A DBN model to study the influence of Epidemiological Surveillance Networks on phytosanitary treatments intensity

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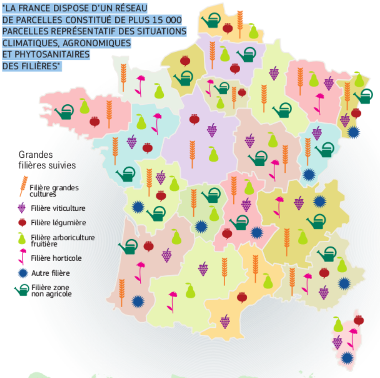
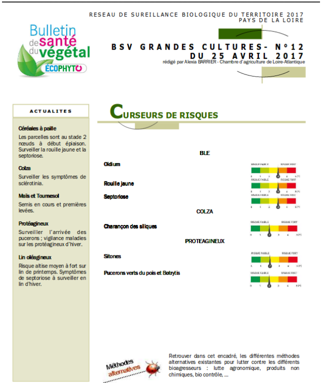
Controlling pests on crops

- Globalisation, environmental and climate changes increase the risks of diseases or animal pests on crops.
- To control and prevent epidemics, epidemiological surveillance systems are becoming more and more important.
- In France, the Ecophyto national plan, to reduce pesticide use, strenghened the national Epidemio Surveillance Network (ESN) [Regional crop health newsletter, http:/draaf.occitanie.agriculture.gouv.fr/Bulletins-desante-du-vegetal].





What are the influences of ESN configuration ?

ESN defined spatially and temporarily.

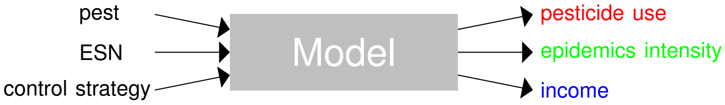
{  →  →  →  } x T years

How to design and optimise such a network is still a research subject [Bonneau *et al.* 16].

? What is the influence on pesticide use of:

- spatial density (number of observed sites) and
- historic length (number of years of past observations).

💡 Development of a **stochastic model of pest dynamics** to **simulate** the application of a **control strategy** using **ESN observations** at the landscape level.



Spatio-temporal evolution of pest

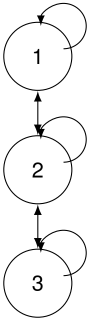
A SIS model: $P(X^t|X^{t-1}, A^t) = \prod_{i=1}^{n} P(X_i^t|X_i^{t-1}, X_{N_i}^{t-1}, A_i^t)$

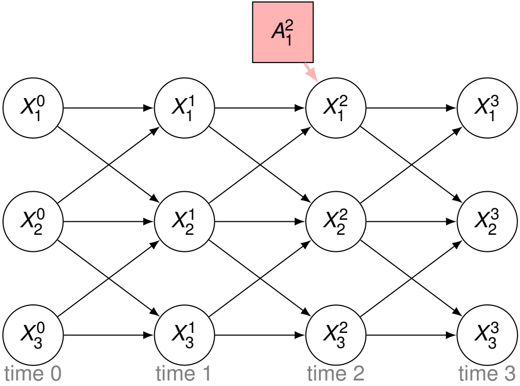
with $X_i^t \in \{0,1\}$ the state (sane/infected) of field i at time t

N_i the set of neighbor fields of field i

$A_i^t \in \{0,1\}$ the action (no treatement/treatment) applied to field i at time t

The stochastic evolution of an epidemic with a time step of 1 year can be represented as a Dynamic Bayesian Network (DBN, Jensen 01).





