A dynamical model for the growth of a stand of Japanese knotweed including mowing as a management technique.

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OUTLINE OF THE PRESENTATION

I) The Japanese knotweed: ecology and model.

II) Simulation study of the model: Calibration.

III) Simulation study of the model: Influence of mowing parameters.

The Japanese knotweed

Japanese knotweed

Rhizome

Stem: from 1 to 3 meters.

Rhizome: up to 8 cm diameter, length: 15 - 20 m, depth: 2 - 3 m, represents 2/3 of the total biomass of the plant.

The rhizome withstands the cold and enables to spend the bad season burried in the ground.

Clonal development of the Japanese knotweed.

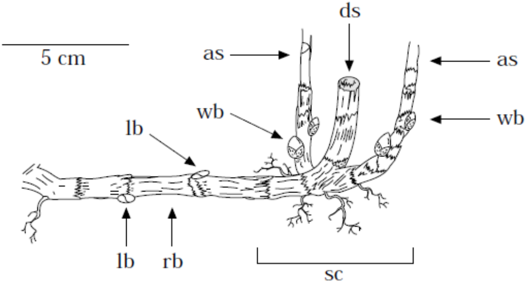

Figure: Diagram of the development of stems and buds along the rhizome, extracted from[Adachi et al., 1996] as: current aerial shoot, ds: dead aerial shoot, rb: rhizome, sc: shoot clump, lb: lateral bud, wb: winter bud.

References: [Adachi et al., 1996], [Dauer and Jongejans, 2013], [Price et al., 2002], [Beerling et al., 1994], [De Waal, 2001].

Dynamical model for the knotweed

Objective: Describe the dynamics of Japanese knotweed at the local scale and the effects of mowing on it.

The mathematical formalism is the one of the **measure-valued stochastic processes**.

The model presented in this section is inspired by the work of [Fournier and Méléard, 2004] and [Tran, 2006].

The individuals, here the crowns (i.e. the places where the terminal buds are located and from which the stems sprout) are characterized by:

- their position (in the plan)
- a trait describing the underground biomass (i.e. that of the rhizome that is connected to the crown).

Events occurring in the model

At each time, we calculate the next time at which there is an event. There are three possible events:

- a birth of a new crown: birth rate depending on positions, law for the dispersal distance and intra-specific competition zone
- a death of a crown: mortality rate depending on biomass
- the mowing of a proportion *proportionMowing* of individuals in the population. The effect of mowing is a decreasing function of the the biomass.

- Between those events, the biomass of each crown evolves in a deterministic way.

Random mowing technique

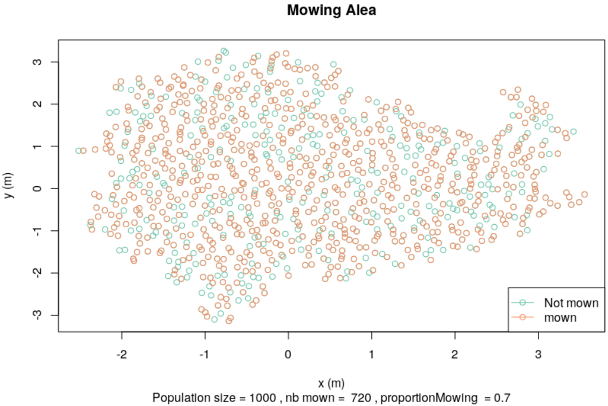

Figure: Represents the crowns that would be mown during a mowing event with the Random technique. A proportion of mown plants is imposed. The coordinates are in meters.

Side mowing technique

Figure: Represents the crowns that would be mown when imposing a *position* at the right of which all plants are mown.

