

# Retour sur l'épidémiologie

*S.I.R.*

$$\left\{ \begin{array}{l} \frac{dS}{dt} = -\beta SI \\ \frac{dI}{dt} = +\beta SI - (\gamma + \mu)I \\ \frac{dR}{dt} = \gamma I \end{array} \right.$$

**Plusieurs sites**

**Coefficients dépendants du temps**

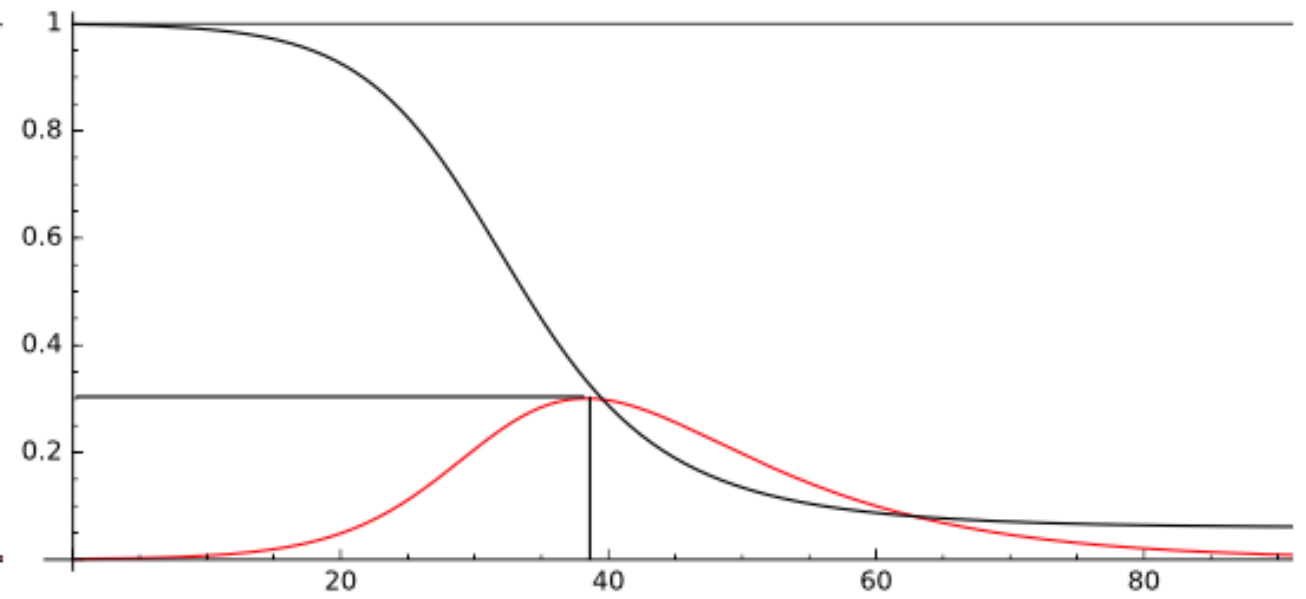
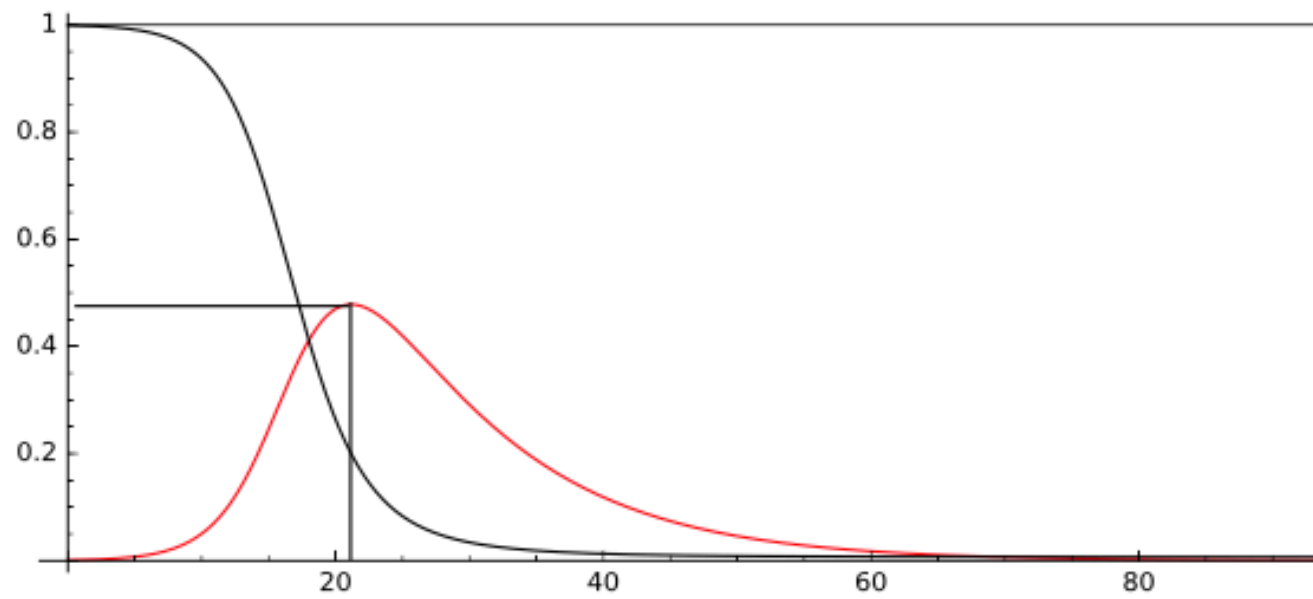
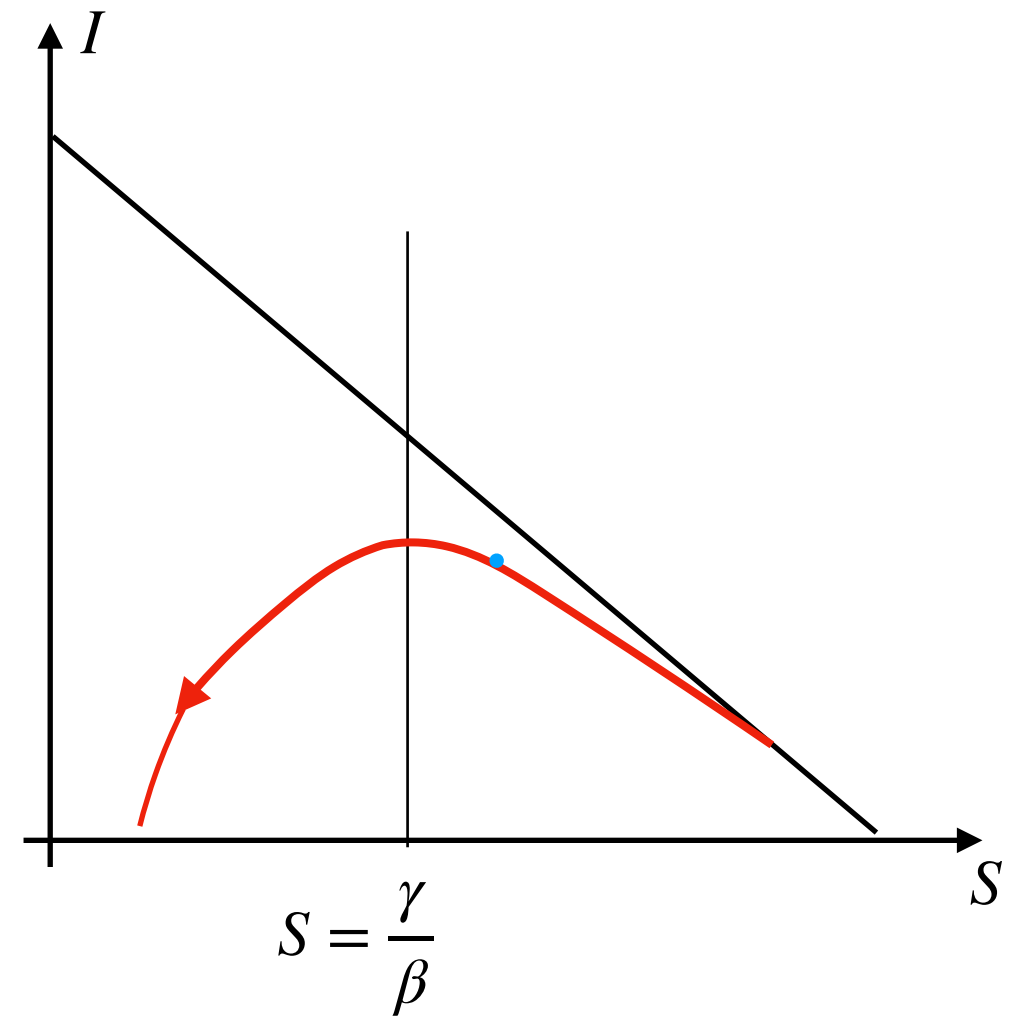
**Deux sites + coefficients périodiques**

**Rappel sur SIR (pour fixer les idées)**

$$S.I.R. \quad \begin{cases} \frac{dS}{dt} = -\beta SI \\ \frac{dI}{dt} = +\beta SI - (\gamma + \mu)I = I(\beta S - (\gamma + \mu)) \\ \frac{dR}{dt} = \gamma I \end{cases}$$

$$\mu \approx 0$$

$$S + I - \frac{\gamma}{\beta} \log(S) = \text{constante}$$

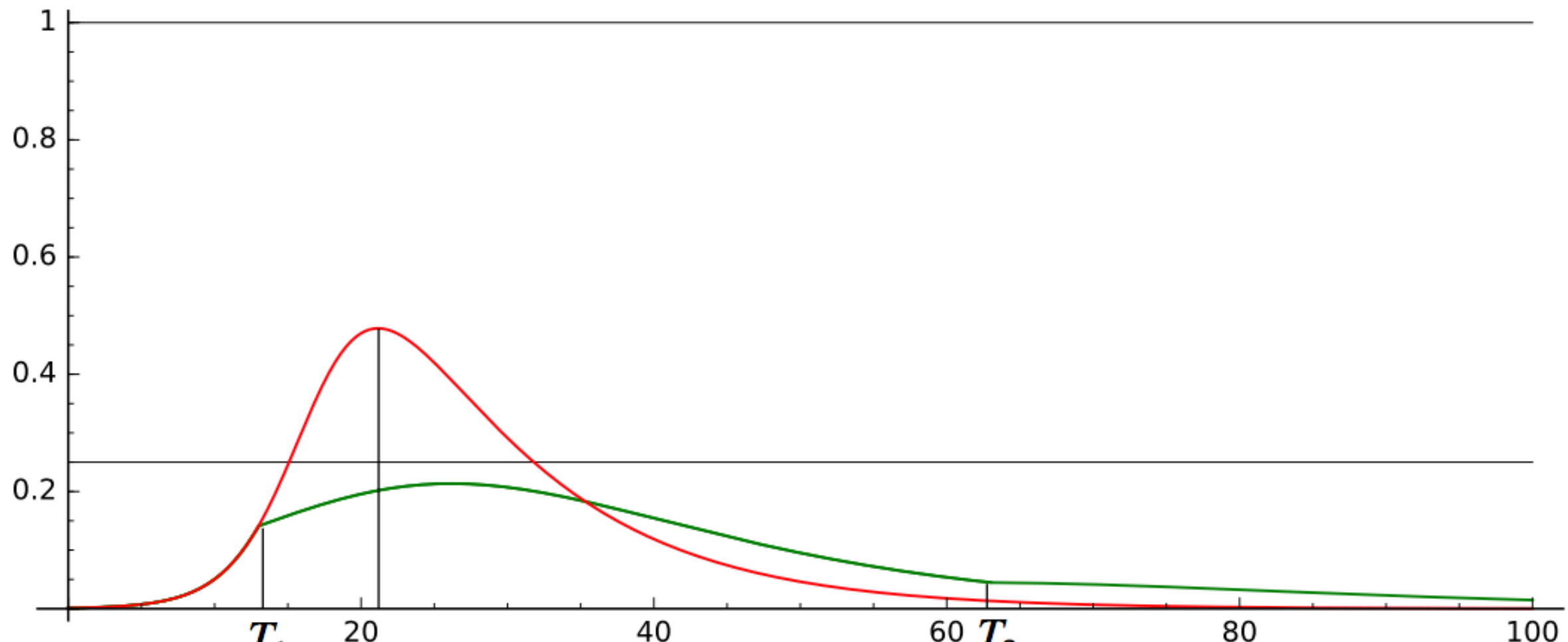
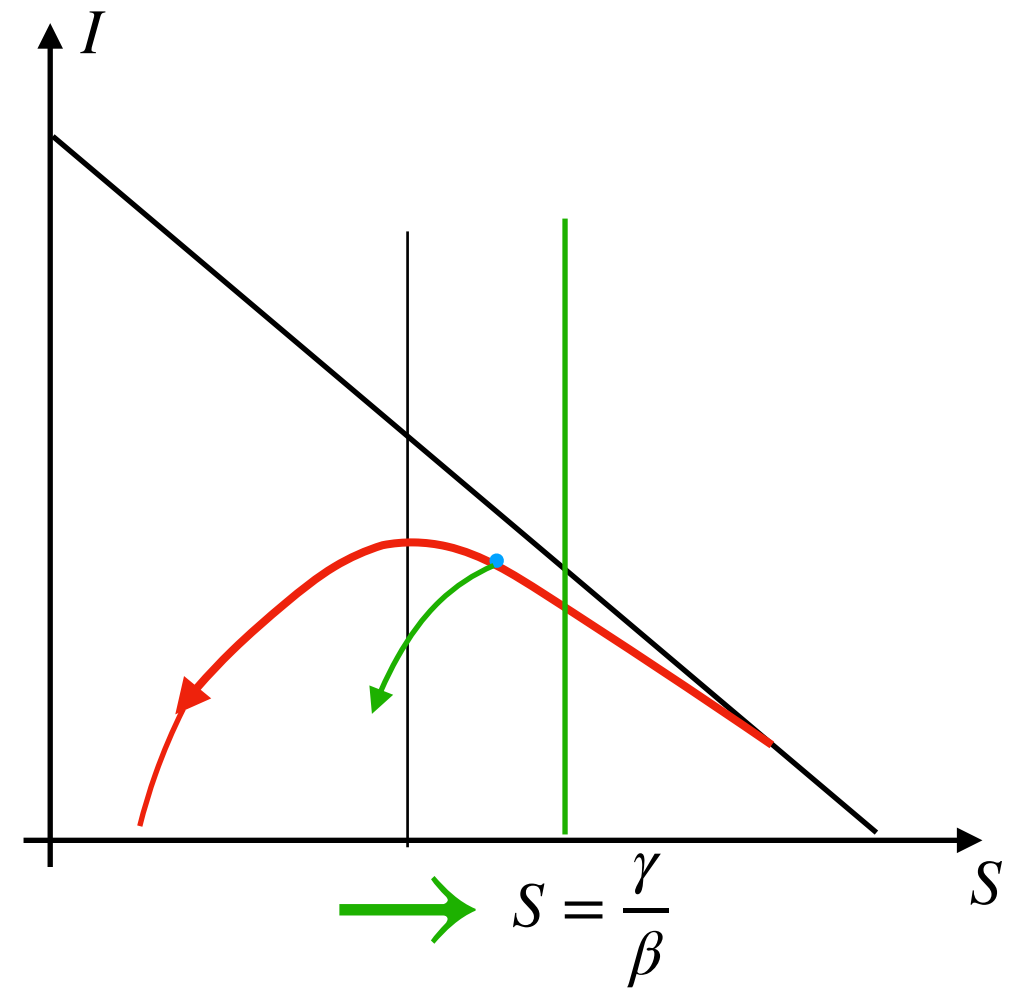


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**Confinement : diminue  $\beta$  et augmente  $\gamma$**

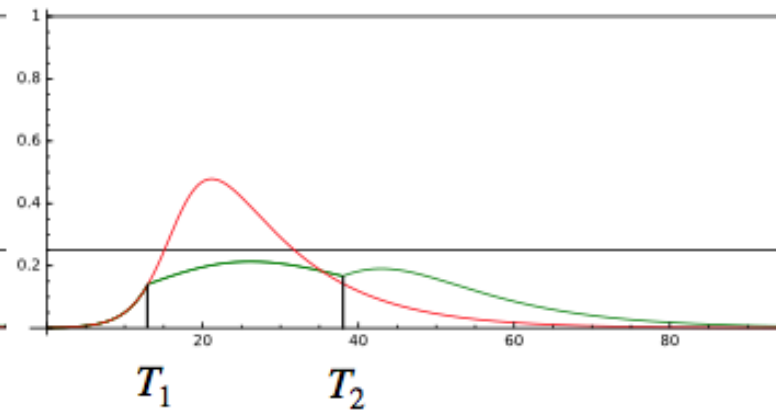
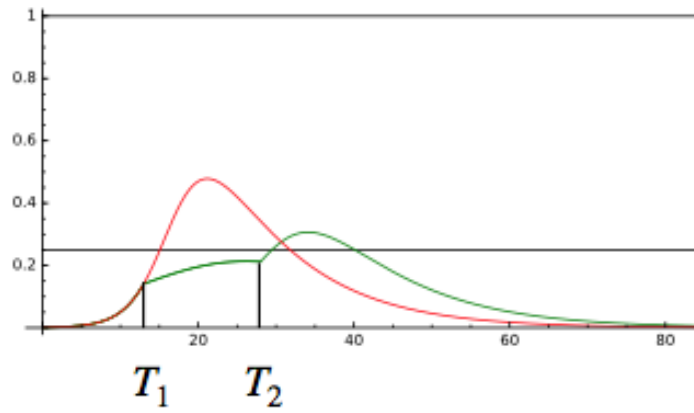
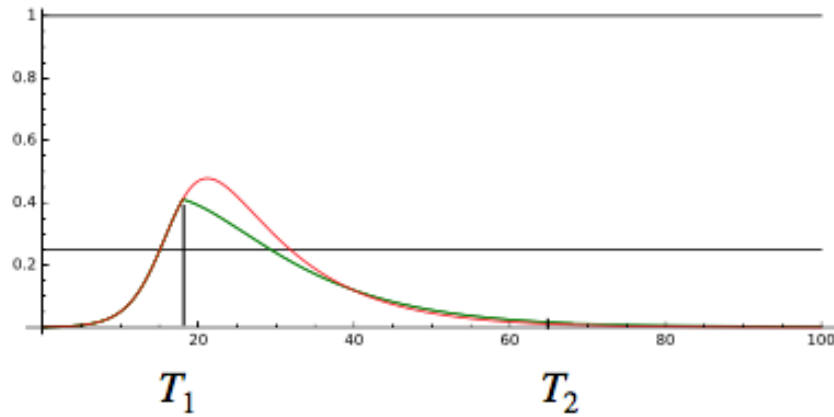
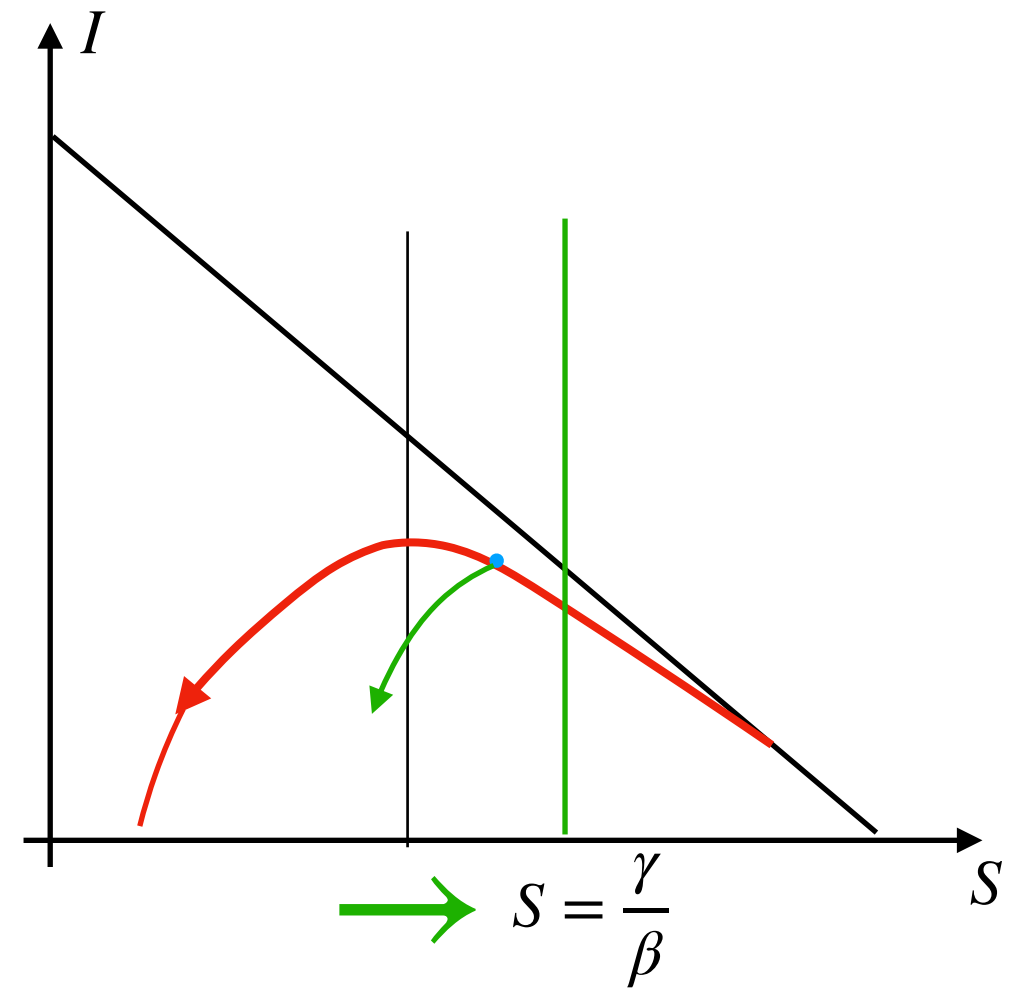


$$S.I.R. \quad \begin{cases} \frac{dS}{dt} = -\beta SI \\ \frac{dI}{dt} = +\beta SI - (\gamma + \mu)I = I(\beta S - (\gamma + \mu)) \\ \frac{dR}{dt} = \gamma I \end{cases}$$