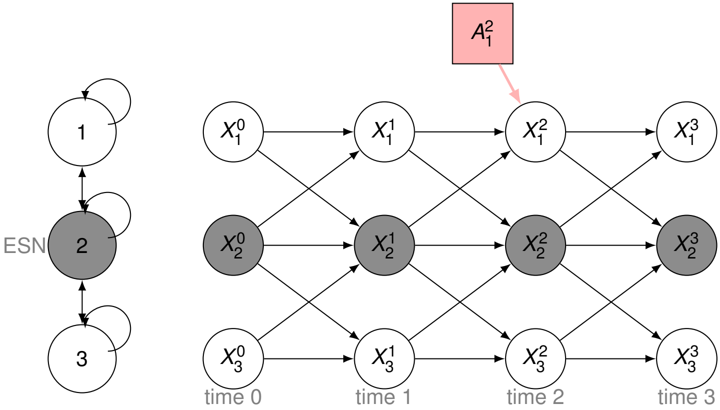
States and A_1^2 action relations

Control strategy

Decision rule d1 ( ) for treatment of field i at a given year t

Apply treatment A_i^t **if** the estimated infection probability $p_i^t(ESN)$ is higher than a threshold $s_i^t(x_i^{t-1}, s0)$

with $s0$: infection probability when avoided loss is equal to treatment cost.



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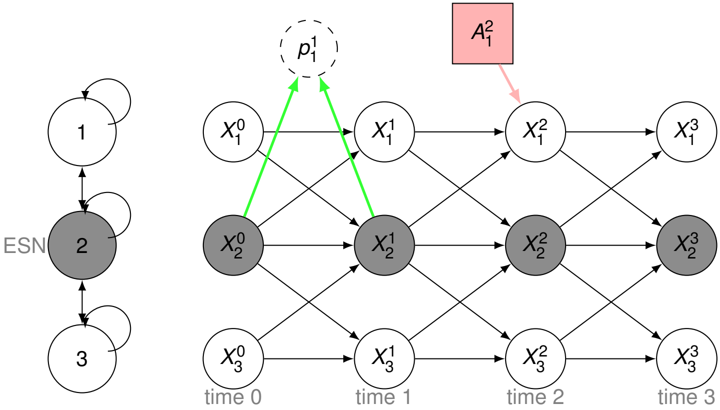

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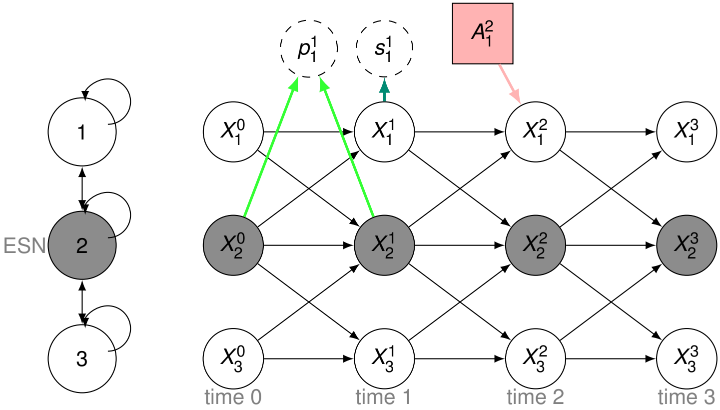

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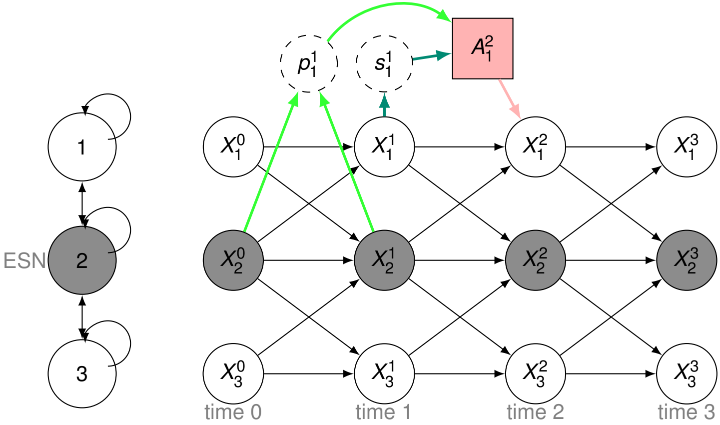

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with $s0$: infection probability when avoided loss is equal to treatment cost.

For comparison purpose, other decision rules

d2: 'Never treat' ( )
d3: 'Always treat' ( ).