Model Parameters

Variable	Description
Biomass	
K	maximal biomass (g)
L	growing rate for low biomasses
a_0	initial biomass of a born crown (g)
Mowing	
mowingParameter	effect of mowing
Mortality	
deathParameterScaling	for the small biomasses
deathParameterDecrease	decrease speed of the mortality rate
Birth	
distanceParent	distance of apical dominance (m)
distanceCompetition	intra spécific competition distance (m)
$\bar{b}$	birth rate (ideal conditions)
$(\text{shape}, \text{scale})$	Gamma law, dispersion of the created individual

Management parameters:

- initial population size: *InitialPopSize*
- mean number of mowing events a year: τ
- management project duration: T
- proportion of mown crowns: *proportionMowing*

ANALYSIS OF THE MODEL BY SIMULATIONS

CALIBRATION

Data

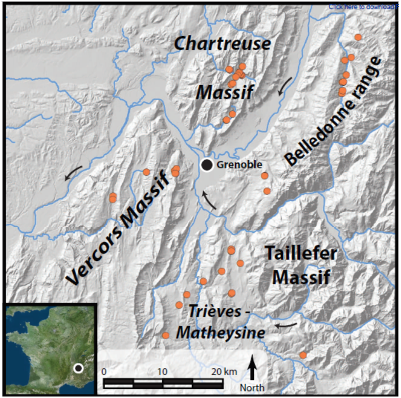

Figure: From [Martin et al., 2018].

19 stands of knotweeds in the French Alps (various altitudes).

Measurements carried out in 2008 and in 2015: on the stands themselves (outline, number of stems, ...) and on biotic and abiotic variables.

Variability in observed stands: size (less than $1m^2$ to more than $100m^2$), area (proximity of watercourse, road, forest, abandoned land)

Data - Calibration

- In model outputs, we have the final and initial population areas and sizes.
- We use data on areas and densities of stands (so we have access to the size of the population) in 2008 and 2015, and information from managers: number of mowing events, proportion mown.

Method for the calibration

The OpenMOLE software proposes a method derived from genetic algorithms for the calibration of models.

The algorithm explores the parameter space to find the minimal distance between the observations and the simulations (the algorithm manages the stochasticity of the model).

As distance between simulations and observations, we take for each stand and each type (area or size) the distance: $\frac{|simu-data|}{data}$.

Reference : [Romain Reuillon, 2013]

The result of the calibration

Variable	Valeur Calibration
K	12.72
L	0.26
distanceCompetition	0.15
distanceParent	0.20
shape	4.34
scale	2.36
deathParameterDecrease	2.32
deathParameterScaling	1.12
mowingParameter	0.11
bbar	0.18
a0	1.73
delta	26.06
evolution.samples	79

These calibrated values agrees with experts' statements on distances, the ratio of the maximum biomass and the biomass of the individuals at birth, mortality rate.

ANALYSIS OF THE MODEL BY SIMULATIONS

INFLUENCE OF MOWING PARAMETERS

Law of the outputs

Results of Shapiro Wilk test (H0 = " Outputs are i.i.d gaussian "):

Output	reject H_0	do not reject H_0	extinction
Initial Area	203	851	0
Final Area	154	754	146

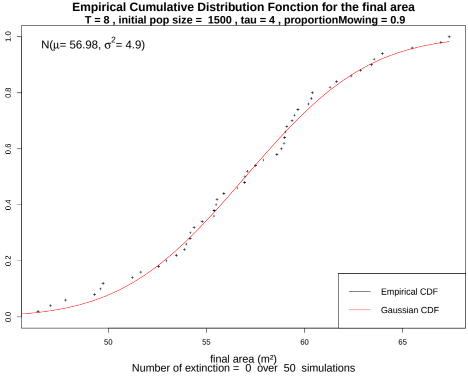

Figure: Probability Distribution Function of the final area, obtained with an initial population size = 1500, $\tau = 4$, $proportionMowing = 0.9$, and $T = 8$.

Comparison of initial and final area densities.