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$$S + I - \frac{\gamma}{\beta} \log(S) = \text{constante}$$

**Confinement : diminue  $\beta$  et augmente  $\gamma$**



## Deux sites $i = 1, 2$

$$\frac{dS_i}{dt} = -S_i I_i \beta_i(t)$$

$$\frac{dI_i}{dt} = S_i I_i \beta_i(t) - [\gamma_i(t) + \mu] I_i$$

$$\frac{dR_i}{dt} = \gamma_i(t) I_i$$

**Le modèle SIR standard**

$$i = 1, 2 \quad j = i + 1(\text{mod } 2)$$

# Deux sites $i = 1, 2$

$$\frac{dS_i}{dt} = -S_i I_i \beta_i(t) - mS_i + mS_j$$

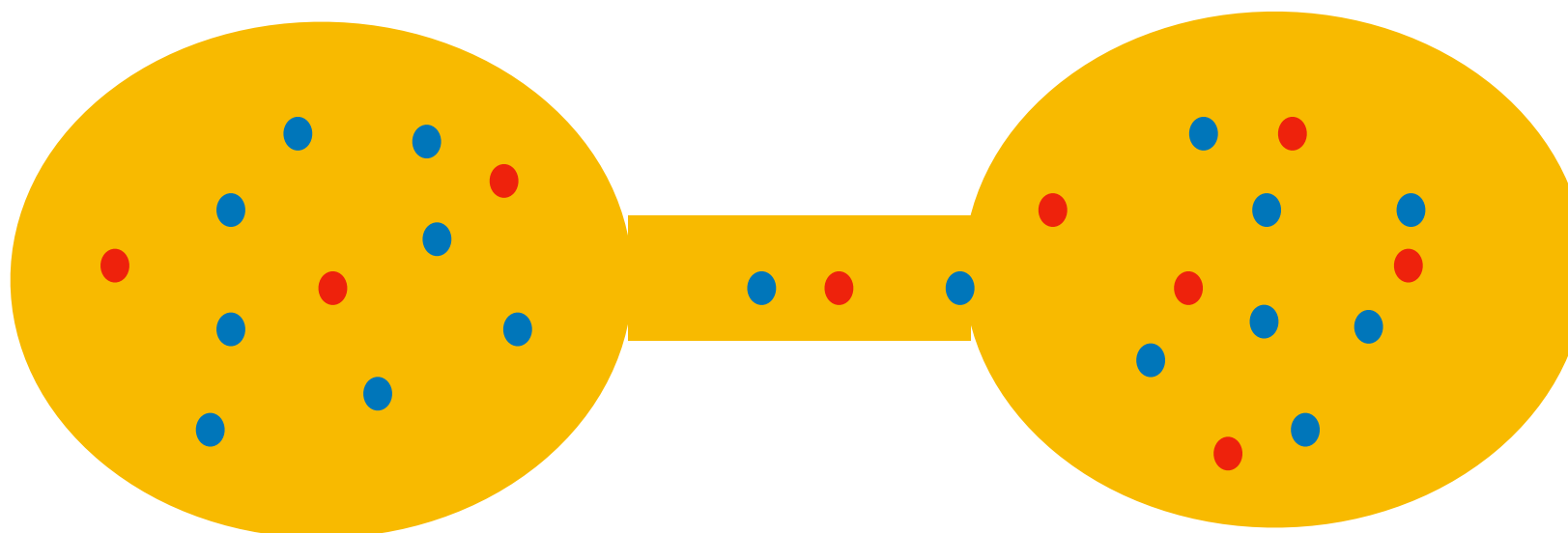
$$\frac{dI_i}{dt} = S_i I_i \beta_i(t) - [\gamma_i(t) + \mu] I_i - mI_i + mI_j$$

$$\frac{dR_i}{dt} = \gamma_i(t) I_i - mR_i + mR_j$$

Le modèle SIR standard

+ Migration

$$i = 1, 2 \quad j = i + 1(\text{mod } 2)$$





## Deux sites $i = 1, 2$

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$$\frac{dR_i}{dt} = \gamma_i(t) I_i - mR_i + mR_j$$

Le modèle SIR standard

+ Migration

Même politique sanitaire sur chaque site

$$\beta_1(t) = \beta_2(t)$$

$$\gamma_1(t) = \gamma_2(t)$$

# Deux sites $i = 1, 2$

$$\frac{dS_i}{dt} = -S_i I_i \beta_i(t) - mS_i + mS_j$$

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$$\frac{dR_i}{dt} = \gamma_i(t) I_i - mR_i + mR_j$$

Le modèle SIR standard

+ Migration

Même politique sanitaire sur chaque site

$$\beta_1(t) = \beta_2(t)$$

$$\gamma_1(t) = \gamma_2(t)$$

Mais déphasée

$$\beta_1(t + \varphi) = \beta_2(t) \quad \gamma_1(t + \varphi) = \gamma_2(t)$$

## Paramètres hors mesures sanitaires

$$\frac{dS_i}{dt} = -S_i I_i \beta_i(t) - mS_i + mS_j$$

$$\frac{dI_i}{dt} = S_i I_i \beta_i(t) - [\gamma_i(t) + \mu] I_i - mI_i + mI_j$$

$$\frac{dR_i}{dt} = \gamma_i(t) I_i - mR_i + mR_j$$

$$\beta_i^- = 0.1988$$

$$\gamma_i^- = 0.098$$

$$\mu_i^- = 0.002$$

## Paramètres avec mesures sanitaires

$$\beta_i^+ = 0.0288$$

$$\gamma_i^+ = 0.128$$

$$\mu_i^+ = 0.002$$

$$I_i(0) = 0.001$$

$$S_i(0) = 0.999$$

$$1 = 10^6 \text{ individus}$$

	$\left[0, \frac{T}{2}\right]$	$\left[\frac{T}{2}, T\right]$
Site n°1	+	—
Site n°2	—	+

**Ce sont les paramètres de Holt et al.**

$$\frac{dS_i}{dt} = -S_i I_i \beta_i(t) - mS_i + mS_j$$

$$\frac{dI_i}{dt} = S_i I_i \beta_i(t) - [\gamma_i(t) + \mu] I_i - mI_i + mI_j$$

$$\frac{dR_i}{dt} = \gamma_i(t) I_i - mR_i + mR_j$$

	$\left[ 0 , \frac{T}{2} \right]$	$\left[ \frac{T}{2} , T \right]$
Site n°1	+	—
Site n°2	—	+

**Site 1 = vertueux :  
confine tout de suite**

**Site 2 = laxiste :  
tarde à confiner**

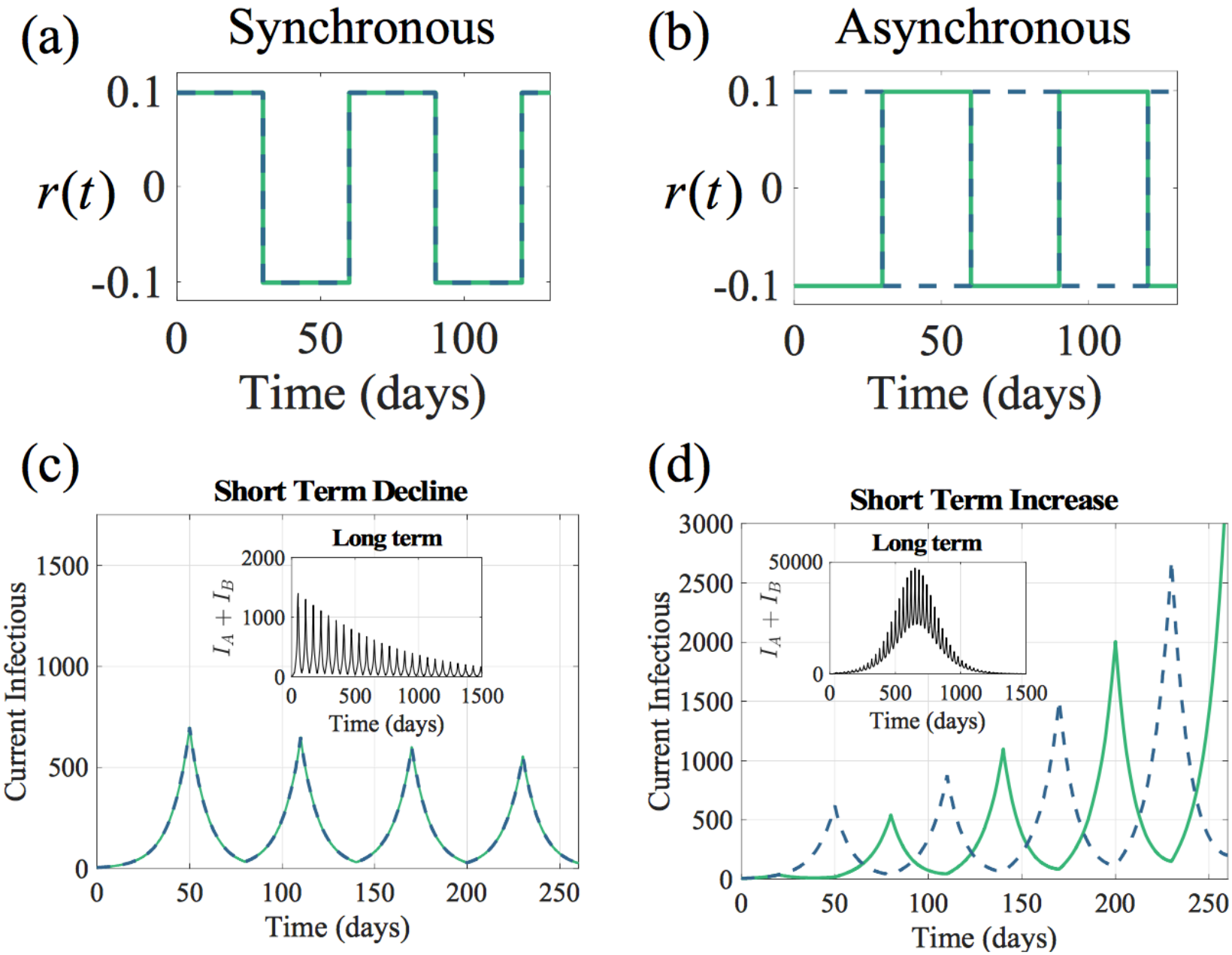
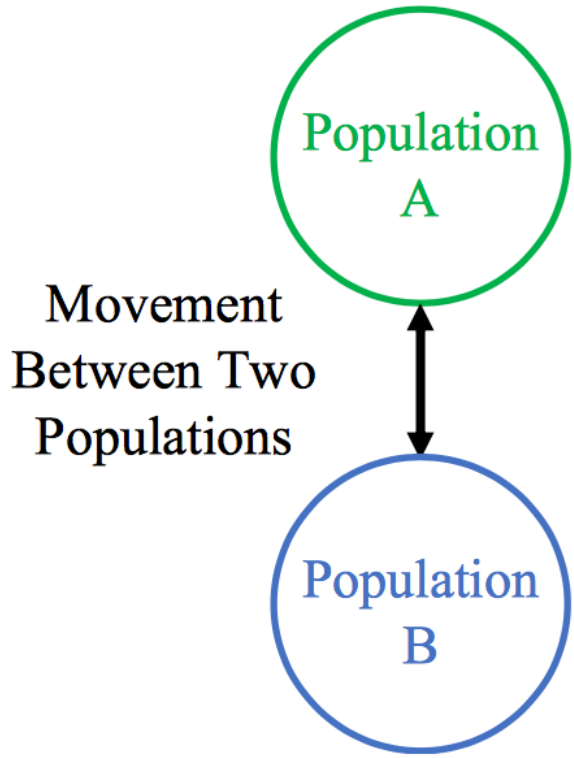
**Paramètres à explorer : T et m**

Figures

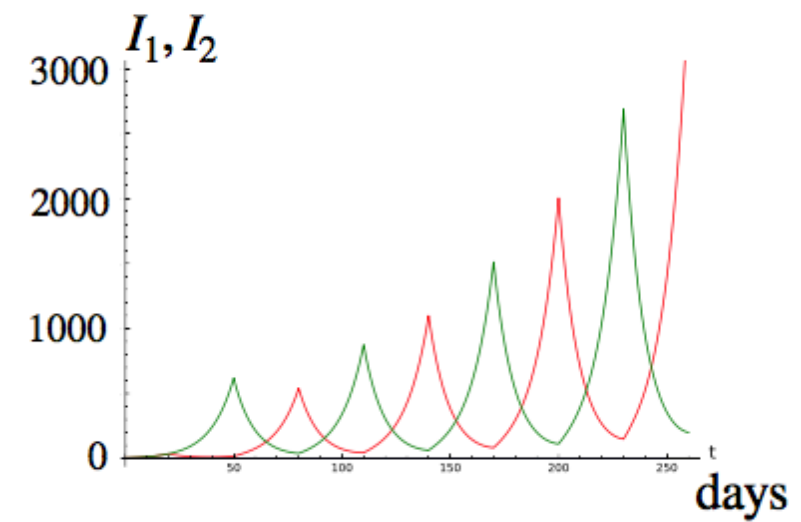
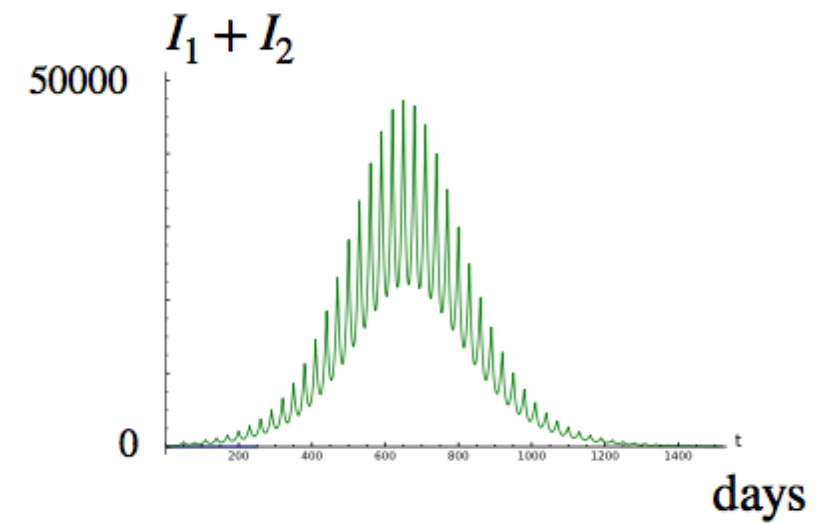
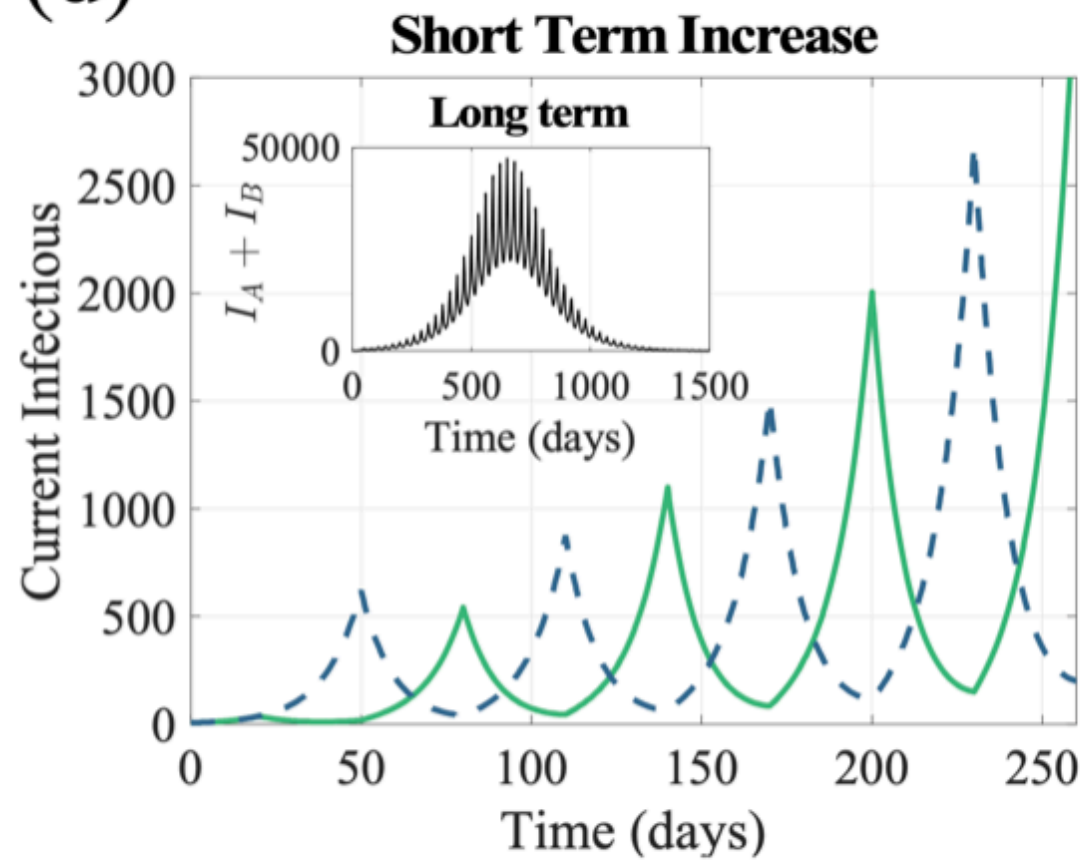
Staggering Disease Mitigation Strategies Can Fail

Time-Varying  
Transmission Dynamics

$$r_i(t) = \underbrace{N_i \beta_i(t)}_{\text{Transmission}} - \underbrace{\gamma_i(t)}_{\text{Recovery}} - \underbrace{\mu}_{\text{Mortality}}$$



(d)

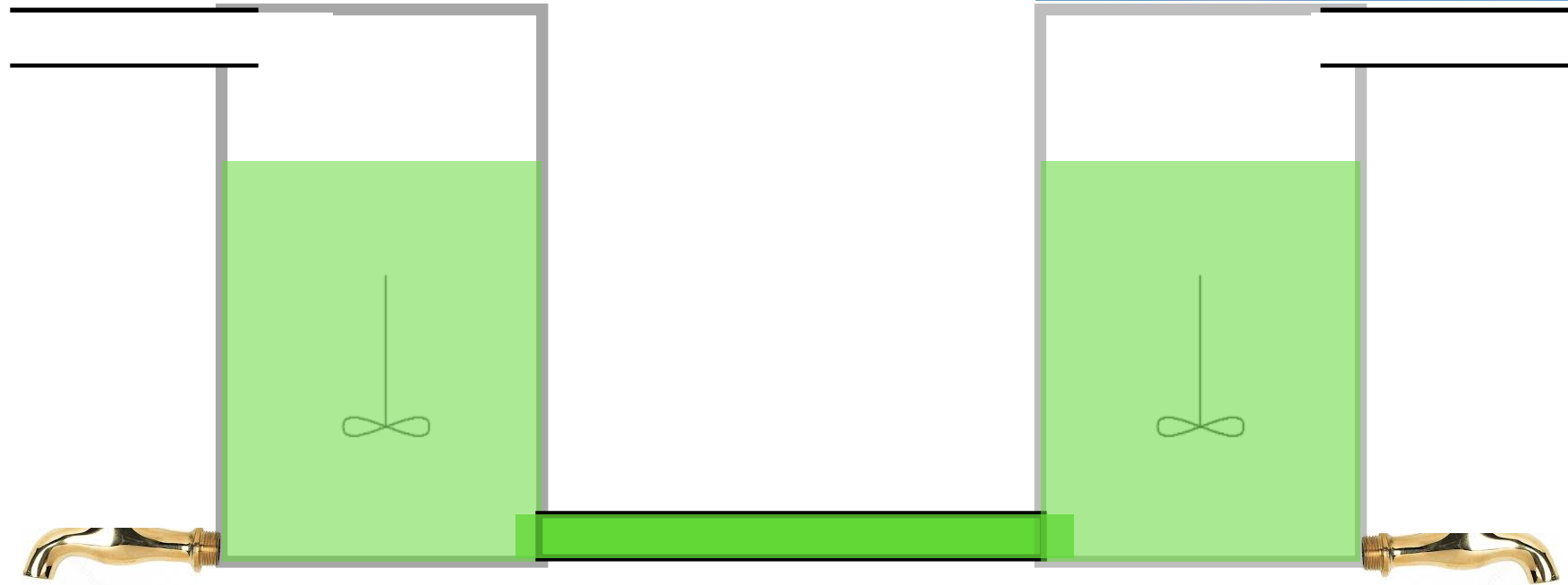


**Même modèle  
simulé par moi**

$\beta_n N = 0.1988$	$\gamma_n = 0.098$	$\mu_n = 0.002$
$\beta_s N = 0.0288$	$\gamma_s = 0.128$	$\mu_s = 0.002$