Parameterisation

- 144 (12 x 12) fields with oilseed rape crop *(yields for healthy or injured crops, purchase price of the harvest, production and treatment costs, treatment efficiency)*,

- 3 types of pests *(contrasted spatial dispersions and temporal soil persistance)* : soil-borne disease, weed, insects pest

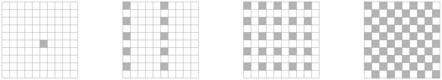
Parameters values for crop, pests, economic income were set by expertise and two studies in France. [Etude FOP, 2015] [Rapport CA-INOSYS, 2015].

Pest type	**soil-borne disease**	**weed**	**insects pest**
			
Mean annual cost of phytosanitary product	30€/ha (1 application)	147€/ha (3 applications)	32€/ha (4 applications)
short distance dispersal	0.10	$<$ 0.20 $\ll$	0.40
long distance dispersal	0.05	$<$ 0.15 $\ll$	0.30
pest survival if not treated	0.50	$\approx$ 0.50 $>$	0.25
Efficiency of treatment	0.8	0.9	0.7
yield if infected	0.7	0.7	0.8

Simulation analysis

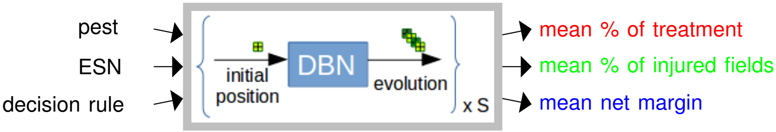
For rule **d1**, several cases:

- 4 spatial densities (1%, 10%, 25%, 50% of all fields, uniformly spatially distributed, stable in time): res1, res2, res3, res4,



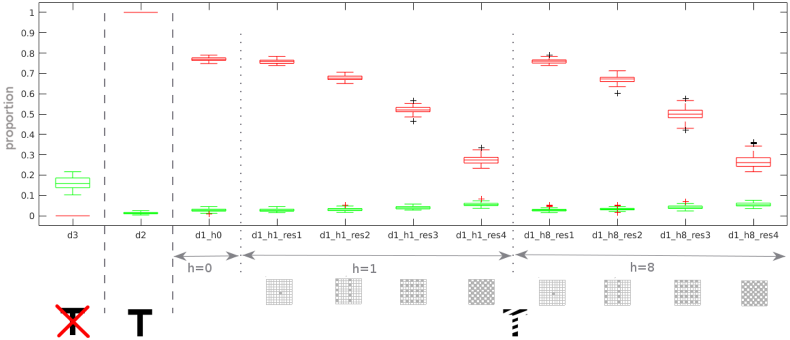
- 2 historic lengths (previous year or all ESN observations): $h = 1$, $h = 8$,
- for comparison purpose, no observation ($h = 0$).

For each case: 3 initial states of fields, 60 replicates (simulations during 8 years).



Implementation in Matlab, using the BNT toolbox [Murphy 10]. Code available on FigShare: https://doi.org/10.6084/m9.figshare.4675759.v3

ESN effect for soil-borne disease (1)



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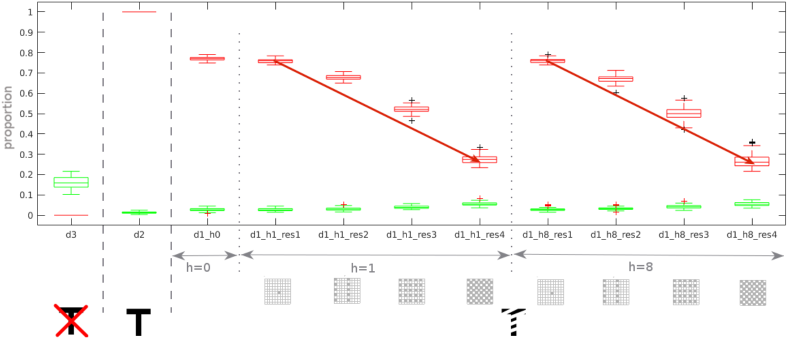

- Mean number of treatment actions decreases when spatial density increases.