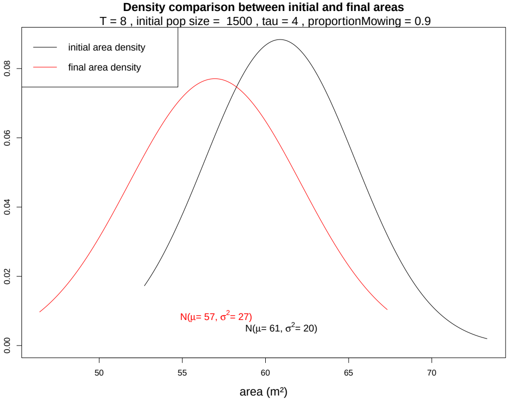

Figure: Density of the Gaussian laws of the initial and final areas, obtained from the empirical averages and variances. Initial population size $= 1500$, $\tau = 4$, $proportionMowing = 0.9$, and $T = 8$.

Influence of T on the mean final area

We plot the regression curves obtained for different τ. [InitialPopSize $= 1500$ and $proportionMowing = 0.9$ fixed].

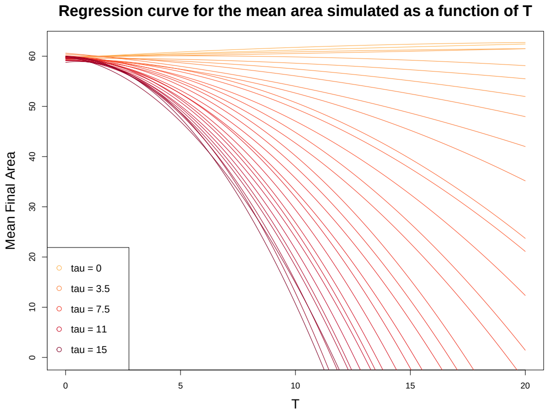

Figure: Quadratic regression curves of the mean final area as a function of T, for different τ.

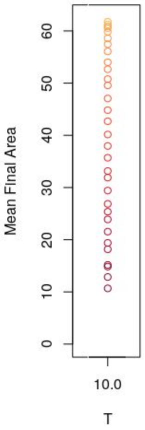

Figure: Cross section.

Influence of T on the mean final area

We perform a quadratic regression on strictly positive values of outputs for the area (using *lm* function in R).

Output	r squared > 0.95	correlation > 0.95	Shapiro > 0.05
Mean Final Area	47	50	49

Table: Each number refers to a number of regressions, over the 50 in the sampling (variation of initial Population size and $\tau > 2.5$).

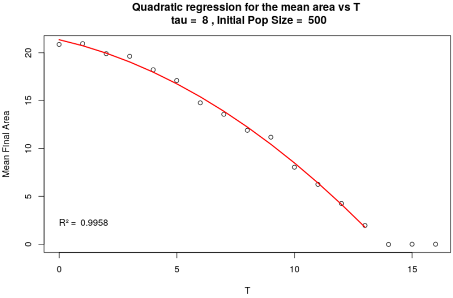

Figure: Quadratic regression for the mean area vs T, with $\tau = 8$, and initial population size $= 500$.

Summary of the influences of the management parameters on the average values of the outputs

Initial / Final	Param	Mean Area	Mean Size
Initial	InitialPopSize	linear $\nearrow$	linear $\nearrow$
Final	InitialPopSize	linear $\nearrow$	linear $\nearrow$
Final	T	linear $\nearrow$ (τ weak)	linear $\nearrow$
		quadratic $\searrow$ (τ high)	exponential $\searrow$
Final	τ weak	linear $\nearrow$ or $\searrow$	linear $\searrow$
Final	τ high	linear $\searrow$	exponential $\searrow$

Formulas for the final size and area

We have the more general result:

Result

For $\tau \gtrsim 2$:

$$\textit{Final Size} = \textit{Initial Size} \times exp(-T.(\tau - a)/b), \tag{1}$$

with $a, b \in \mathbb{R}$ constants,

and,

$$\textit{Final Area} = \max((c \times \tau + d) \times T^2 + 0.04 \times \textit{Initial Size}, 0)$$

with $c, d \in \mathbb{R}$ constant.