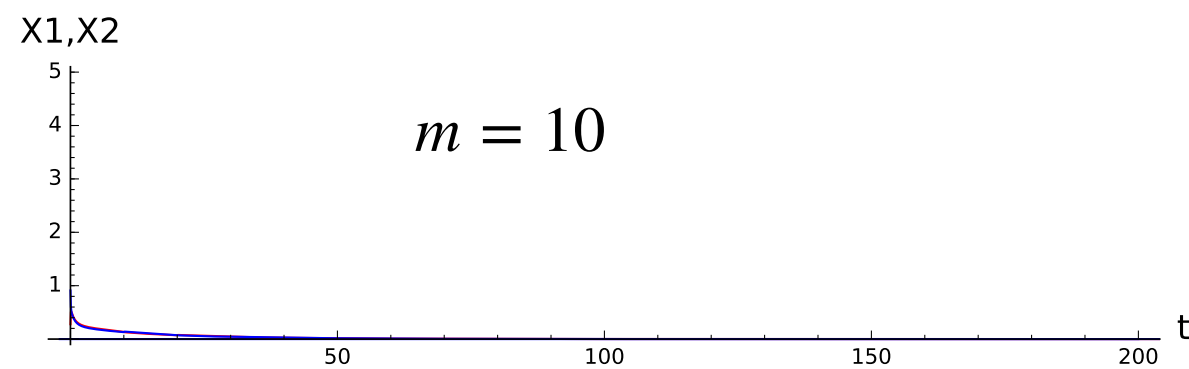
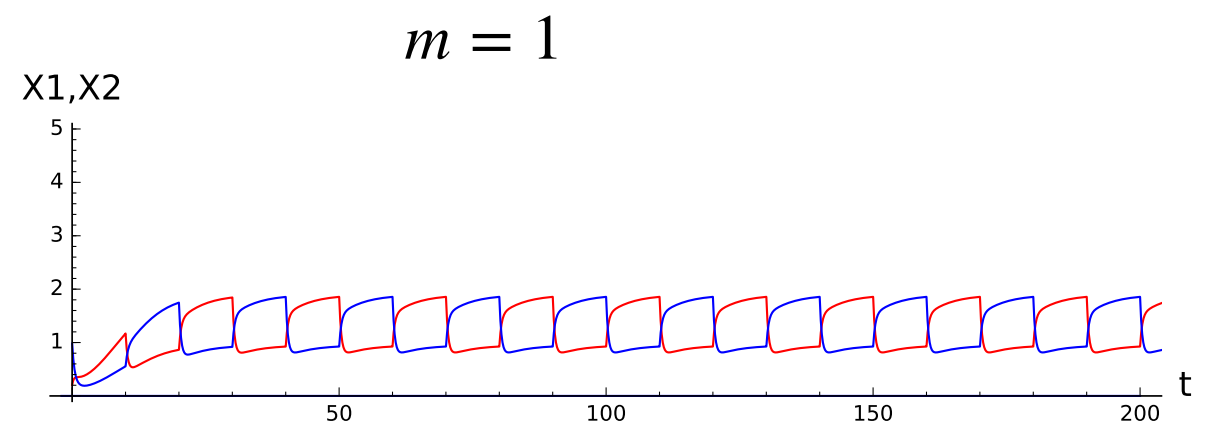
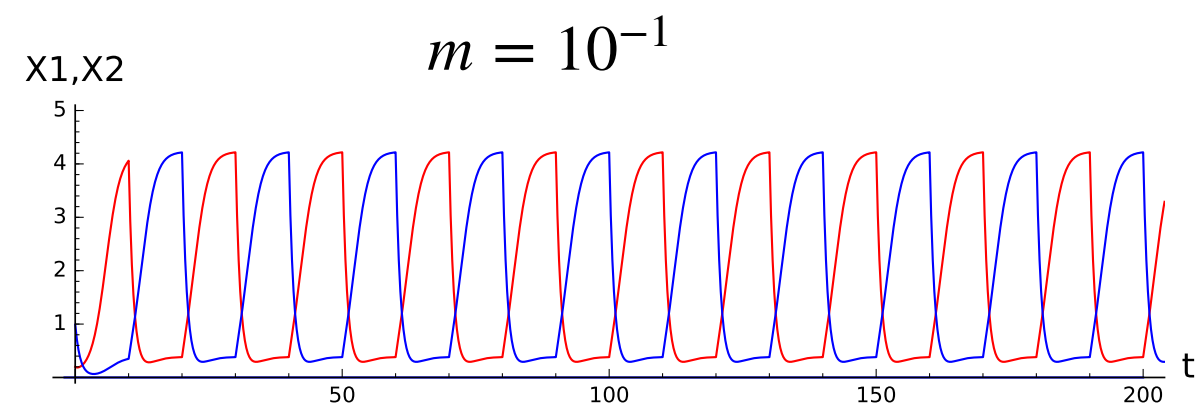
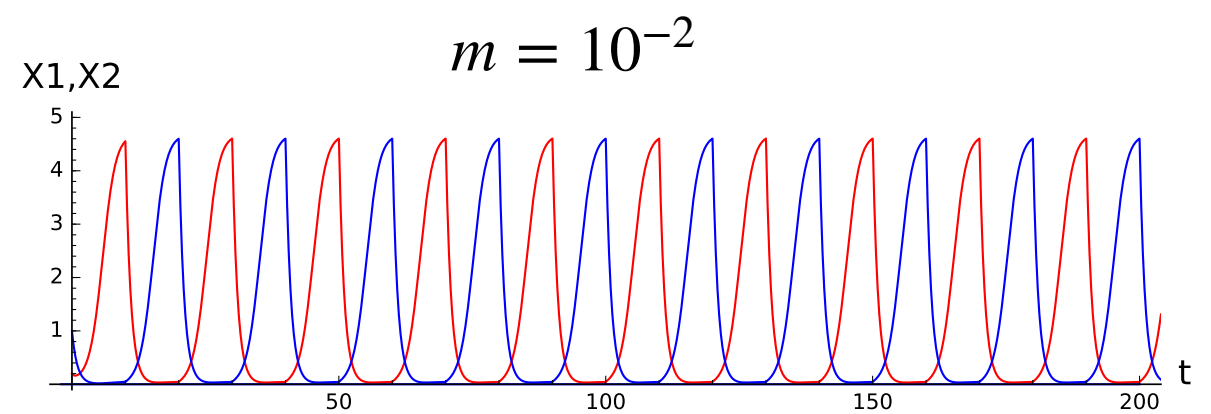
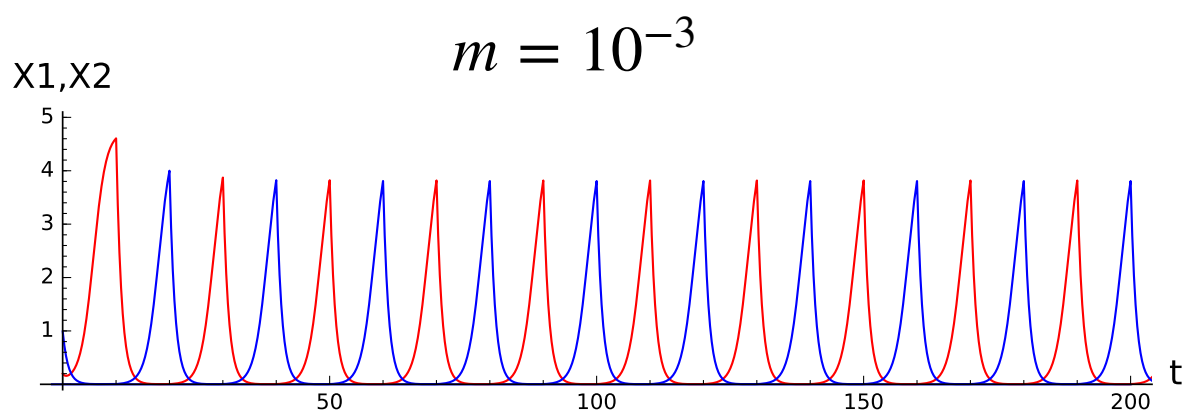
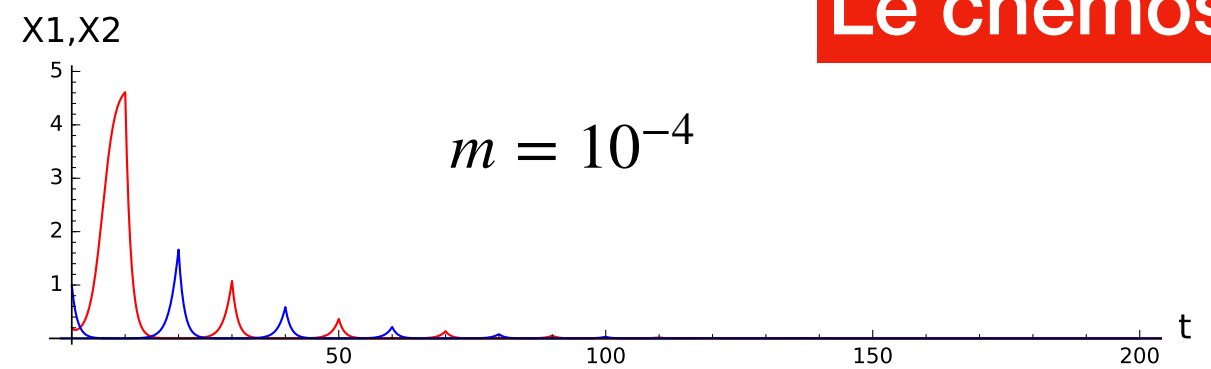
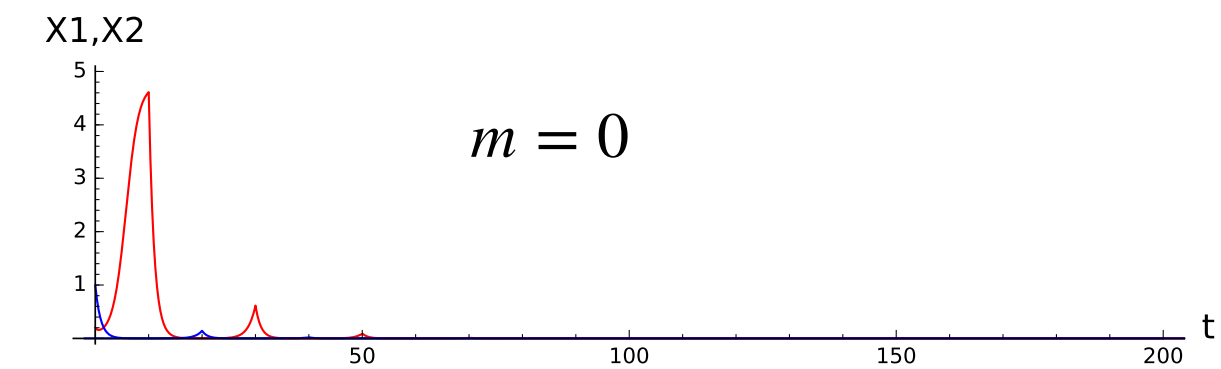
$\beta_n N - (\gamma_n + \mu_n) = 0.0988$
$\beta_s N - (\gamma_s + \mu_s) = -0.1012$

**Parenthèse sur le chémostat**





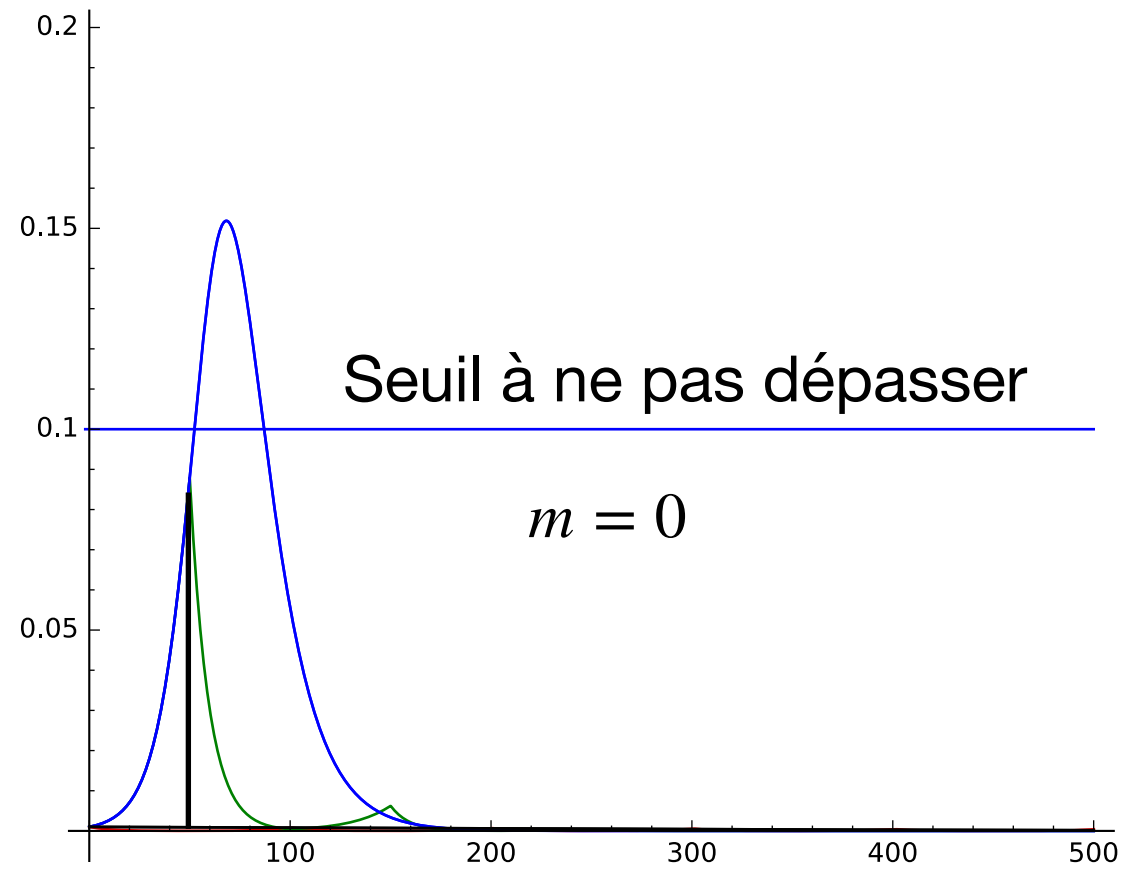
$$\left\{ \begin{array}{l} \frac{ds_1}{dt} = D(S_{in} - s_1) - r_1(t)\mu(s)x_1 + m(s_2 - s_1) \\ \frac{dx_1}{dt} = (r_1(t)\mu(s) - D)x_1 + m(x_2 - x_1) \\ \frac{ds_2}{dt} = D(S_{in} - s_2) - r_2(t)\mu(s)x_2 + m(s_1 - s_2) \\ \frac{dx_2}{dt} = (r_2(t)\mu(s_2) - D)x_2 + m(x_1 - x_2) \end{array} \right.$$



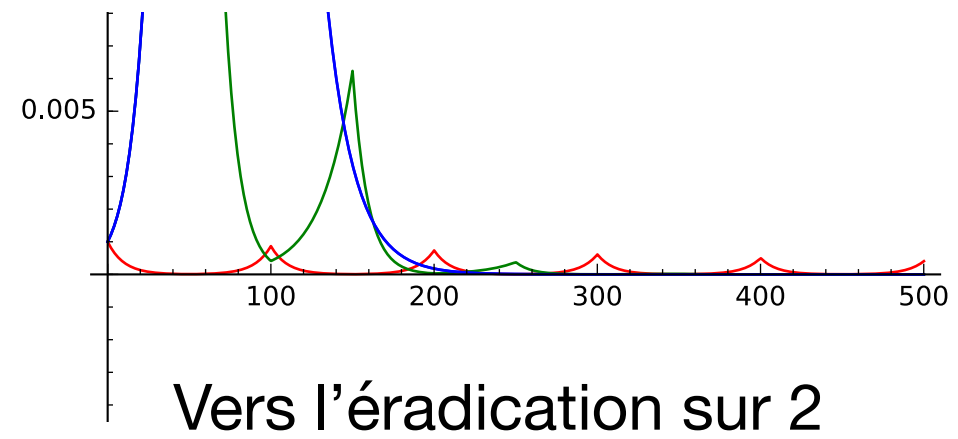
**Fin parenthèse**

**T = 100**

**Modèle diffusion**

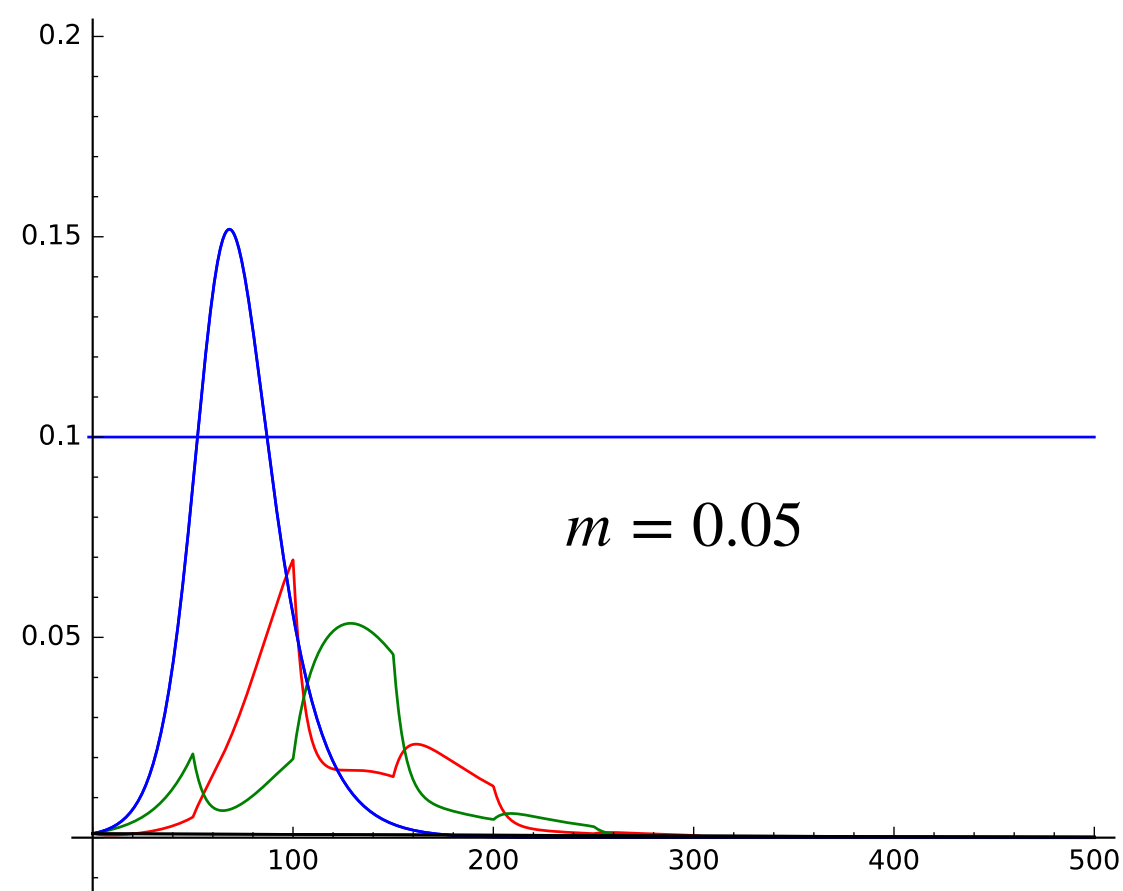
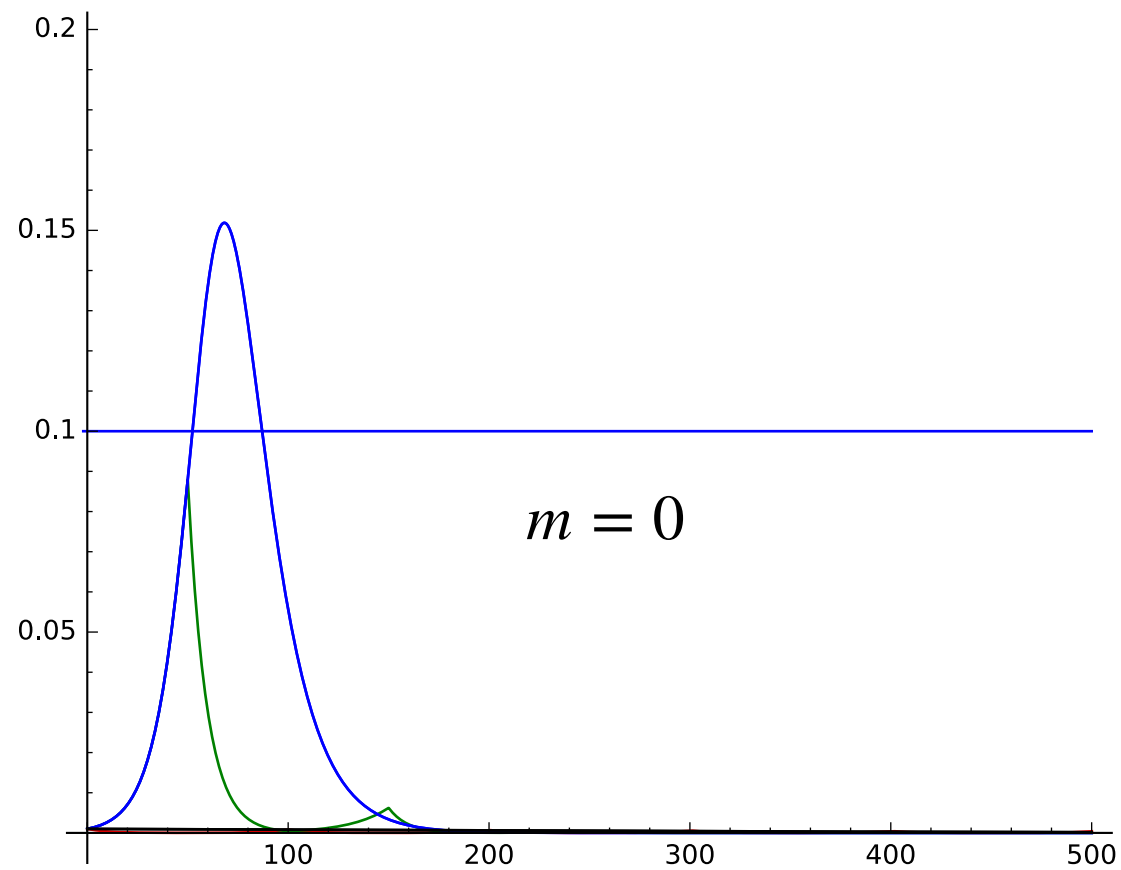


