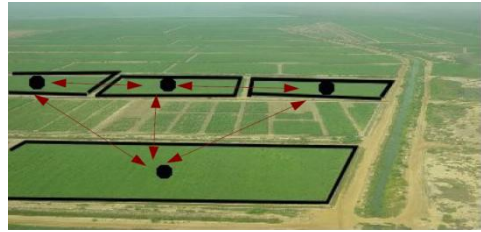
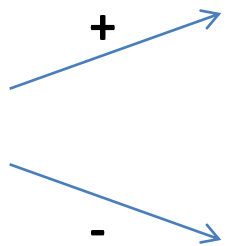
- Heuristics (static/adaptive)
- Reinforcement learning
- Planning under uncertainty



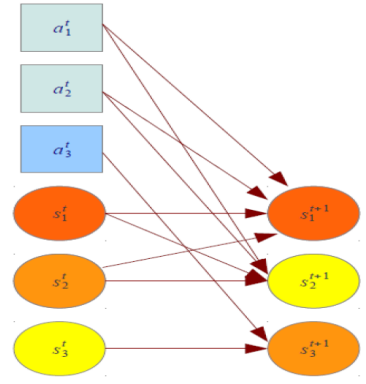
➤ M. Bonneau, S. Gaba, N. Peyrard and R. Sabbadin. Reinforcement learning-based design of sampling policies under cost constraints in Markov random fields: Application to weed map reconstruction, CSDA, 2014

➤ A. Albore, N. Peyrard, R. Sabbadin and F. Teichtel. An Online Replanning Approach for Crop Fields Mapping with Autonomous UAVs, ICAPS, 2015.

Problem III: Optimal crop allocation to maximize ecosystem services provision



Many state variables and action variables (here one for each plot)



Factored representation : dynamic bayesian network (DBN)

« How to allocate crops in space/time to optimize the expected compromise between Ecosystem services through time? »

$$P(S^{t+1}|S^t, A^t) = \prod_{i=1}^n P(S_i^{t+1}|pa(S_i^{t+1}))$$

Approximate resolution

Problem III: Optimal crop allocation to maximize ecosystem services provision

Model: “triple factored Markov Decision process”

- A Dynamic BN ($t=0..T$): $P(s^{t+1} | s^t, a^t) = \prod_{j=1}^n P_j(s_j^{t+1} | pa_p(s_j^{t+1}))$
- Local instant rewards: $R(s^t, a^t) = \sum_{\alpha=1}^m R_{\alpha}(pa_r(R_{\alpha}^t))$
- Local stochastic policies: $\delta(a^t | s^t) = \prod_{j=1}^m \delta_j(a_j^t | pa_{\delta}(a_j^t))$

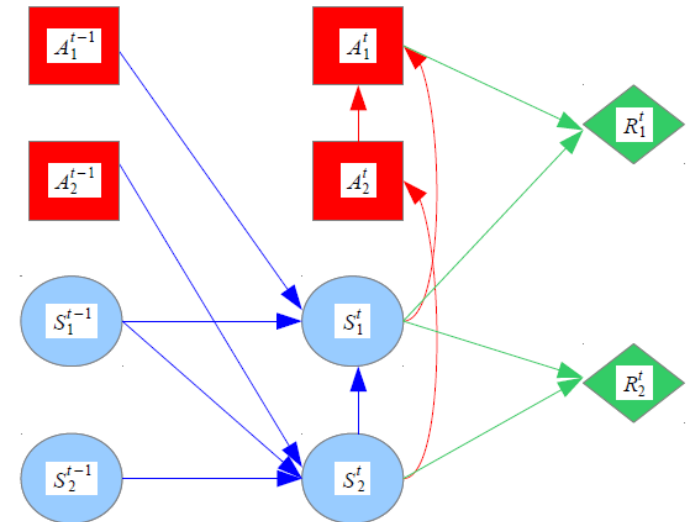
Policy value and continuous optimization:

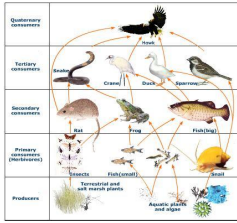
$$V_{\delta}^{R,T}(P^0) = \mathbf{E}_{P_{\delta}^T} \left[\sum_{t=0}^T R(S^t, A^t) | P^0, \delta \right]$$

$$\max_{\delta} V_{\delta}^{R,T}(P^0)$$

Solution: successive evaluation/improvement of policies

- Approximate evaluation of δ^t through marginal probs (ex. Loopy BP)
- Improvement of δ^t through Gradient Descent



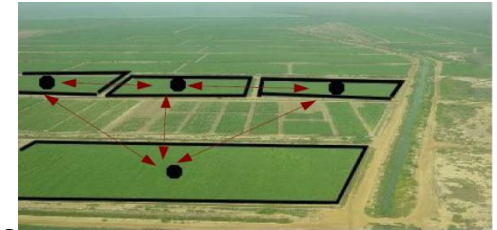


General conclusions



➤ 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 (all problems are at least NP^{PP}-hard)

Current research focuses on approximate resolution

➤ Still some challenges!

- **Sampling dynamic processes**
 - How to sample a system where the underlying process changes through time?
- How to manage processes over an **ill-know network?**
 - Combine network learning and control/conservation actions optimization
- ...

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GMDP, FA-FMDP, applications to agro-ecological processes management

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