Method to assess formulas

Sobol sampling of 5000 points with $\tau \in [0; 15.0]$, $T \in [0; 20]$, and *initialPopSize* $\in [100; 1500]$.

	Mean Area	Mean Size
Regression tool	*lm*	*nls*
Correlation	> 0.99	> 0.99
Residual standard error	2.23	26.12
95 % confident interval	$c \in [-0.0342; -0.0336]$	$a \in [0.90; 0.94]$
	$d \in [0.0960; 0.0998]$	$b \in [20.46; 20.77]$

Important remark for the formulas

Formulas obtained for the mean output quantities are still relevant for direct outputs.

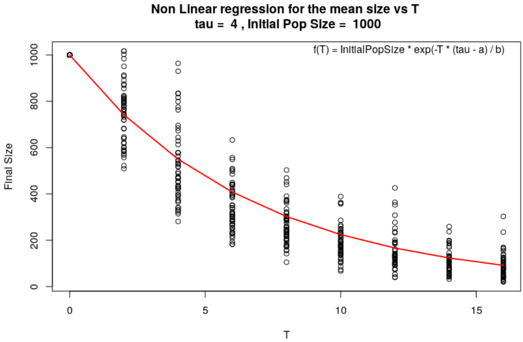

Figure: Black circles represent stand sizes resulting of 50 replications with $\tau = 4$, initial population size $= 1000$, and varying T. The red line is the function of T defined by Equation (1). It has been found with a regression on a far bigger set of points than the subset selected to plot this example.

Perspectives

Take an interest in two other questions managers face:

- At the scale of a landscape with several knotweed stands, how to distribute the mowing effort (intensity / frequency) between the different stands?
  $\rightarrow$ Modeling the dispersion due to mowing.
- Compare mechanical engineering (mowing) vs ecological engineering (willow)?
  $\rightarrow$ Model the influence of the shadow on the dynamics of knotweed.

Pose viability problems in stochastic formalism.

Question:

- about the statistical method used to study the influence of management parameters: regression, Shapiro test,...

Thanks for your attention.

- OpenMOLE user case, joint work with G.Chérel

  `https://blog.openmole.org/`

- The eX Modelo school on model exploration methodology

https://exmodelo.org/

Poisson Point Measure

An application $M : \Omega \times E \to \mathbb{R}_+$ is a **random measure** if

- $\omega \to M(\omega, A)$ is a random variable for each $A \in E$
- $A \to M(\omega, A)$ is a measure on $(E, \mathcal{E})$ for each $\omega \in \Omega$. We denote $M(A)$ this random variable.

The term "random measure" means that M is a random variable that associate a measure M_ω to each event $\omega \in \Omega$.

Définition

Let $(E, \mathcal{E})$ be a measurable set and ν be a measure on $(E, \mathcal{E})$. A random measure N on $(E, \mathcal{E})$ is a Poisson random measure with intensity ν if :
- for each $A \in E$, the random $N(A)$ has a Poisson law with parameter $\nu(A)$.
- for each $A_1, \ldots, A_n \in \mathcal{E}$ disjoints, random variables $(N(A_1), \ldots, N(A_n))$ are independents, for all $n \geq 2$.

Law of the output, with extinction

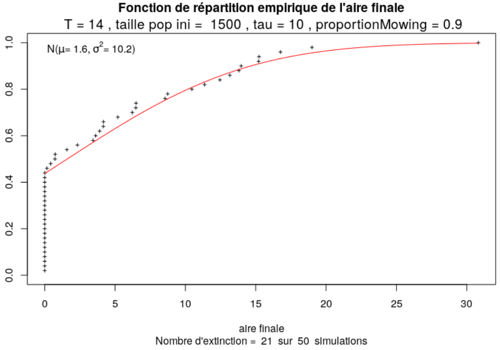

Figure: Empirical Cumulative Distribution Function of a Gausssian law with empirical mean and variance of the final area, for an initial population size $= 1500$, $\tau = 10$, *proportionMowing* $= 0.9$, et $T = 14$. There are 21 extinctions (over 50 simulations).

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