**Politique tardive sur 1 : passe de justesse**



**T = 100**

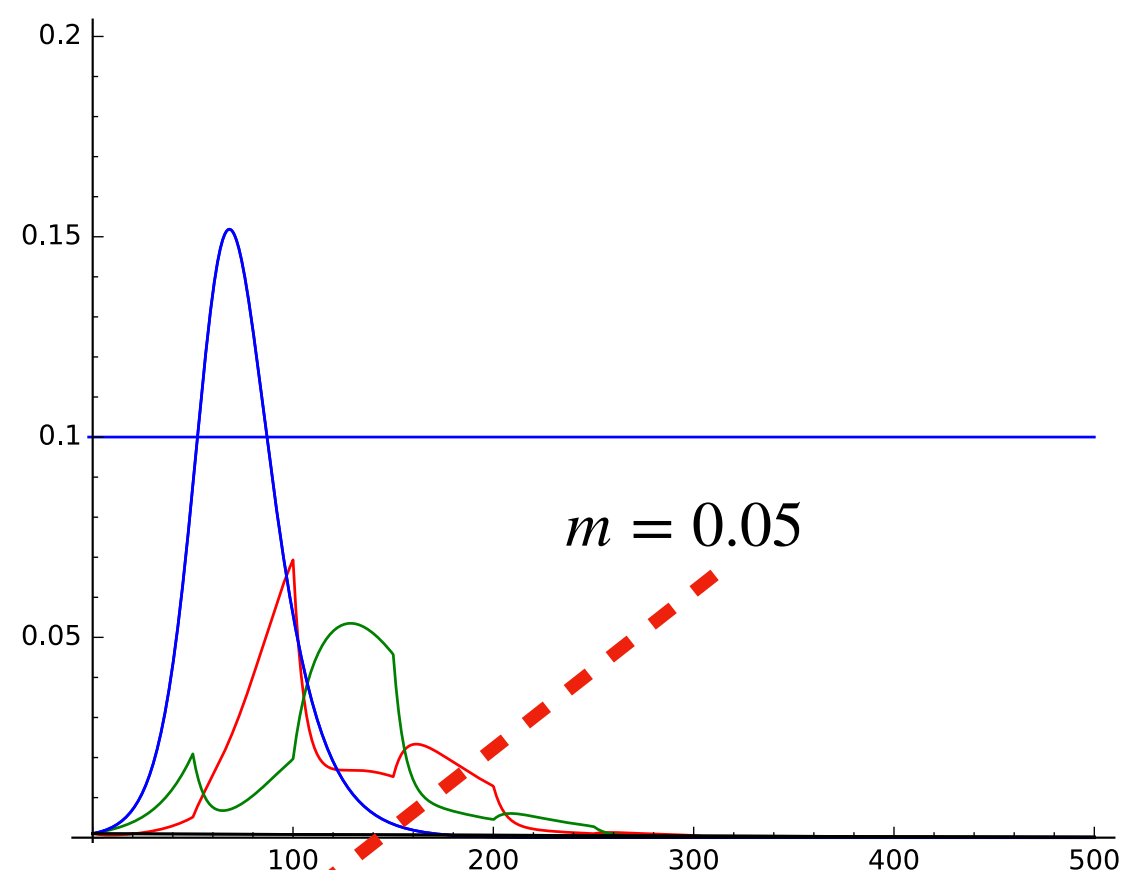
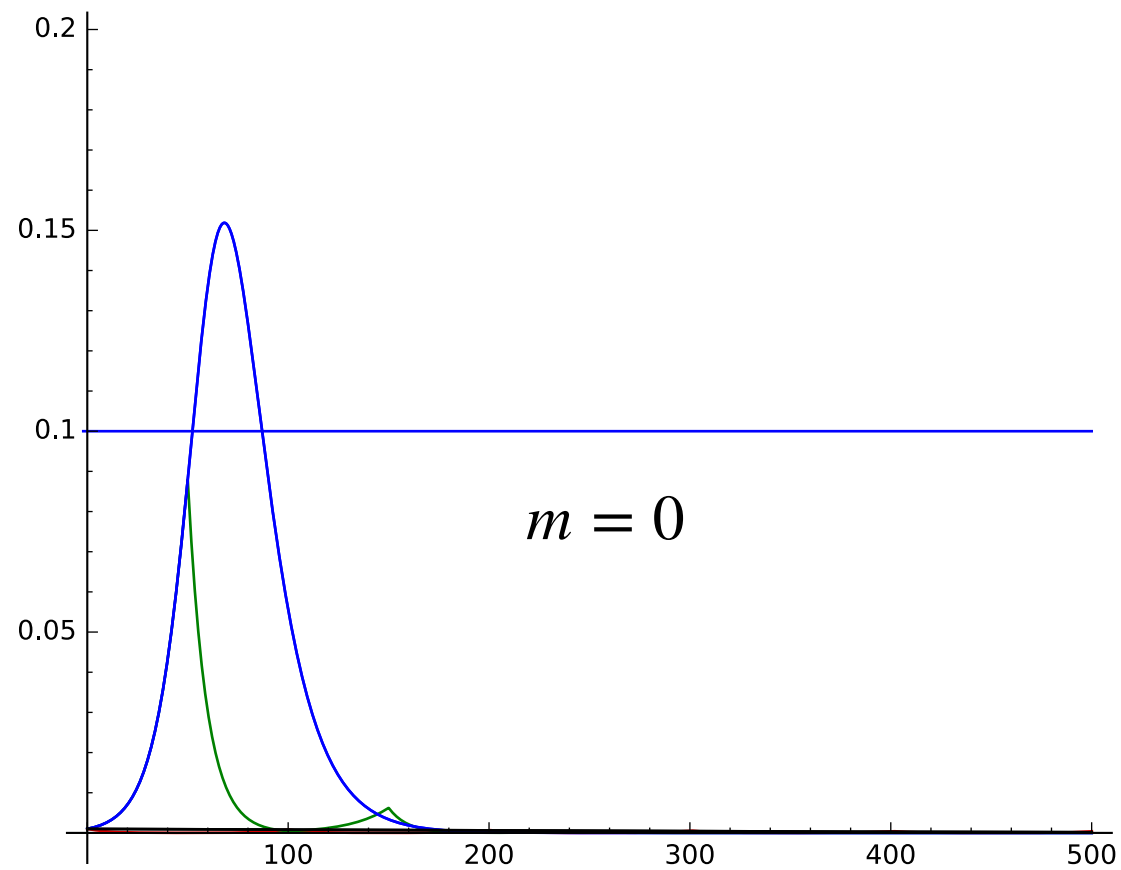
**Modèle diffusion**



La migration menace le site vertueux

**T = 100**

Modèle diffusion

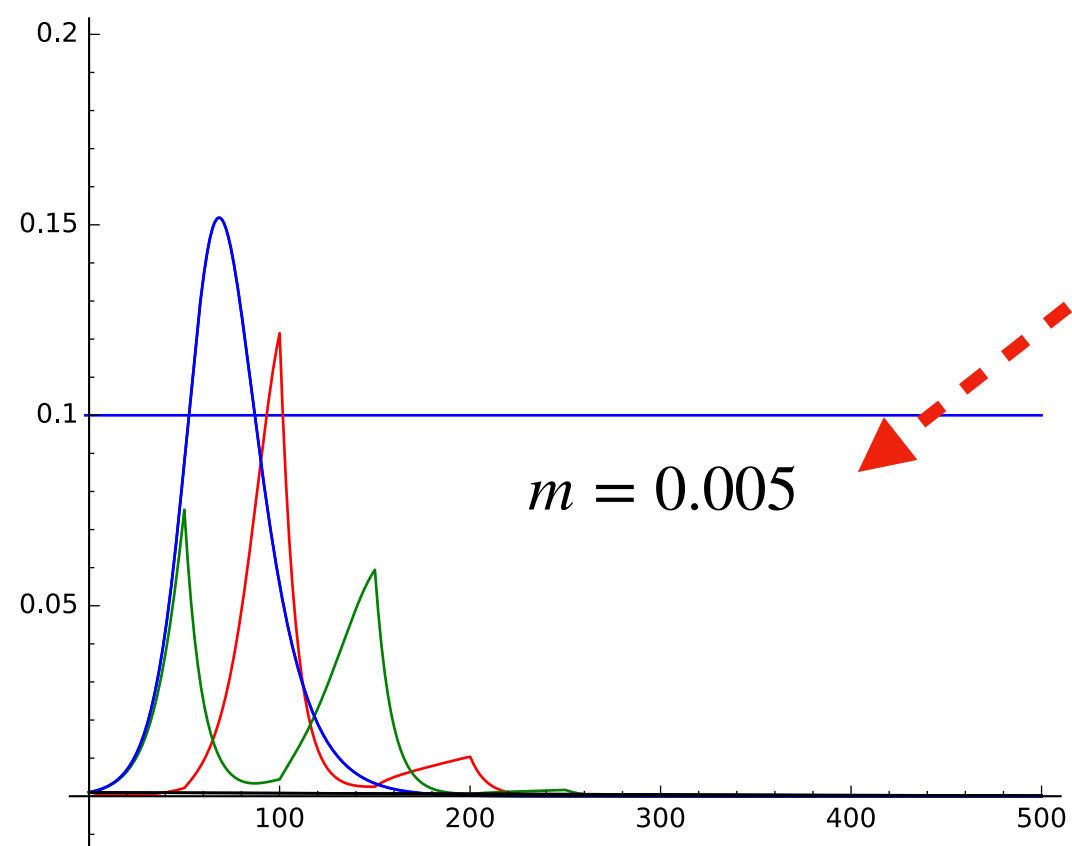
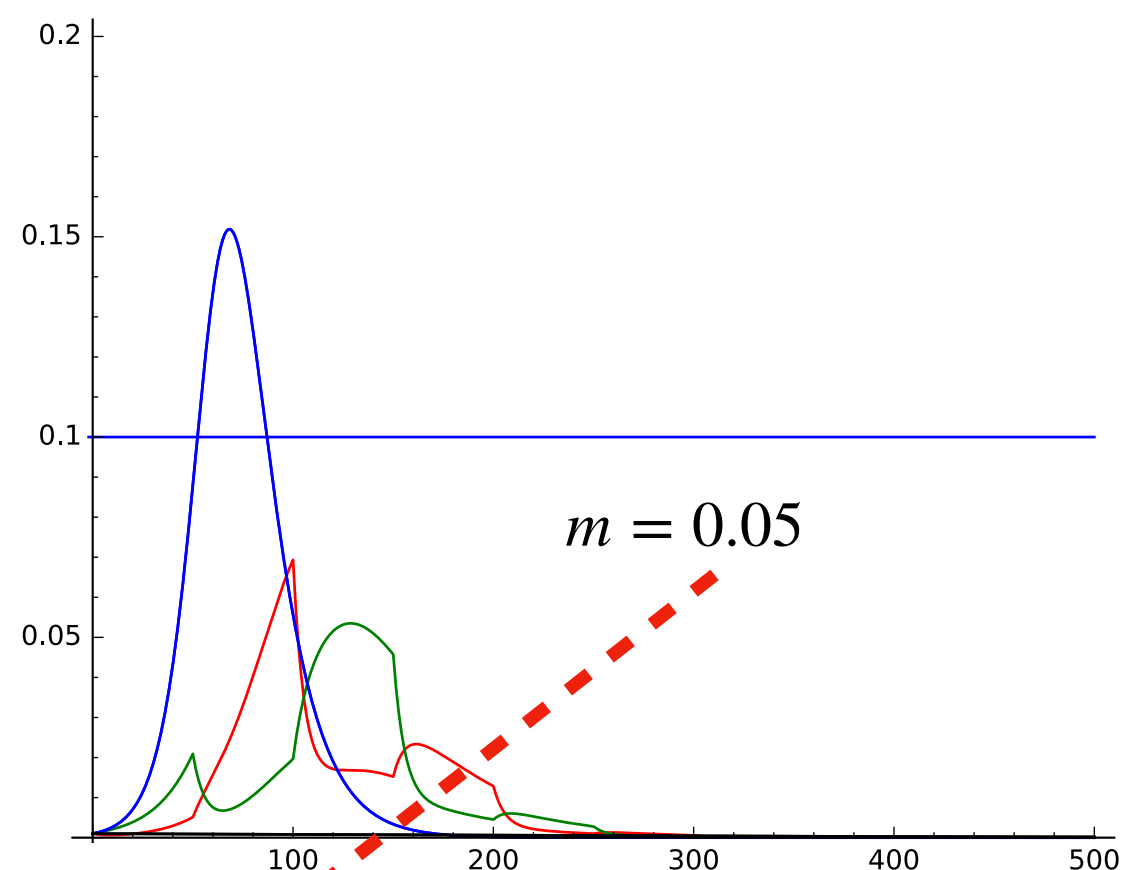
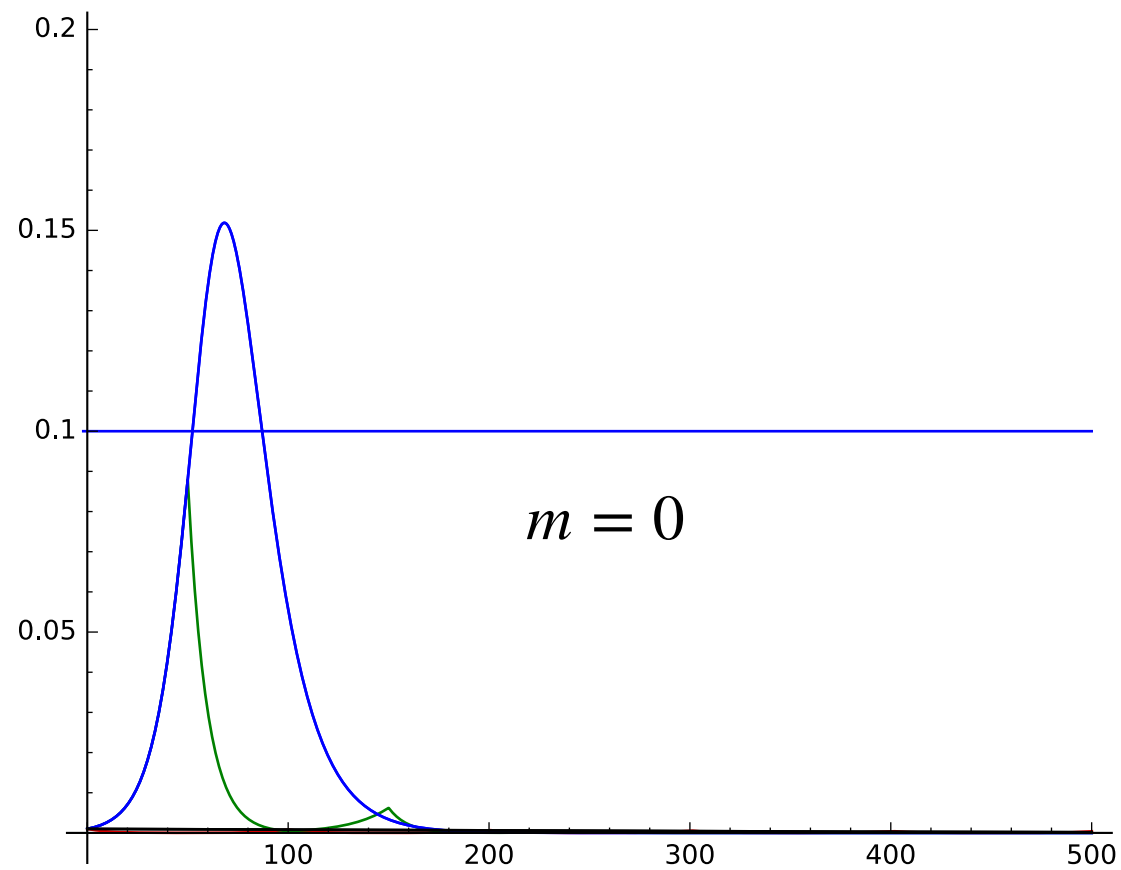