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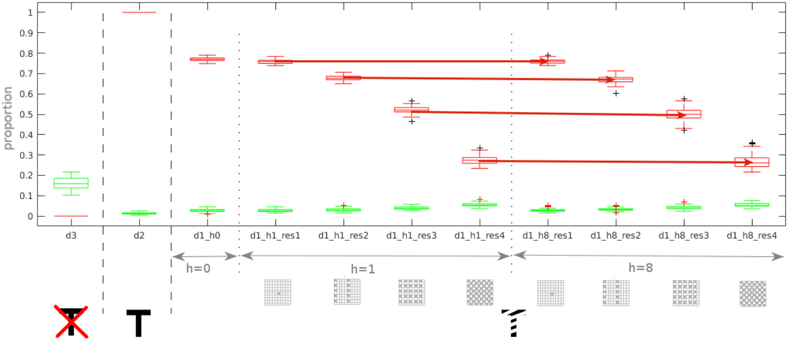
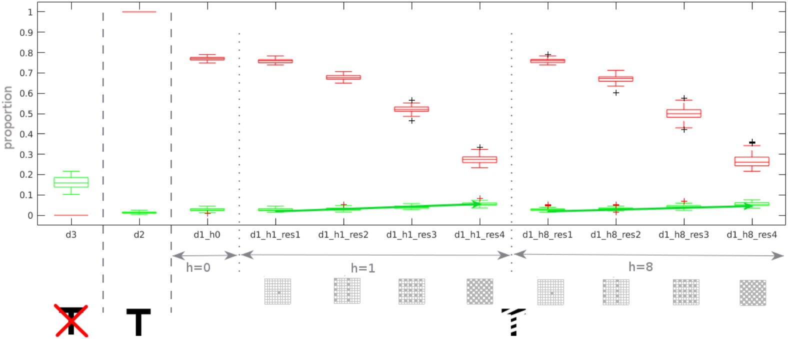


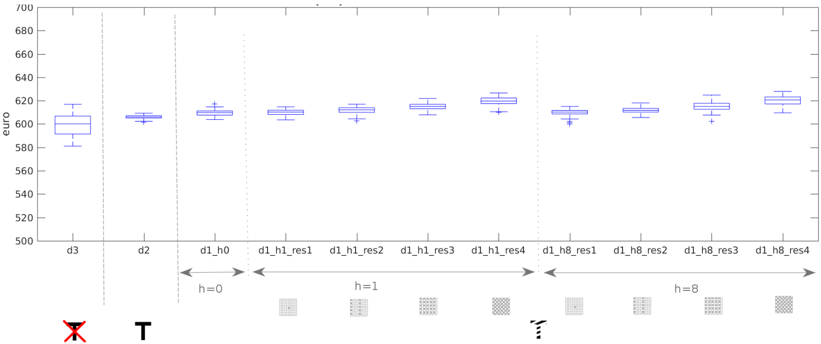
- Mean number of treatment actions decreases when spatial density increases.
- Mean number of treatment actions sligthly decreases when length historic increases.

ESN effect for soil-borne disease (1)

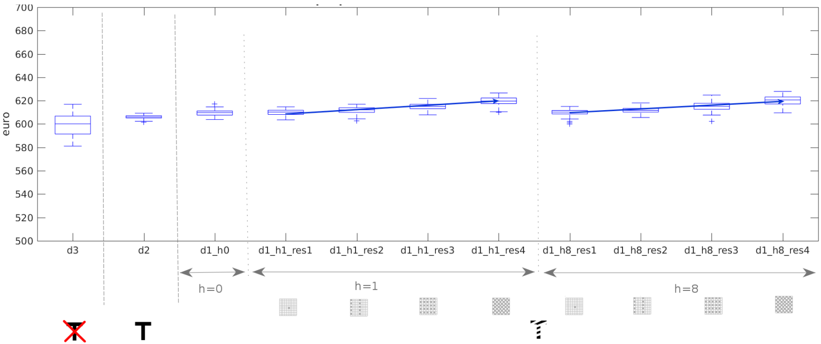


- Mean number of treatment actions decreases when spatial density increases.
- Mean number of treatment actions sligthly decreases when length historic increases.
- Although infection intensity slightly increases with larger ESN, the pest remains under control.