$m = 0.005$

Contrôle des frontières

**T = 100**

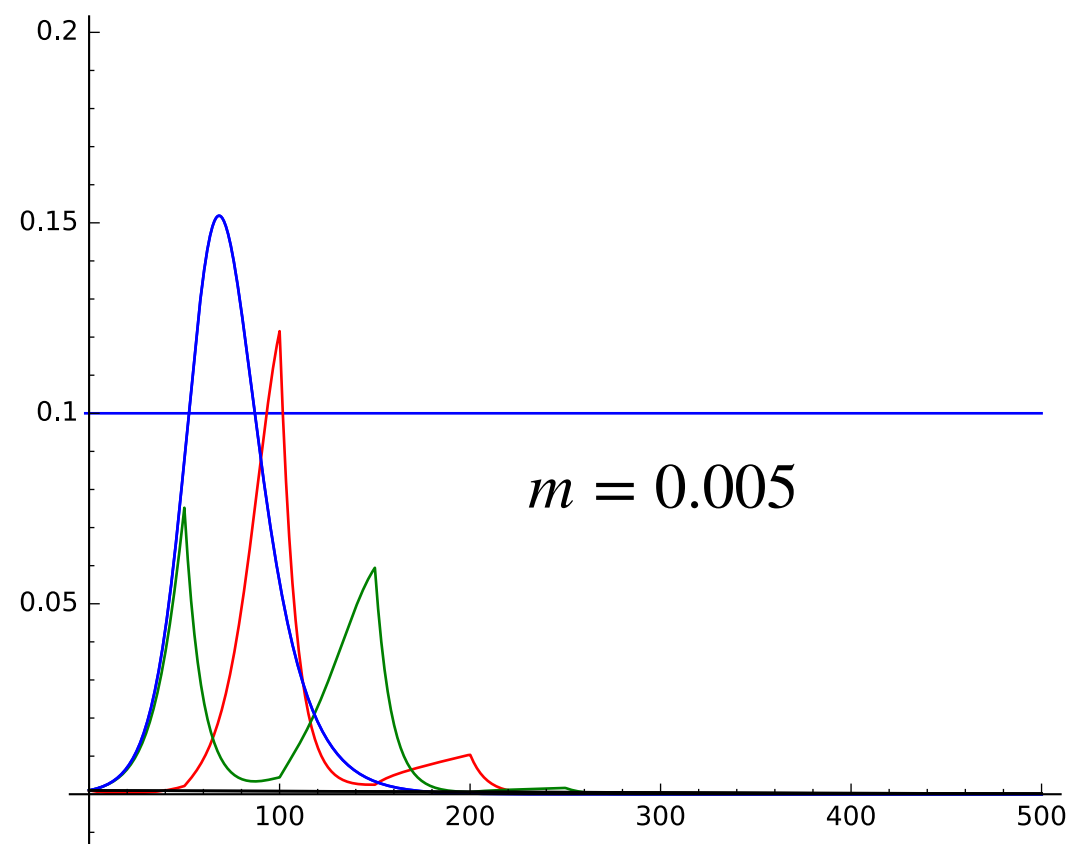
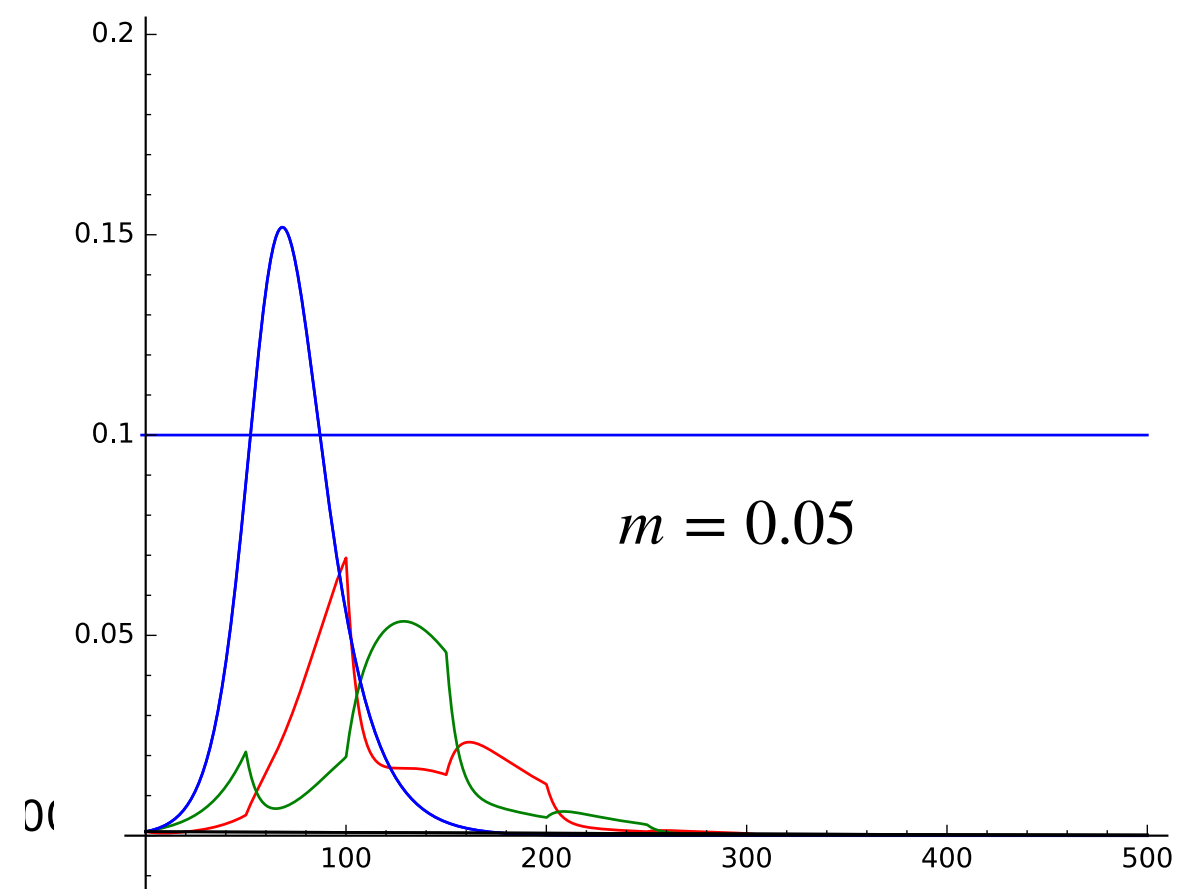
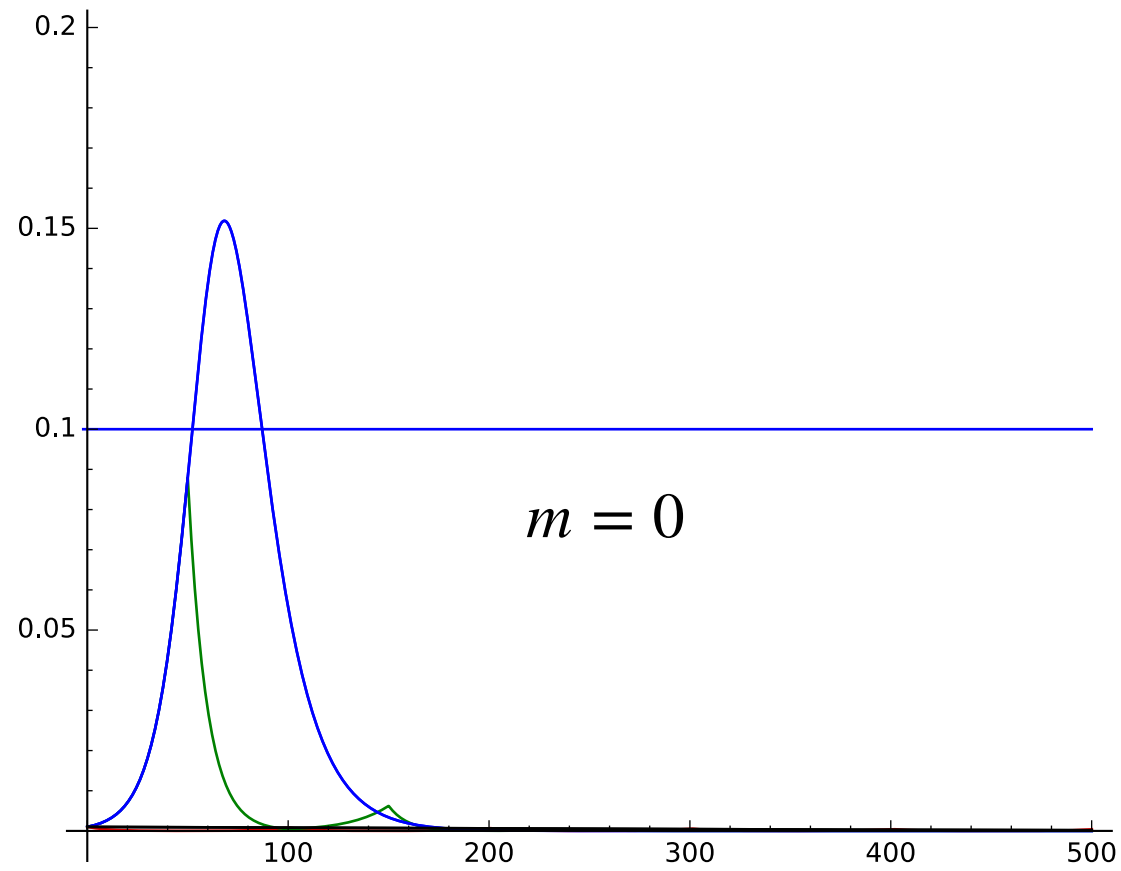
**Modèle diffusion**



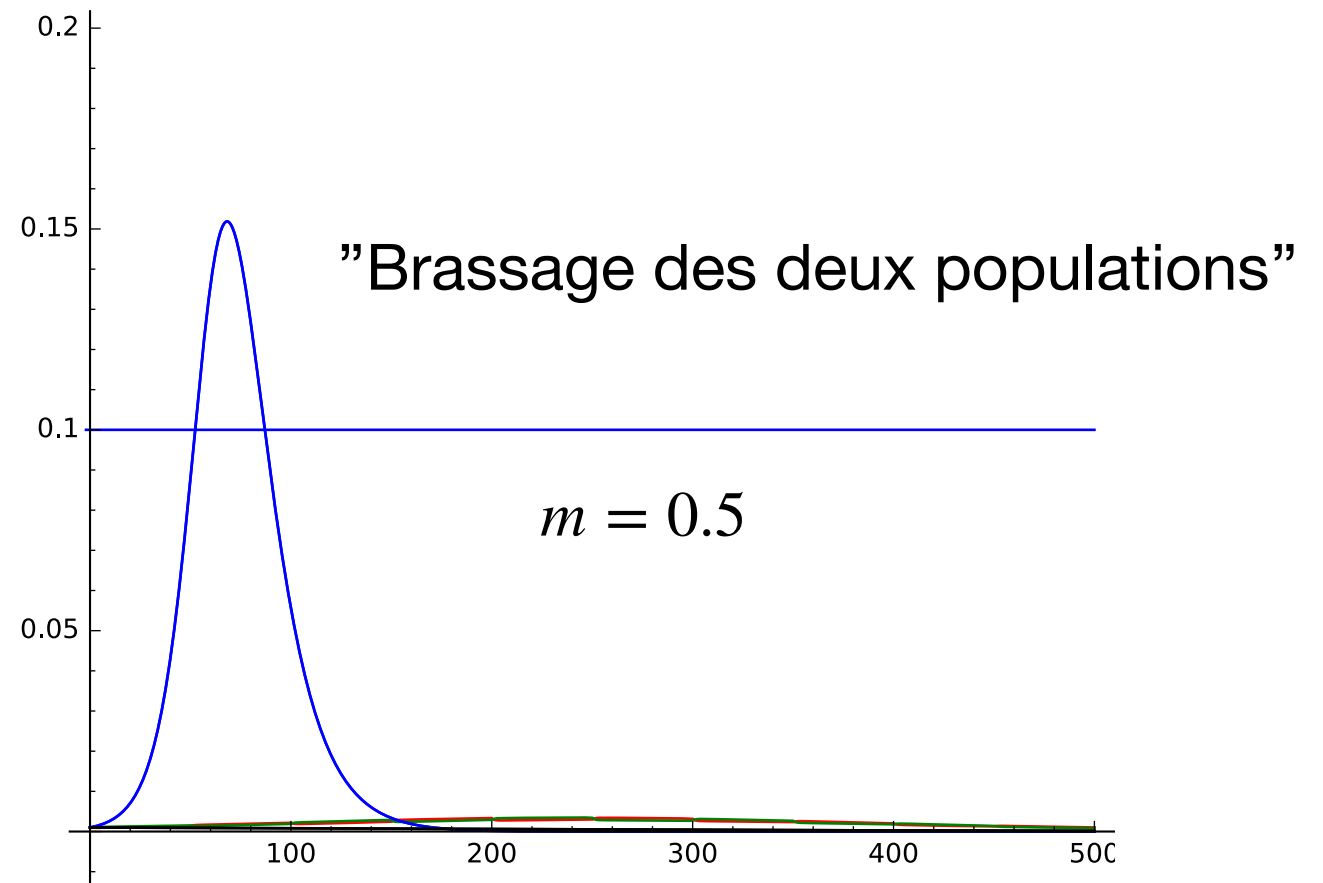
Contrôle des frontières

**T = 100**

Modèle diffusion



50





# Le Modèle-( $\pm 1$ )

**Au démarrage de l'épidémie**

~~$$\frac{dS_i}{dt} = -S_i I_i \beta_i(t) - mS_i + mS_j$$~~

$$\frac{dI_i}{dt} = S_i I_i \beta_i(t) - [\gamma_i(t) + \mu] I_i - mI_i + mI_j.$$

~~$$\frac{dR_i}{dt} = \gamma_i(t) I_i - mR_i + mR_j$$~~

$$S_i \approx 1$$

$$\frac{dI_1}{dt} = r_1(t) I_1 + m(I_2 - I_1)$$

$$\frac{dI_2}{dt} = r_2(t) I_2 + m(I_1 - I_2)$$

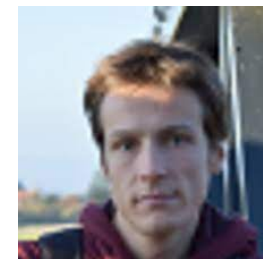
$$\frac{dI_1}{dt} = (1 \times \beta_1 - \gamma_1 - \mu_1) I_1 + m(I_2 - I_1)$$

$$\frac{dI_2}{dt} = (1 \times \beta_2 - \gamma_2 - \mu_2) I_2 + m(I_1 - I_2)$$

**Système linéaire en dimension 2**

Analyse (presque) triviale

*Work in progress....*



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T.S. INRAE Montpellier

E.S. Institut Élie Cartan de Lorraine

} = **BLSS**

Le modèle le plus simple qui contient les caractéristiques essentielles de l'**inflation**

$$\Sigma(\varepsilon, m, T) \quad \left\{ \begin{array}{l} \frac{dx_1}{dt} = (+u(t) - \varepsilon)x_1 + m(x_2 - x_1) \\ \frac{dx_2}{dt} = (-u(t) - \varepsilon)x_2 + m(x_1 - x_2) \end{array} \right.$$

$$t \in [0, T[ \Rightarrow u(t) = 1 \quad t \in [T, 2T[ \Rightarrow u(t) = -1$$



# Dispersal-induced growth in a time-periodic environment

Guy Katriel<sup>1</sup> 

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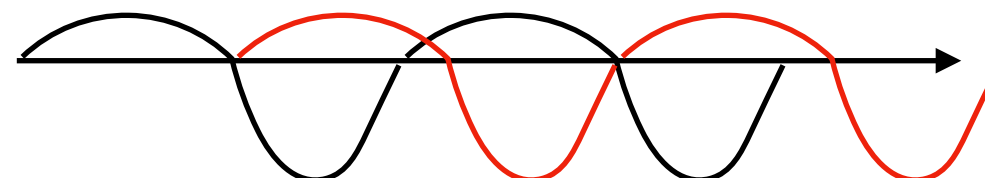
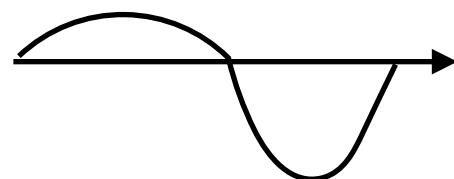
## Une remarque (importante) de G. Katriel

$$\frac{dx}{dt} = r(t)x \quad x(T) = x(0) \exp \left( \int_0^T r(s) ds \right)$$

$$\frac{dx_1}{dt} = r_1(t)x_1 + m(x_2 - x_1)$$

$$\frac{dx_2}{dt} = r_2(t)x_2 + m(x_1 - x_2)$$

$$\frac{d(x_1 + x_2)}{dt} \leq \max(r_1(t), r_2(t))(x_1 + x_2)$$





# Dispersal-induced growth in a time-periodic environment

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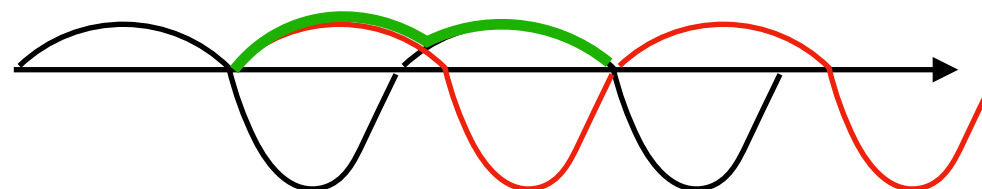
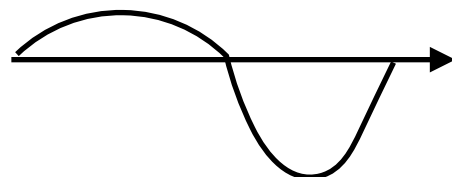
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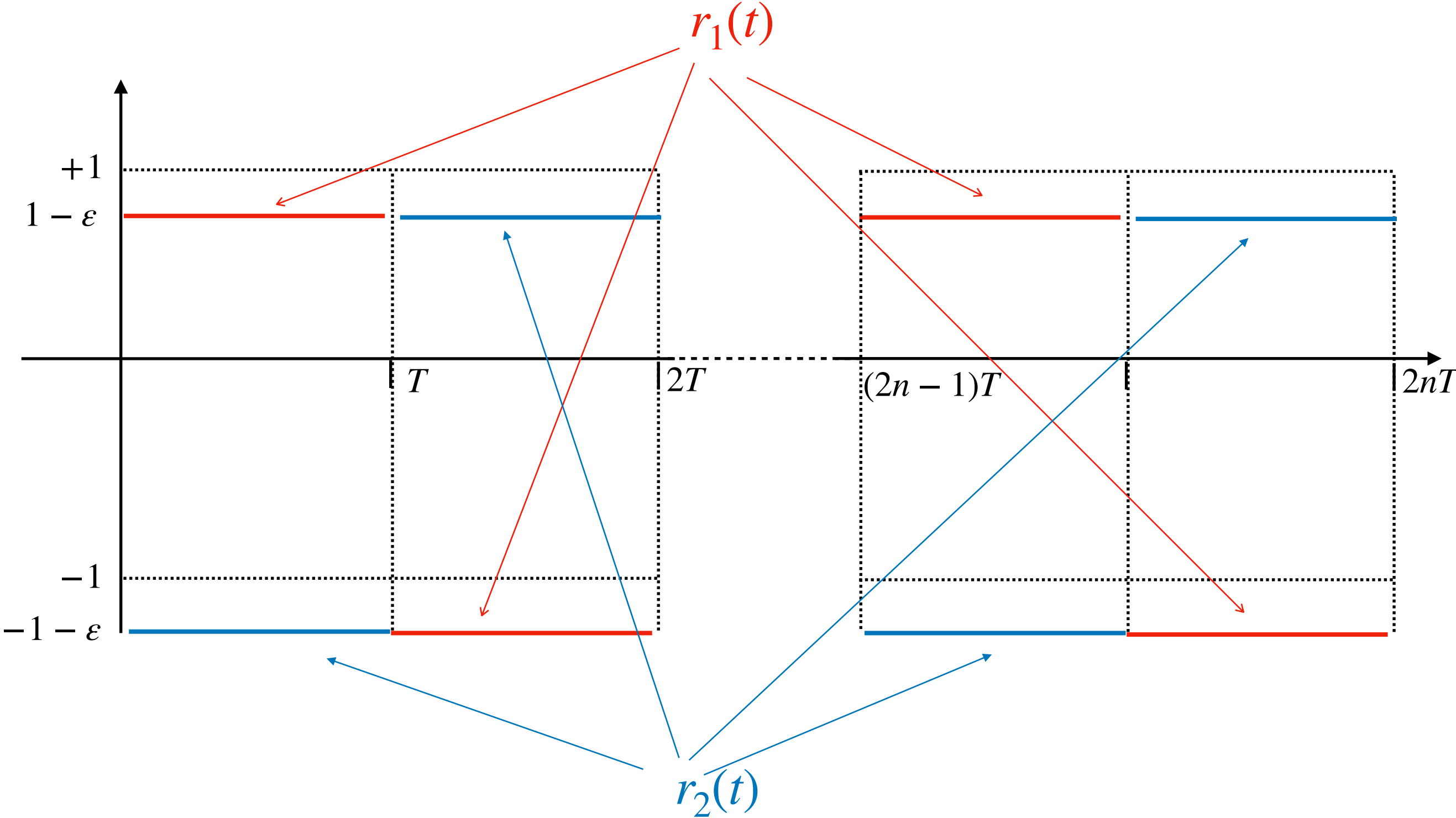
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$$\frac{d(x_1 + x_2)}{dt} \leq \max(r_1(t), r_2(t))(x_1 + x_2)$$



Le modèle ( $\pm 1$ )



**Les seconds membres discontinus ne posent pas de problèmes**

**Systemes commutés**



$$\Sigma(\varepsilon, m, T) \quad \left\{ \begin{array}{l} \frac{dx_1}{dt} = (+u(t) - \varepsilon)x_1 + m(x_2 - x_1) \\ \frac{dx_2}{dt} = (-u(t) - \varepsilon)x_2 + m(x_1 - x_2) \end{array} \right.$$

$$t \in [0, T[ \Rightarrow u(t) = 1 \quad t \in [T, 2T[ \Rightarrow u(t) = -1$$

**Système périodique de périodes  $2T$**

**Considéré comme .....**

$$\begin{array}{ll}
 \Sigma^+(\varepsilon, m) & \left\{ \begin{array}{l} \frac{dx_1}{dt} = (+1 - \varepsilon)x_1 + m(x_2 - x_1) \\ \frac{dx_2}{dt} = (-1 - \varepsilon)x_2 + m(x_1 - x_2) \end{array} \right. \quad \begin{array}{l} \text{sur } [0, T[ \\ \\ \text{commute} \end{array} \\
 \Sigma^-(\varepsilon, m) & \left\{ \begin{array}{l} \frac{dx_1}{dt} = (-1 - \varepsilon)x_1 + m(x_2 - x_1) \\ \frac{dx_2}{dt} = (+1 - \varepsilon)x_2 + m(x_1 - x_2) \end{array} \right. \quad \begin{array}{l} \text{sur } [T, 2T[ \\ \\ \text{commute} \end{array} \\
 \Sigma^+(\varepsilon, m) & \left\{ \begin{array}{l} \frac{dx_1}{dt} = (+1 - \varepsilon)x_1 + m(x_2 - x_1) \\ \frac{dx_2}{dt} = (-1 - \varepsilon)x_2 + m(x_1 - x_2) \end{array} \right. \quad \begin{array}{l} \text{sur } [2T, 3T[ \\ \\ \text{etc...} \end{array}
 \end{array}$$

Une façon d'introduire les PDMP

....les durées successives ne sont pas constantes, mais des v.a. indépendantes

$$\begin{array}{lcl}
 \Sigma^+(\varepsilon, m) & \left\{ \begin{array}{l} \frac{dx_1}{dt} = (+1 - \varepsilon)x_1 + m(x_2 - x_1) \\ \frac{dx_2}{dt} = (-1 - \varepsilon)x_2 + m(x_1 - x_2) \end{array} \right. & \begin{array}{l} \text{sur } [0, T[ \\ T_1 \end{array} \\
 \Sigma^-(\varepsilon, m) & \left\{ \begin{array}{l} \frac{dx_1}{dt} = (-1 - \varepsilon)x_1 + m(x_2 - x_1) \\ \frac{dx_2}{dt} = (+1 - \varepsilon)x_2 + m(x_1 - x_2) \end{array} \right. & \begin{array}{l} \text{sur } [T, 2T[ \\ T_2 \end{array} \\
 \Sigma^+(\varepsilon, m) & \left\{ \begin{array}{l} \frac{dx_1}{dt} = (+1 - \varepsilon)x_1 + m(x_2 - x_1) \\ \frac{dx_2}{dt} = (-1 - \varepsilon)x_2 + m(x_1 - x_2) \end{array} \right. & \begin{array}{l} \text{sur } [2T, 3T[ \\ T_3 \end{array} \\
 & & \text{etc...}
 \end{array}$$

$$T_1, T_2, \dots, T_n, \dots$$

$$P(T < x) = \frac{1}{\lambda} \int_0^x e^{-\lambda t} dt$$

$$E[T] = \frac{1}{\lambda}$$

....les durées successives ne sont pas constantes, mais des v.a. indépendantes

$$\Sigma^+(\varepsilon, m) \quad \begin{cases} \frac{dx_1}{dt} = (+1 - \varepsilon)x_1 + m(x_2 - x_1) \\ \frac{dx_2}{dt} = (-1 - \varepsilon)x_2 + m(x_1 - x_2) \end{cases}$$