ESN effect for soil-borne disease (2)



ESN effect for soil-borne disease (2)

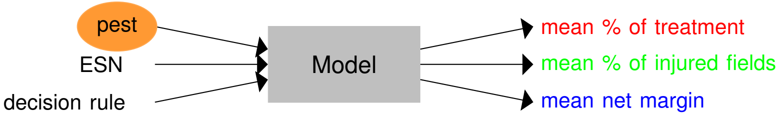


- Mean net margin increases when spatial and temporal network size increase, in particular for ESN with large spatial size (and weed)

Similar results for weeds, but for pest insects treatments always choosen.

Sensitivity analysis

Identify which factors have a strong influence on an output variable.



Process

1. Define factors

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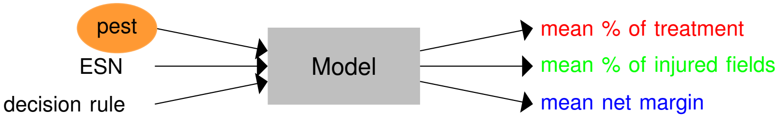

Process

1. Define factors and domains: 6 factors related to pest
2. Sample factors: 60 samples (R package lhs)
3. Evaluate output variable on sampled points: simulations
4. Create a metamodel: a kriging metamodel (R packages DiceKriging, DiceView)
5. Compute sensitivity indices for each pest type: Sobol indices (R package sensitivity)

Global and total sensitivity indices

	long distance dispersal	short distance dispersal	survival without treatment	treatment cost	treatment efficiency	yield if infected
Mean treatment actions						
Soil-borne pathogens	0.06	0.27	0.03	0.54	0.02	0.32
Weeds	0.05	0.28	0.03	0.53	0.02	0.31
Pest insects	0.10	0.21	0.02	0.16	0.48	0.69
Mean Infection intensity						
Soil-borne pathogens	0.04	0.03	0.01	0.41	0.15	0.41
Weeds	0.03	0.03	0.01	0.40	0.12	0.37
Pest insects	0.03	0.02	0.00	0.30	0.13	0.48
Mean net margin						
Soil-borne pathogens	0.14	0.45	0.01	0.23	0.29	0.60
Weeds	0.14	0.45	0.01	0.23	0.30	0.57
Pest insects	0.07	0.86	0.08	0.00	0.00	0.00

- 2 parameters not very influent
- 2 parameters highly influent
- Same influence of factors for soil-borne pathogens and weeds.
- Different influence for pest insects, specially for mean net margin

Conclusion (1)

An original and simple model to study the influence of spatial and temporal size of ESN on phytosanitary treatments use for crops.

Main conclusions for soil-borne disease and weed:

- Increasing spatial size (number of observered fields) of ESN may help in reducing pesticide use.
- Increasing temporal size (number of past observations) of ESN, may also sligthly help.

For insects pest, ESN alone is not sufficient to decrease treatment application due to a high mobility of insects (implying a high risk of injuries) and a low treatment cost.

Conclusion (2)

Beware: results of the sensitivity analysis also related to:

- the choice of factors,
- the domains given for factors,
- the values taken for other parameters of the model.

However, the results help to:

- validate this complex model
  $\rightarrow$ increase confidence (no seemingly illogical results),
- evaluate the model robustness
  $\rightarrow$ same outputs when some parameters vary,
- identify leverage effects
  $\rightarrow$ new valuable simulations to evaluate effects of little variations of very influent factors.

Perspectives

The model could be extended with:

- others decision rules,
- cropping practices to reduce infection risk or increase treatment efficiency,
- landscape heterogeneity.

The development of a new Matlab toolbox **GM**toolbox (v0.9) should help in reducing execution time for inference [http://www.inra.fr/mia/T/GMtoolbox].

A support tool for participative training .

An interactive tool for discussion between farmers and advisors to better understand the benefice of ESN to control epidemics at the landscape level.

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