~~sur  $[0, T[$~~   $T_1$

commute

$$\Sigma^-(\varepsilon, m) \quad \begin{cases} \frac{dx_1}{dt} = (-1 - \varepsilon)x_1 + m(x_2 - x_1) \\ \frac{dx_2}{dt} = (+1 - \varepsilon)x_2 + m(x_1 - x_2) \end{cases}$$

~~sur  $[T, 2T[$~~   $T_2$

$$\Sigma^+(\varepsilon, m) \quad \begin{cases} \frac{dx_1}{dt} = (+1 - \varepsilon)x_1 + m(x_2 - x_1) \\ \frac{dx_2}{dt} = (-1 - \varepsilon)x_2 + m(x_1 - x_2) \end{cases}$$

$$T_1, T_2, \dots, T_n, \dots \quad P(T < x) = \frac{1}{\lambda} \int_0^x e^{-\lambda t} dt \quad E[T] = \frac{1}{\lambda}$$

$\lambda = 10$

1.30918738247732)  
1.6896908115807752)  
6.409479737184405)  
11.47888404120739)  
2.449504973595646)  
0.7323416871722689)  
1.3192797900626687)  
9.589230475300862)  
1.5408555851557373)  
3.601378318397804)  
9.775184895956325)  
0.24849029174721698)  
2.788466773217008)  
4.576052287994896)  
17.208079692209598)  
11.806385212760608)  
3.851421482224009)  
24.928717042065404)

$$\Sigma(\varepsilon, m, T) \quad \left\{ \begin{array}{l} \frac{dx_1}{dt} = (+u(t) - \varepsilon)x_1 + m(x_2 - x_1) \\ \frac{dx_2}{dt} = (-u(t) - \varepsilon)x_2 + m(x_1 - x_2) \end{array} \right.$$

$$t \in [0, T[ \Rightarrow u(t) = 1 \quad t \in [T, 2T[ \Rightarrow u(t) = -1$$

$$\begin{pmatrix} x_1(2T) \\ x_2(2T) \end{pmatrix} = M(\varepsilon, m, T) \begin{pmatrix} x_1(0) \\ x_2(0) \end{pmatrix} \quad M_{\varepsilon, m}^u = \begin{pmatrix} u - m - \varepsilon & +m \\ +m & -u - m - \varepsilon \end{pmatrix}$$

$$\left. \begin{array}{l} \lambda_1(\varepsilon, m, T) \\ \lambda_2(\varepsilon, m, T) \end{array} \right\} \text{v.p. de } M(\varepsilon, m, T) = e^{TM_{\varepsilon, m}^{-1}} e^{TM_{\varepsilon, m}^{+1}}$$

En principe on peut résoudre à la main

$$M_{\varepsilon, m}^u = \begin{pmatrix} u - m - \varepsilon & +m \\ +m & -u - m - \varepsilon \end{pmatrix} \longrightarrow \text{calculer les V. P.}$$

$$M(\varepsilon, m, T) = e^{TM_{\varepsilon, m}^{-1}} e^{TM_{\varepsilon, m}^{+1}} \quad \text{Calculer le produit}$$

et calculer les v.p.

Maple calcule

$$\lambda_1(\varepsilon, m, T) = \dots$$

$$\frac{1}{2(e^{TA})^2(m^2+1)(e^{Tm})^2(e^{T\varepsilon})^2} \left( (e^{TA})^4 m^2 + 2(e^{TA})^2 + m^2 + \sqrt{(e^{TA})^8 m^4 + 4(e^{TA})^6 m^2 - 2(e^{TA})^4 m^4 - 8(e^{TA})^4 m^2 + 4(e^{TA})^2 m^2 + m^4} \right)$$

$$\lambda_2(\varepsilon, m, T) = \dots$$

$$\frac{1}{2(e^{TA})^2(m^2+1)(e^{Tm})^2(e^{T\varepsilon})^2} \left( (e^{TA})^4 m^2 + 2(e^{TA})^2 + m^2 - \sqrt{(e^{TA})^8 m^4 + 4(e^{TA})^6 m^2 - 2(e^{TA})^4 m^4 - 8(e^{TA})^4 m^2 + 4(e^{TA})^2 m^2 + m^4} \right)$$

with  $A = \sqrt{m^2 + 1}$ .

*pas particulièrement éclairant*



$$\lambda_1(\varepsilon, m, T) = \dots$$

$$\frac{1}{2(e^{TA})^2(m^2+1)(e^{Tm})^2(e^{T\varepsilon})^2} \left( (e^{TA})^4 m^2 + 2(e^{TA})^2 + m^2 + \sqrt{(e^{TA})^8 m^4 + 4(e^{TA})^6 m^2 - 2(e^{TA})^4 m^4 - 8(e^{TA})^4 m^2 + 4(e^{TA})^2 m^2 + m^4} \right)$$

$$\lambda_2(\varepsilon, m, T) = \dots$$

$$\frac{1}{2(e^{TA})^2(m^2+1)(e^{Tm})^2(e^{T\varepsilon})^2} \left( (e^{TA})^4 m^2 + 2(e^{TA})^2 + m^2 - \sqrt{(e^{TA})^8 m^4 + 4(e^{TA})^6 m^2 - 2(e^{TA})^4 m^4 - 8(e^{TA})^4 m^2 + 4(e^{TA})^2 m^2 + m^4} \right)$$

$$\text{with } A = \sqrt{m^2 + 1}.$$

On demande à Maple le graphe de l'exposant de Liapunov

$$(m, T) \mapsto \frac{\ln(\lambda_1(\varepsilon, m, T))}{2T} = \Delta(\varepsilon, m, T)$$

puisque

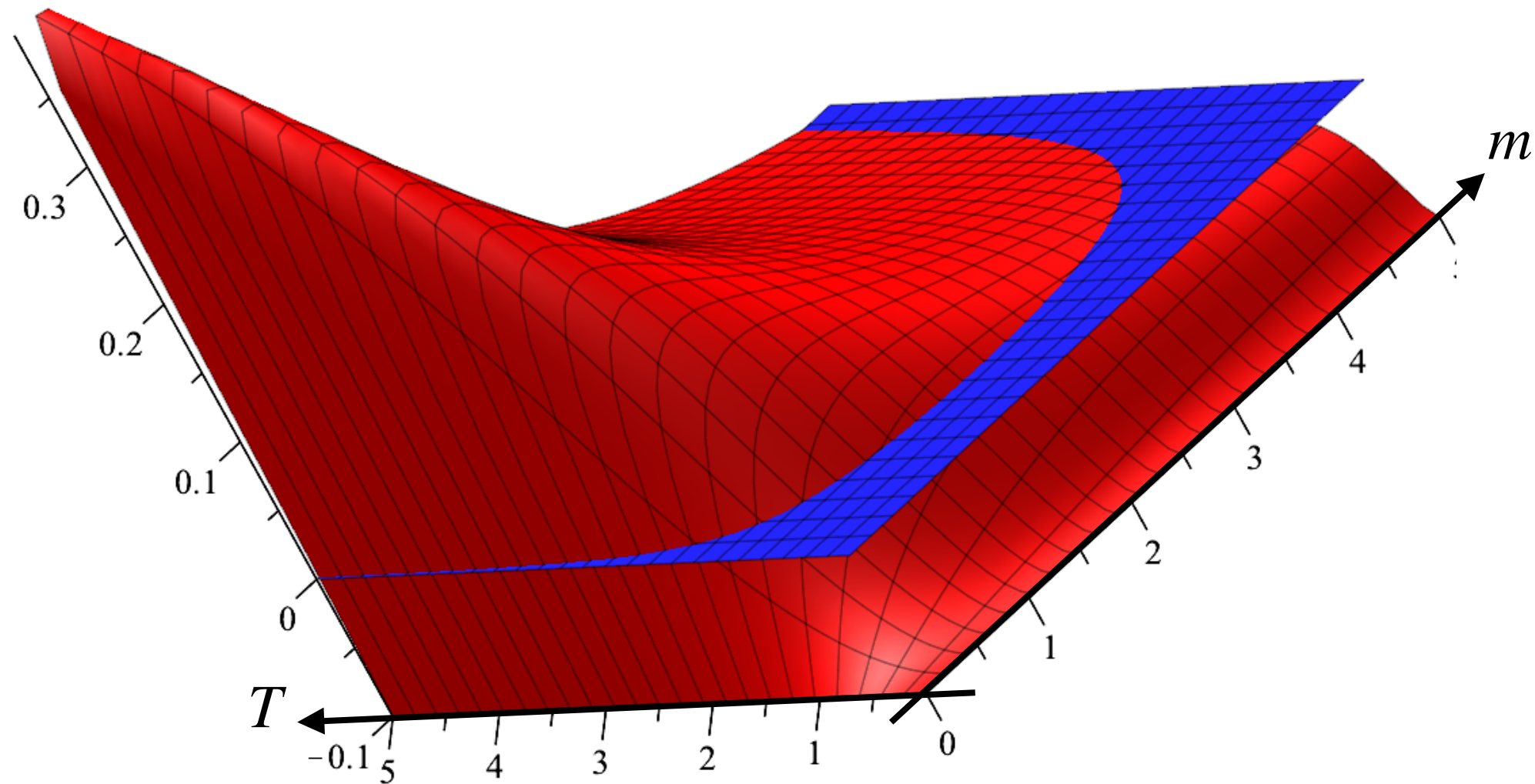
$$\lim_{t \rightarrow \infty} \frac{1}{t} \ln(x_1(t)) = \lim_{t \rightarrow \infty} \frac{1}{t} \ln(x_2(t)) = \Delta(\varepsilon, m, T)$$



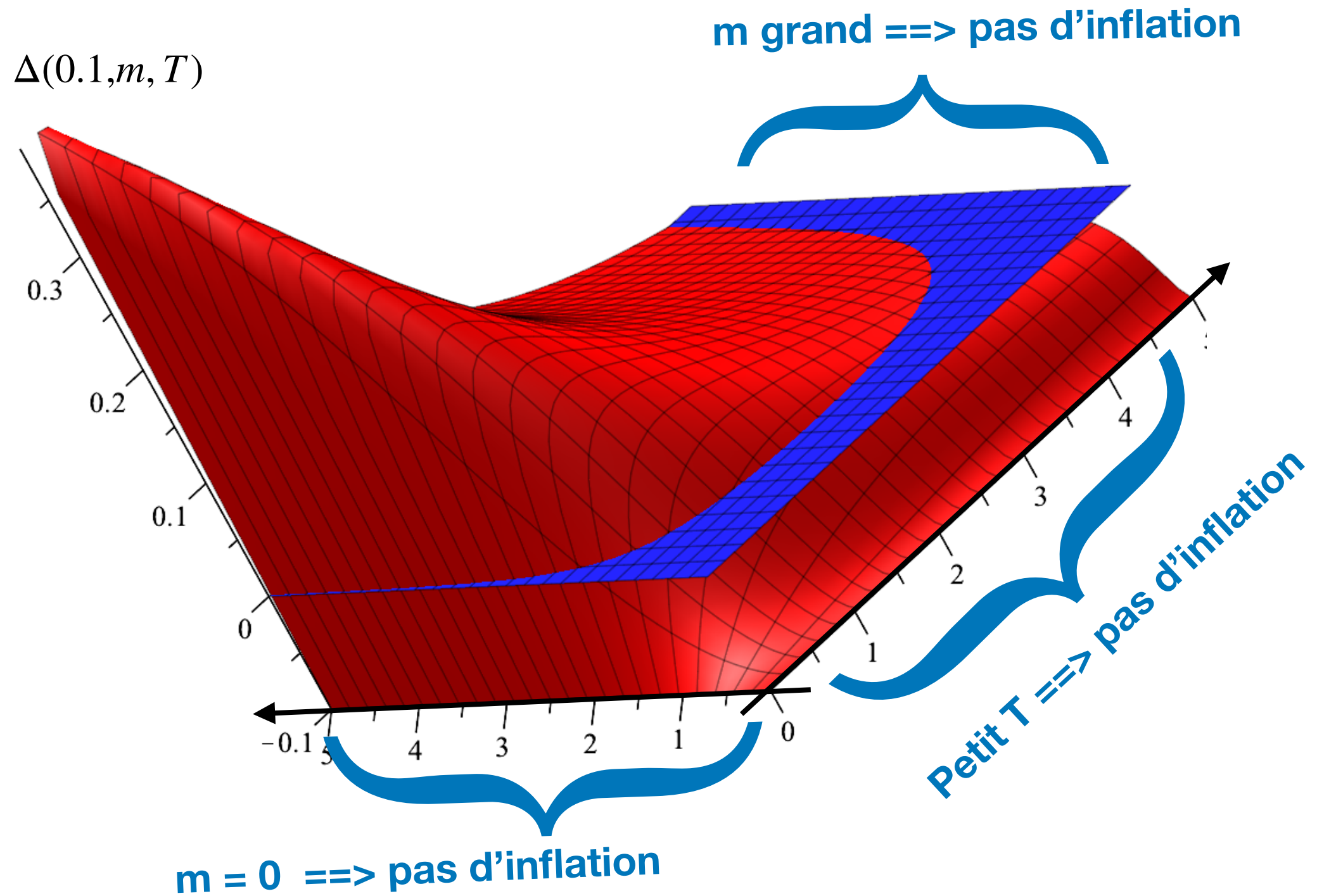
**DIG**

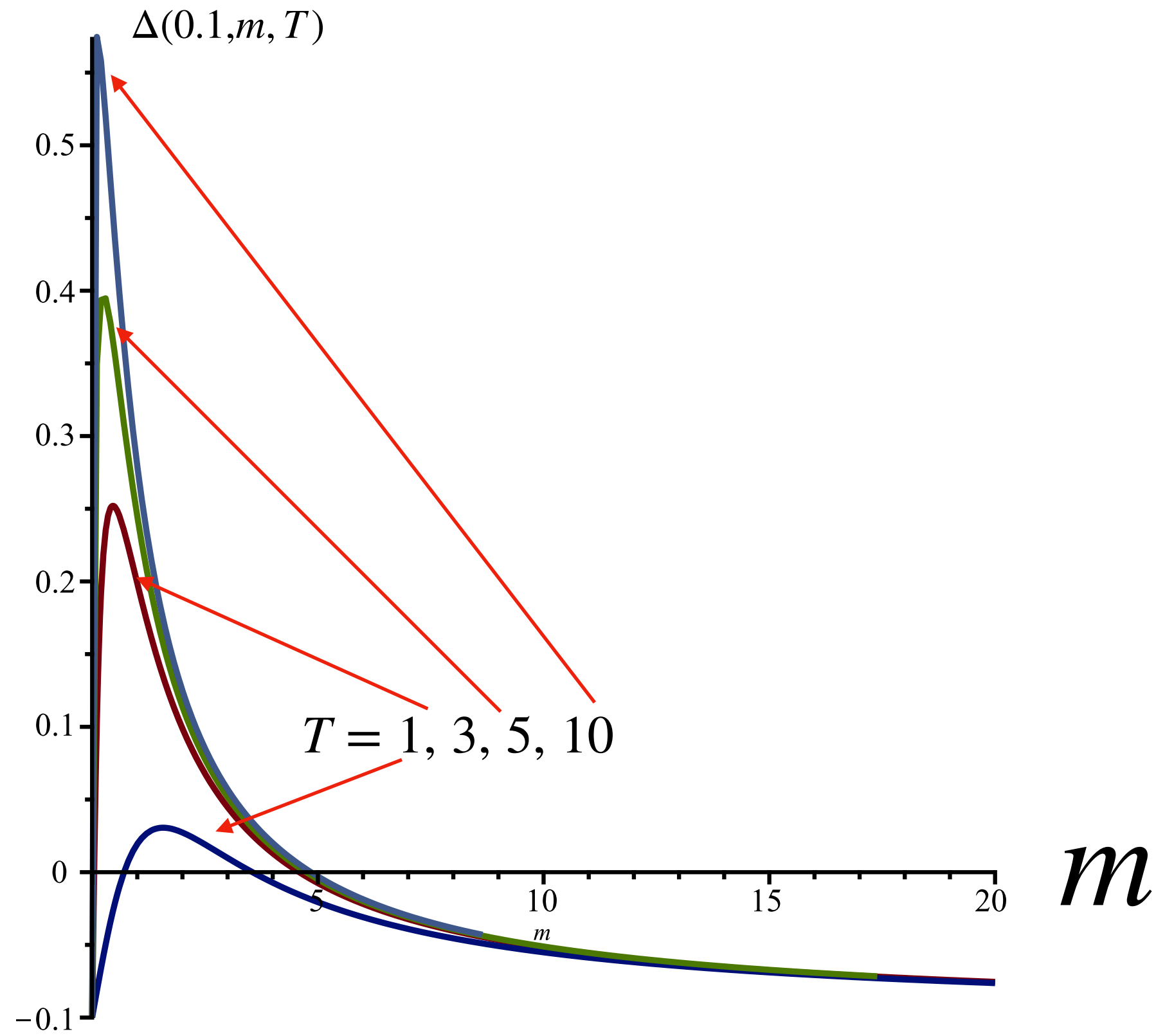
On dit qu'il y a inflation si :

$$\Delta(\varepsilon, m, T) > 0$$

 $\Delta(0.1, m, T)$ 

Grands  $T \Rightarrow$  Forte sensibilité à  $m$





.  $m = 0 \implies$  pas d'inflation**Trivial : Les deux sites décroissent indépendamment**

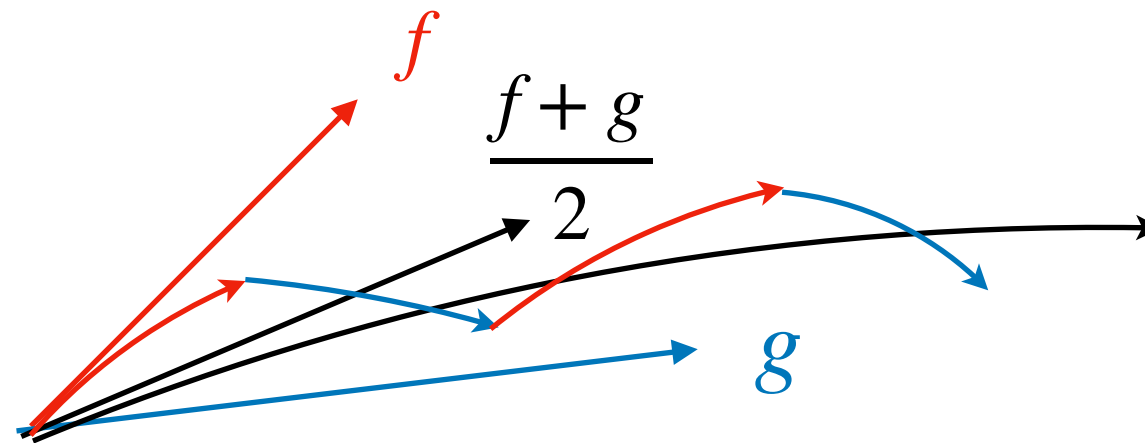
$$\left. \begin{aligned} x_1(2T) &= \exp((T(-1 - \varepsilon))\exp(T(1 - \varepsilon))x_1(0) = \exp(-2T\varepsilon)x_1(0) \\ x_2(2T) &= \exp((T(-1 - \varepsilon))\exp(T(1 - \varepsilon))x_2(0) = \exp(-2T\varepsilon)x_2(0) \end{aligned} \right\} \implies \frac{\ln(\lambda_1(\varepsilon, m, T))}{2T} = -\varepsilon$$

**T petit ==> pas d'inflation**

**Forçage périodique constant par morceaux**

**Presque trivial: voir la figure:**

**En général**



**Moyennisation**

**Quand  $T \rightarrow 0$   
les solutions du commuté  
convergent vers la solution  
de la 1/2 somme**

**Dans notre cas**

$$\Sigma^+(\varepsilon, m) \quad \left\{ \begin{array}{l} \frac{dx_1}{dt} = (+1 - \varepsilon)x_1 + m(x_2 - x_1) \\ \frac{dx_2}{dt} = (-1 - \varepsilon)x_2 + m(x_1 - x_2) \end{array} \right. \quad \text{sur } [0, T[$$

**commute**

$$\Sigma^-(\varepsilon, m) \quad \left\{ \begin{array}{l} \frac{dx_1}{dt} = (-1 - \varepsilon)x_1 + m(x_2 - x_1) \\ \frac{dx_2}{dt} = (+1 - \varepsilon)x_2 + m(x_1 - x_2) \end{array} \right. \quad \text{sur } [T, 2T[$$

$$\frac{\Sigma^+ + \Sigma^-}{2} \quad \left\{ \begin{array}{l} \frac{dx_1}{dt} = -(\varepsilon + m)x_1 + mx_2 \\ \frac{dx_2}{dt} = mx_1 - (\varepsilon + m)x_2 \end{array} \right. \quad \Longrightarrow \quad \frac{\lambda_1(\varepsilon, m, T)}{2T} = -\varepsilon$$

$. m \rightarrow +\infty \Rightarrow$  pas d'inflation

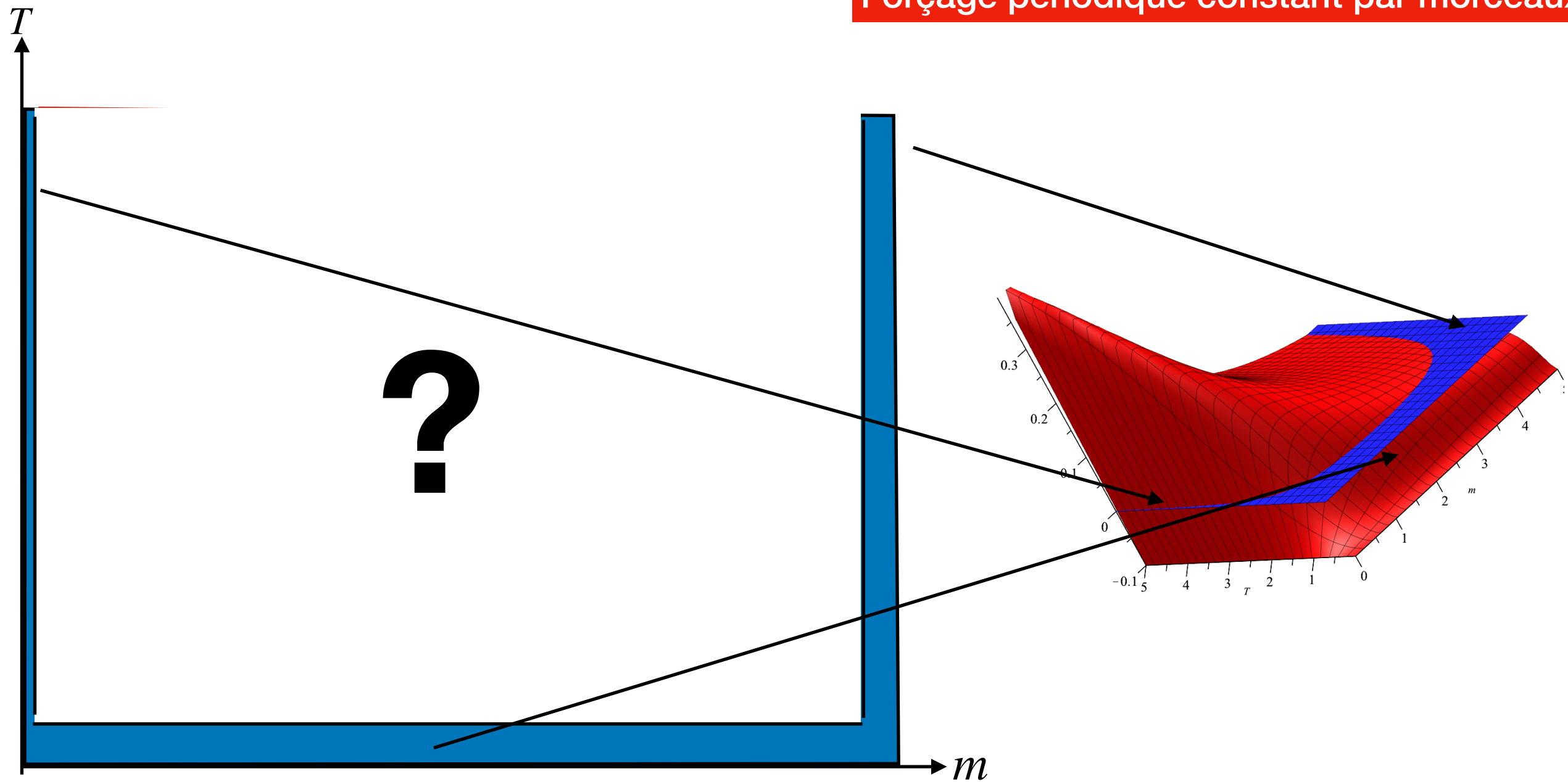
Intuitivement

$$\begin{aligned} \frac{dx_1}{dt} &= f(x_1, x_2) + m(x_2 - x_1) & u &= (x_1 + x_2)/2 & x_1 &= (u + v) \\ \frac{dx_2}{dt} &= g(x_1, x_2) + m(x_1 - x_2) & v &= (x_1 - x_2)/2 & x_2 &= (u - v) \end{aligned}$$

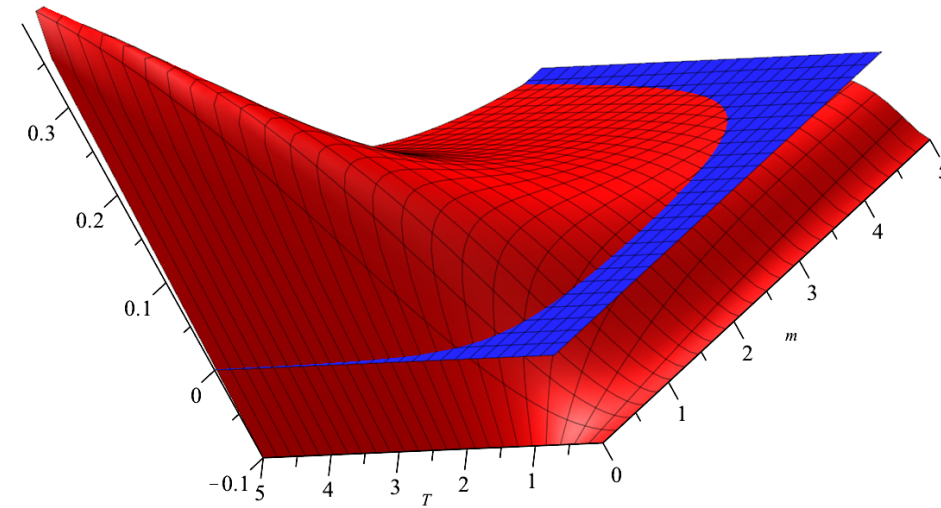
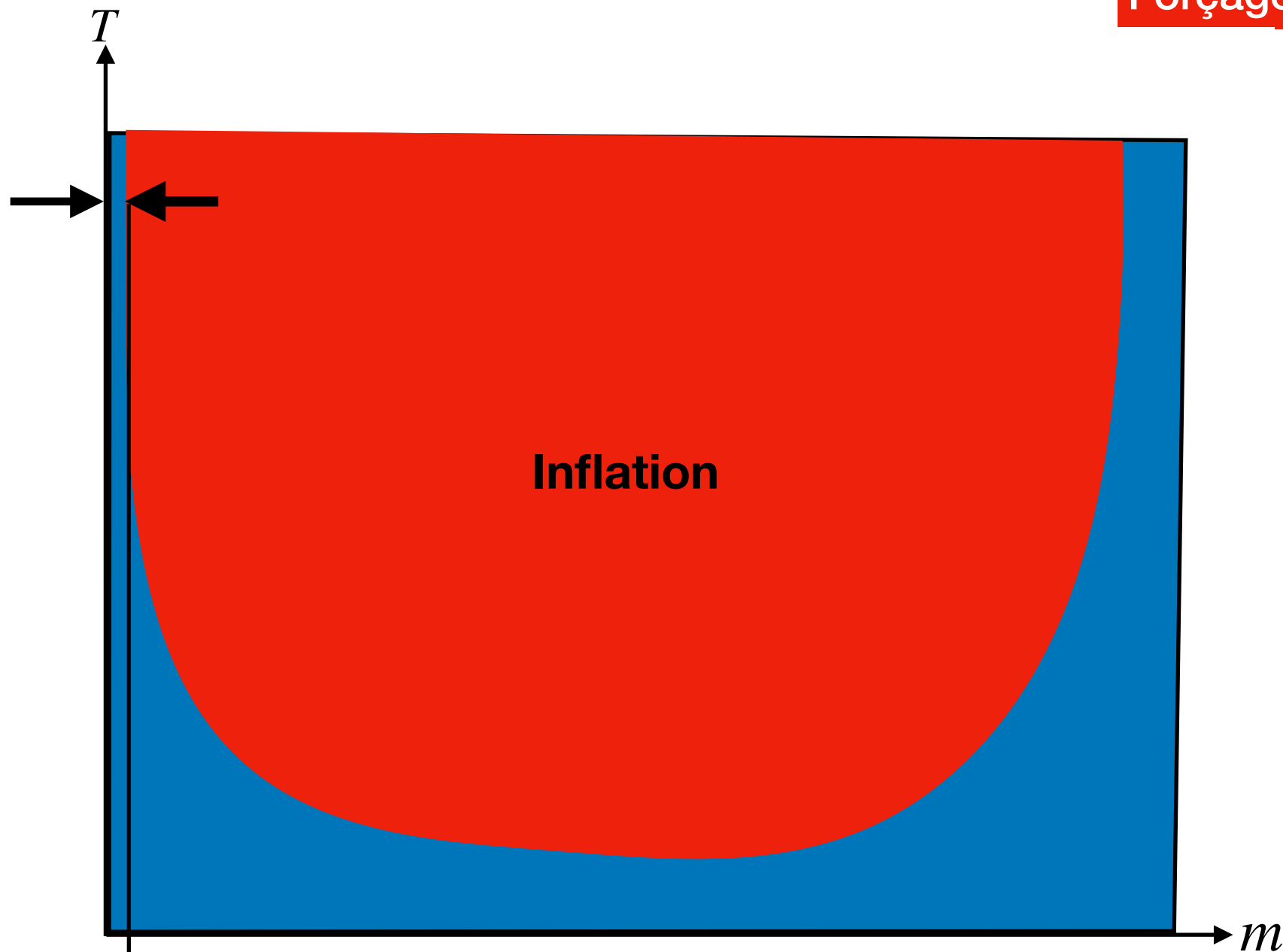
$$\begin{aligned} \frac{du}{dt} &= \frac{1}{2}(f(u, v) + g(u, v)) \\ \frac{dv}{dt} &= (f - g)/2 - mv \end{aligned}$$

**Théorème de Tychonov**

$$mi . g . \implies v \approx 0$$



On a expliqué ce qui se passe au bord avec des arguments généraux, non basés sur la forme explicite du modèle ( $\pm 1$ )



Reste à expliquer l'inflation et pourquoi c'est un phénomène brutal.

$m^*(T)$  Seuil de l'inflation

$$m^*(T) \sim \exp(-T)$$

$$\lim_{T \rightarrow +\infty} m^*(T) \exp(T) = l$$



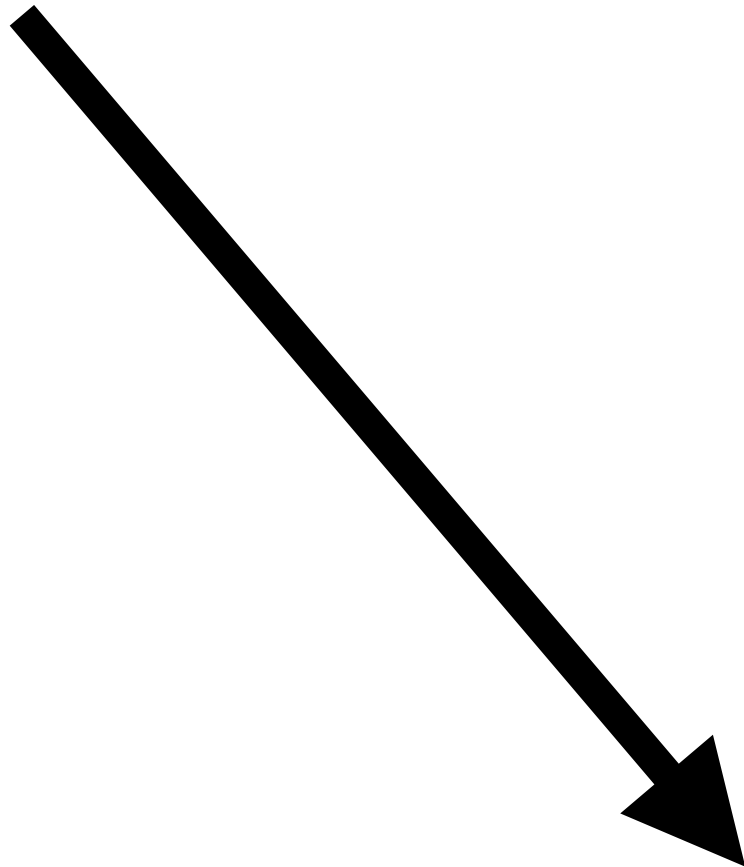


Se démontre par un calcul sur la formule explicite :

$$\Delta(\varepsilon, m, T) := 2 \ln \frac{m^2 b^4 + 2b^2 + m^2 + m(b^2 - 1)\sqrt{C}}{2(1 + m^2)b^2} - 4(m + \varepsilon)T$$

avec  $b = e^{T\sqrt{1+m^2}}$  et  $C = m^2 b^4 + 2m^2 b^2 + 4b^2 + m^2$ .

...fait ici



$$\Delta(\varepsilon, m, T) = 2 \ln \frac{m^2 b^4 + 2b^2 + m^2 + m(b^2 - 1)\sqrt{C}}{2(1 + m^2)b^2} - 4(m + \varepsilon)T \quad (72)$$

$$\text{with } b = e^{T\sqrt{1+m^2}} \text{ and } C = m^2 b^4 + 2m^2 b^2 + 4b^2 + m^2. \quad (73)$$

Equation (72) is equivalent to :

$$\frac{m^2 b^4 + 2b^2 + m^2 + m(b^2 - 1)\sqrt{C}}{2(1 + m^2)b^2} = e^{2(m+\varepsilon)T} \quad (74)$$

From (73) one have :

$$mb = e^{Tx} e^{T\sqrt{1+e^{2Tx}}} = e^{T(1+x+\frac{1}{2}e^{2Tx}(1+o))} \quad (75)$$

since for  $x < 0$  we have  $Te^{2Tx} = o$  we deduce  $mb = e^{T(1+x+o)}$  which tends to  $\infty$  as long as  $x > -1$ . from which we deduce that as long as  $x > -1$  :

$$m^2 b^4 + 2b^2 + m^2 = m^2 b^4(1 + o) \quad m(b^2 - 1)\sqrt{C} = m^2 b^4(1 + o) \quad (76)$$

which introduced in (73) gives :

$$m^2 b^2(1 + o) = e^{2T(1+x)}(1 + o) = e^{2T(\varepsilon+o)} \quad (77)$$

from which we deduce :

$$2T(1+x)(1+o) = 2T(\varepsilon+o) \implies x = -(1-\varepsilon) + o \quad (78)$$

which is the evaluation of proposition 2.4.

$$\Delta(\varepsilon, m, T); = 2 \ln \frac{m^2 b^4 + 2b^2 + m^2 + m(b^2 - 1)\sqrt{C}}{2(1 + m^2)b^2} - 4(m + \varepsilon)T \quad (72)$$

$$\text{with } b = e^{T\sqrt{1+m^2}} \text{ and } C = m^2 b^4 + 2m^2 b^2 + 4b^2 + m^2. \quad (73)$$

Equation (72) is equivalent to :

$$\frac{m^2 b^4 + 2b^2 + m^2 + m(b^2 - 1)\sqrt{C}}{2(1 + m^2)b^2} = e^{2(m+\varepsilon)T} \quad (74)$$

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since for  $x < 0$  we have  $Te^{2Tx} = o$  we deduce  $mb = e^{T(1+x+o)}$  which tends to  $\infty$  as long as  $x > -1$ . from which we deduce that as  $x \rightarrow -1$  :

$$m^2 b^4 + 2b^2 + m^2 = m^2 b^4(1+o) \quad m(b^2 - 1)\sqrt{C} = m^2 b^4(1+o) \quad (76)$$

which introduced in (73) gives :

$$m^2 b^2(1+o) = e^{2T(1+x)}(1+o) = e^{2T(\varepsilon+o)} \quad (77)$$

from which we deduce :

$$2T(1+x)(1+o) = 2T(\varepsilon+o) \implies x = -(1-\varepsilon) + o \quad (78)$$

which is the evaluation of proposition 2.4.

$$\frac{dx_1}{dt} = (+u(t) - \varepsilon)x_1 + m(x_2 - x_1)$$

$$\frac{dx_2}{dt} = (-u(t) - \varepsilon)x_2 + m(x_1 - x_2)$$

$$\xi_1 = \ln(x_1)$$

$$\xi_2 = \ln(x_2)$$

$$\frac{d\xi_1}{dt} = (+u(t) - \varepsilon) + m \left( e^{\xi_2 - \xi_1} - 1 \right)$$

$$\frac{d\xi_2}{dt} = (-u(t) - \varepsilon) + m \left( e^{\xi_1 - \xi_2} - 1 \right)$$

$$\frac{d\xi_1}{dt} = (+u(t) - \varepsilon) + m \left( e^{\xi_2 - \xi_1} - 1 \right)$$

$$\frac{d\xi_2}{dt} = (-u(t) - \varepsilon) + m \left( e^{\xi_1 - \xi_2} - 1 \right)$$

$$U = \xi_1 + \xi_2$$

$$V = \xi_1 - \xi_2$$

$$\frac{dU}{dt} = 2(m \cosh(V) - m - \varepsilon)$$

$$\frac{dV}{dt} = 2(u(t) - m \sinh(V))$$

$$U = \ln(x_1 \cdot x_2)$$

$$V = \ln(x_1/x_2)$$

$$\overline{\Delta}(\varepsilon, mT) = \lim_{t \rightarrow \infty} \frac{1}{t} U(t) = \lim_{t \rightarrow \infty} \frac{1}{t} \ln(x_1(t)) + \lim_{t \rightarrow \infty} \frac{1}{t} \ln(x_2(t)) = 2\Delta(\varepsilon, mT)$$

$$\begin{cases} \frac{dU}{dt} = 2(m \cosh(V) - m - \varepsilon) \\ \frac{dV}{dt} = 2(u(t) - m \sinh(V)) \end{cases}$$

$$F(m, T) \quad \frac{dV}{dt} = 2(u(t) - m \sinh(V)) \quad \text{système commuté 1D}$$


$$U(t) = U_0 + \int_0^t 2(m \cosh(V(s)) - m - \varepsilon) ds \quad \text{Simple quadrature}$$

$$\overline{\Delta}(\varepsilon, mT) = \lim_{t \rightarrow \infty} \frac{1}{t} U(t)$$

$$\begin{cases} \frac{dU}{dt} = 2(m \cosh(V) - m - \varepsilon) \\ \frac{dV}{dt} = 2(u(t) - m \sinh(V)) \end{cases}$$

$$F(m, T) \quad \frac{dV}{dt} = 2(u(t) - m \sinh(V)) \quad \text{Système 1D}$$

$$U(t) = U_0 + \int_0^t 2(m \cosh(V(s)) - m - \varepsilon) ds \quad \text{Quadrature}$$

$$\bar{\Delta}(\varepsilon, mT) = \lim_{t \rightarrow \infty} \frac{1}{t} U(t) = \lim_{t \rightarrow \infty} \frac{1}{t} \ln(x_1(t)) + \lim_{t \rightarrow \infty} \frac{1}{t} \ln(x_2(t)) = 2\Delta(\varepsilon, mT)$$


$F(m, T)$ 
$$\frac{dV}{dt} = 2(u(t) - m \sinh(V))$$

Système commuté 1D

$F_m^{+1}$ 
$$\frac{dV}{dt} = 2(+1 - m \sinh(V))$$
$$V_m^+ = \sinh^{-1}(+1/m)$$

**G.A.S**

$F_m^{-1}$ 
$$\frac{dV}{dt} = 2(-1 - m \sinh(V))$$
$$V_m^- = \sinh^{-1}(-1/m)$$

**G.A.S**



**Theorem :**  $F(m, T)$  a une solution périodique unique .

**Preuve**

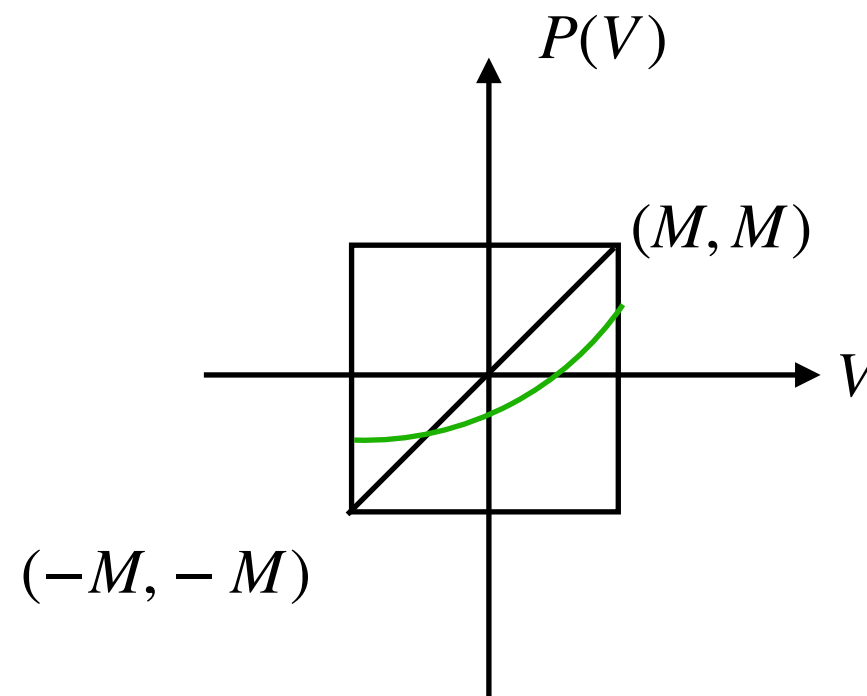
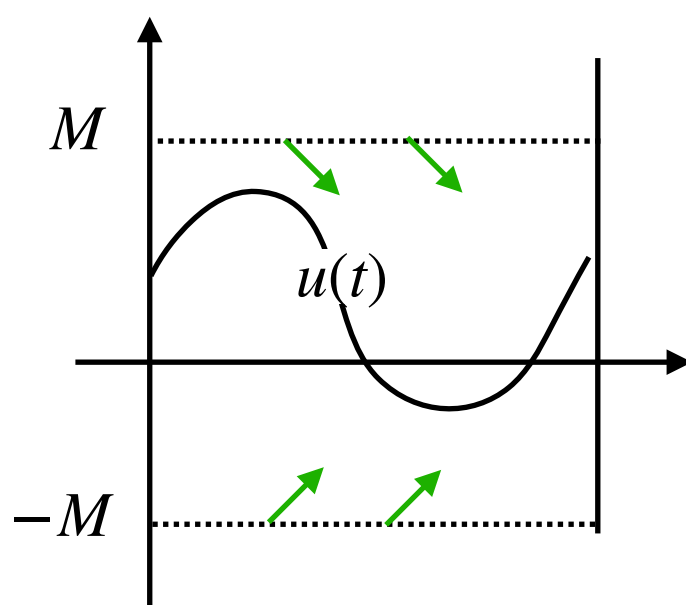




$$\frac{dV}{dt} = 2(u(t) - m \sinh(V))$$

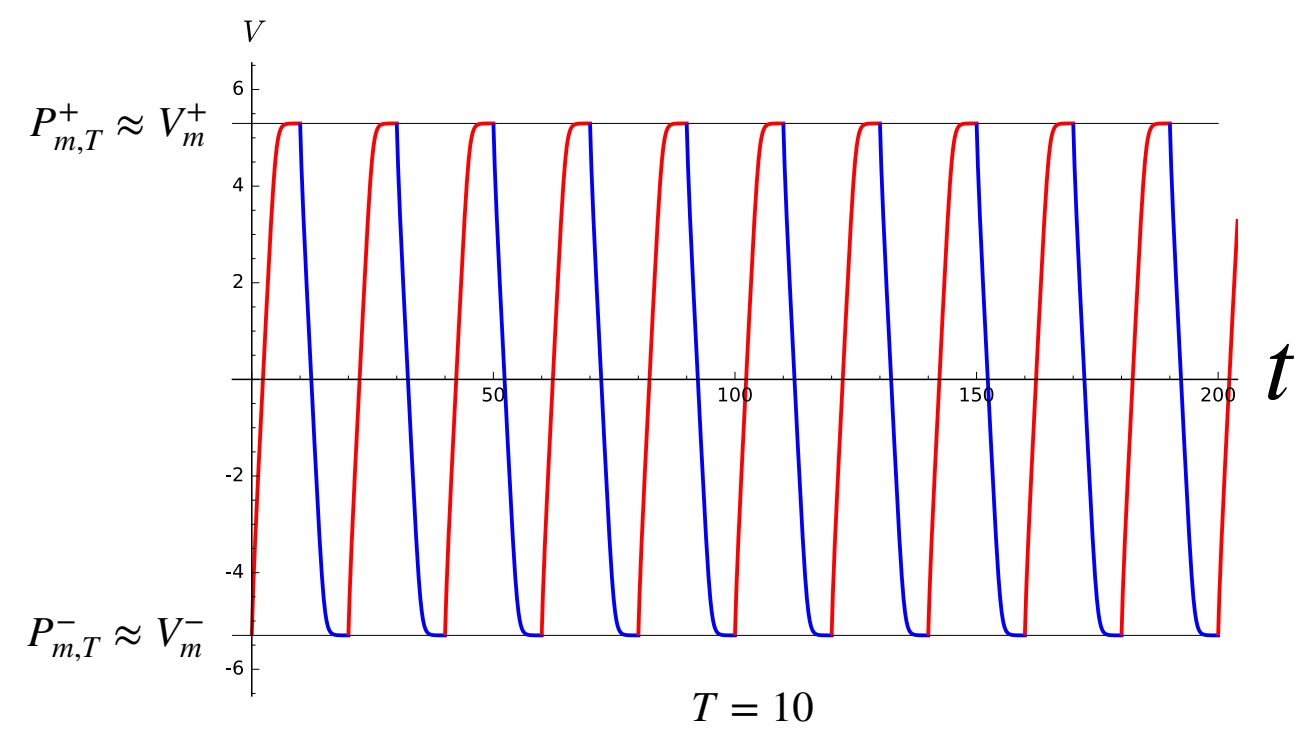
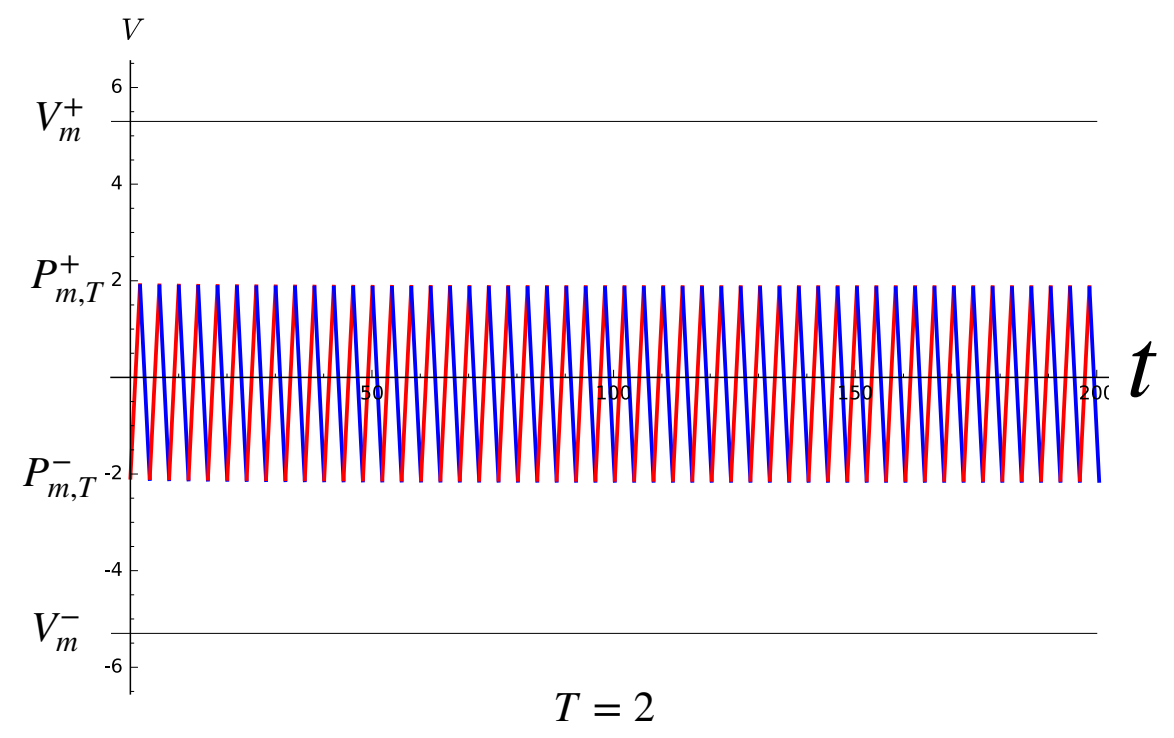
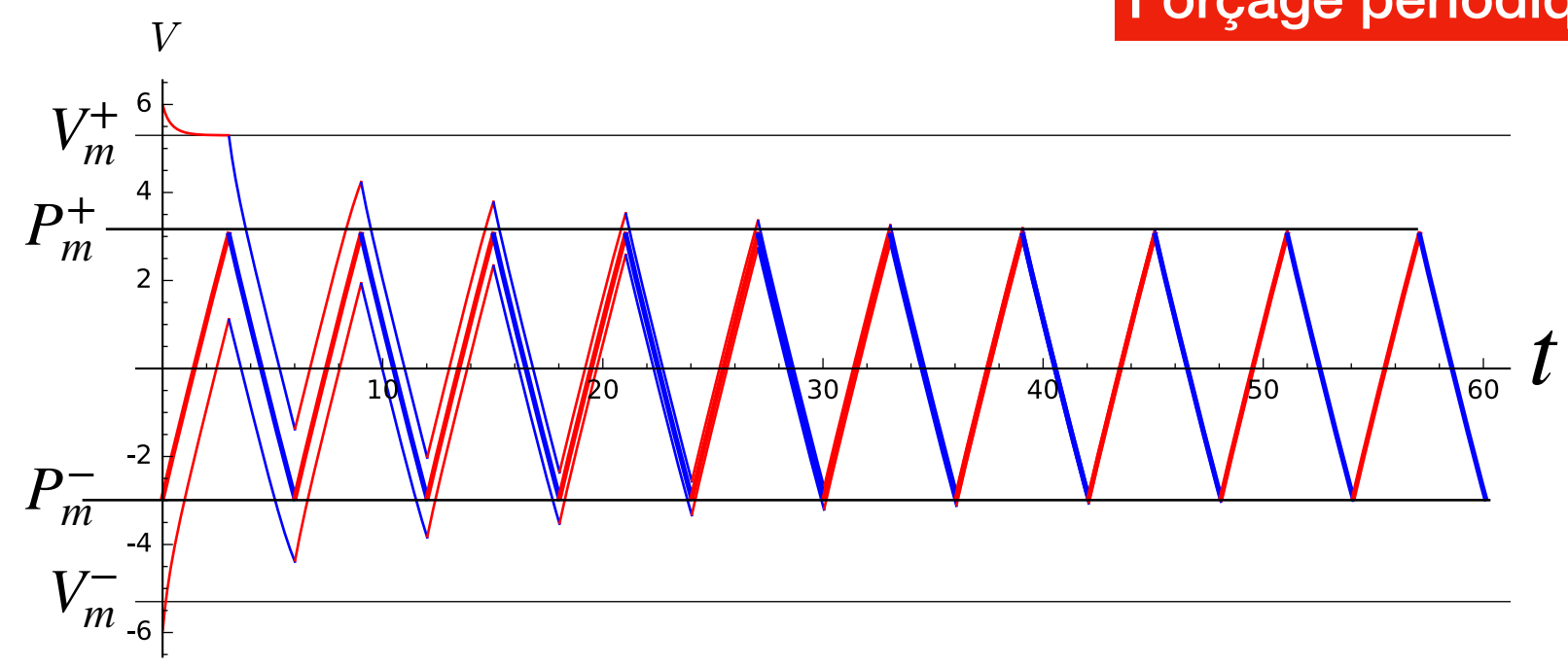
$u(t)$  périodique  $\Rightarrow V_p(t)$  est une unique solution périodique G.A.S

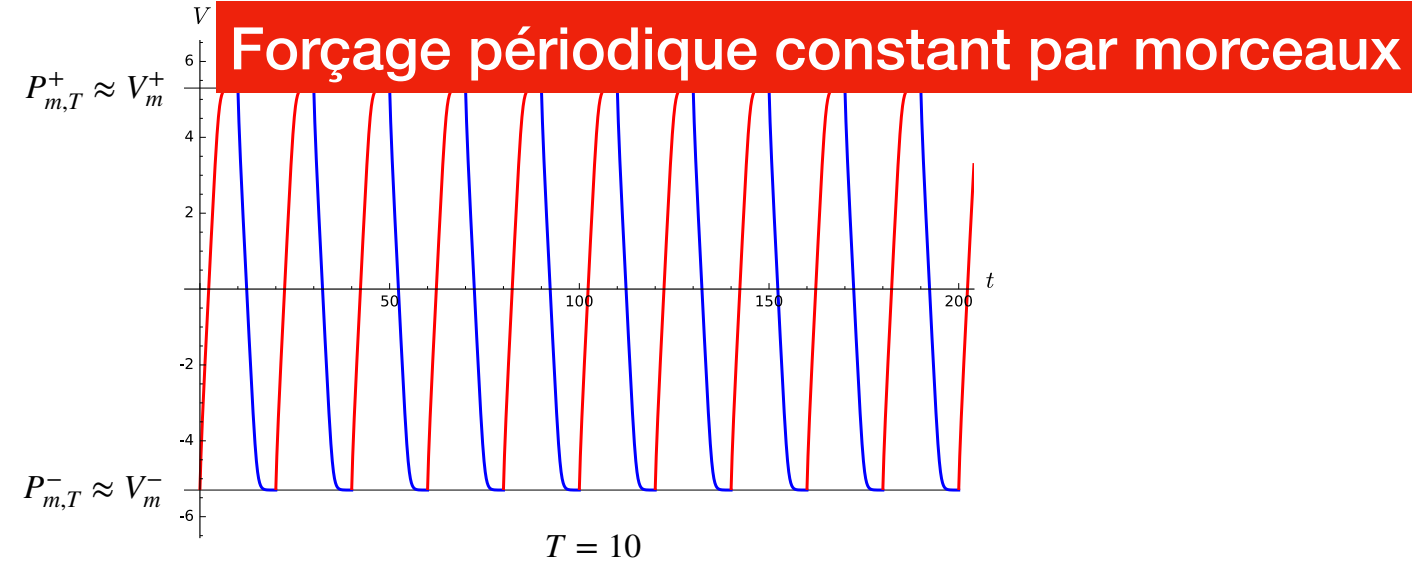
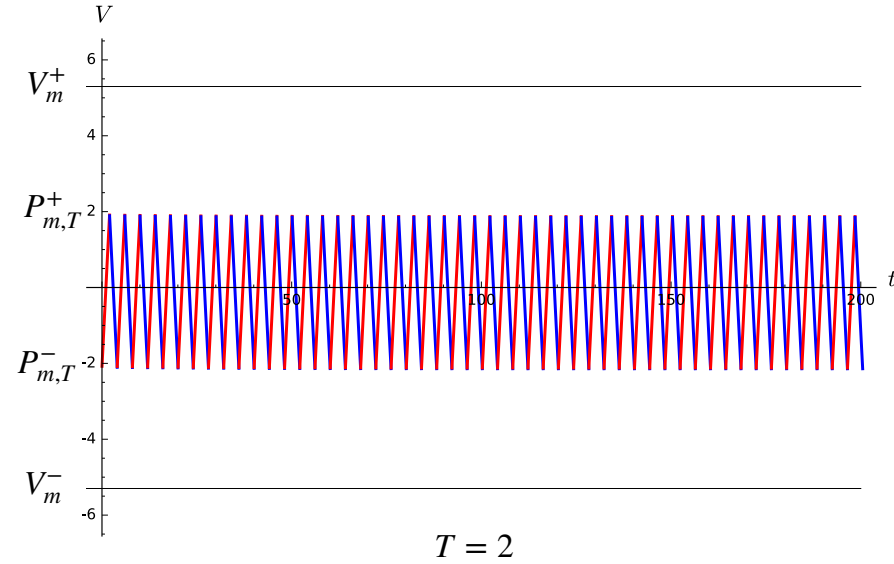
$P(V_0) = V(T, V_0)$  est croissante, telle que  $P' < 1$



$$\bar{\Delta}(\varepsilon, mT) = \int_0^T 2(m \cosh(V_p(t)) - m - \varepsilon) dt$$

Forçage périodique constant par morceaux

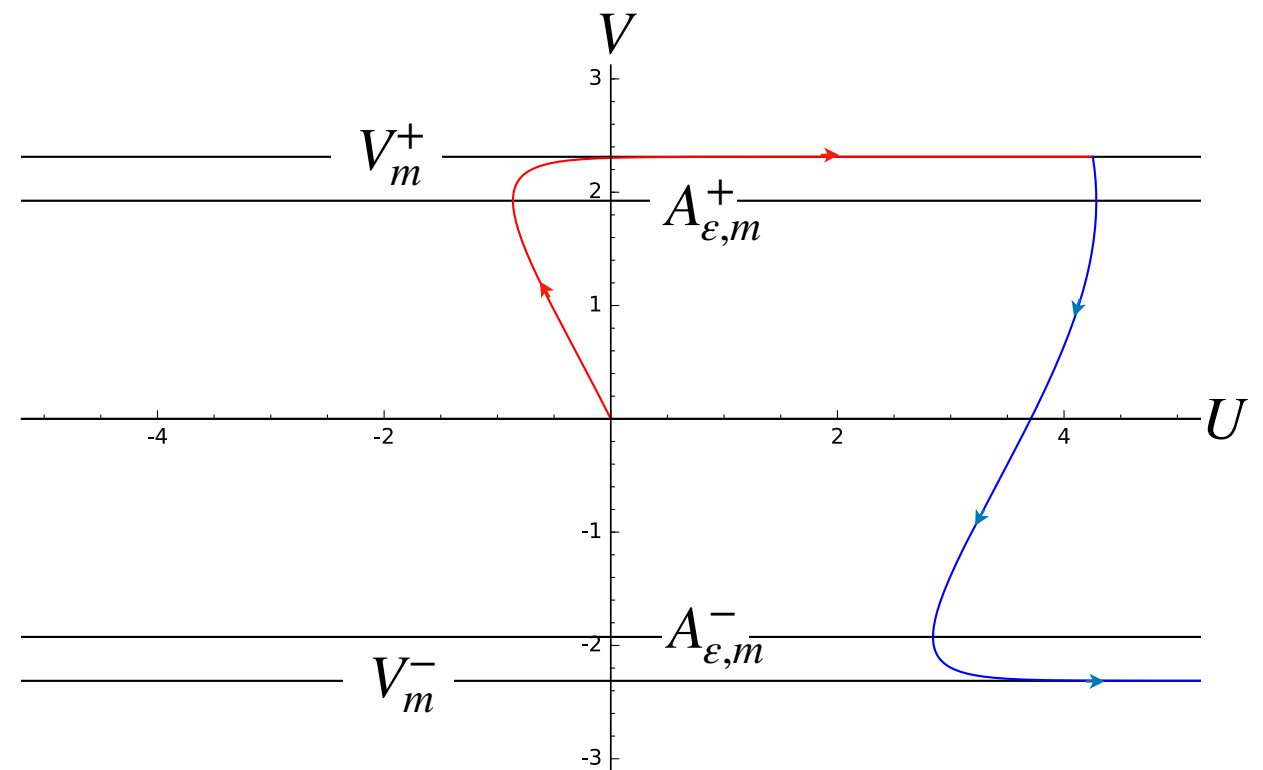
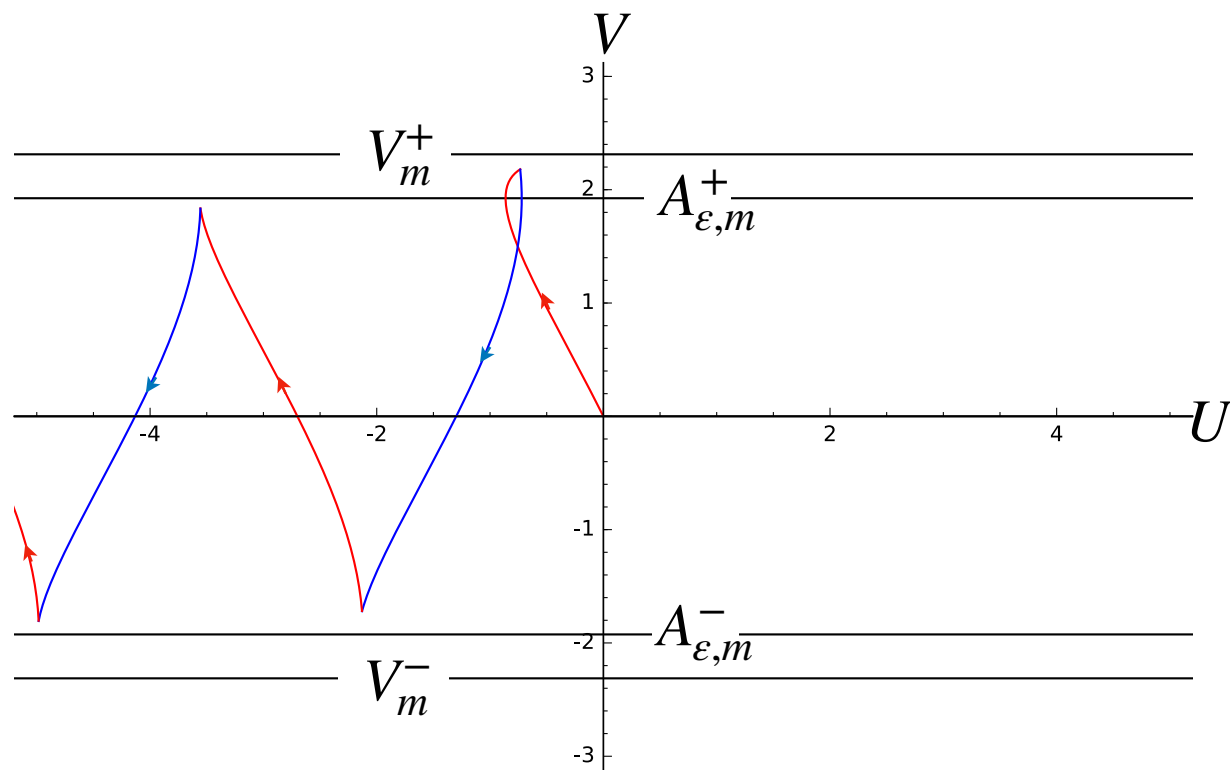


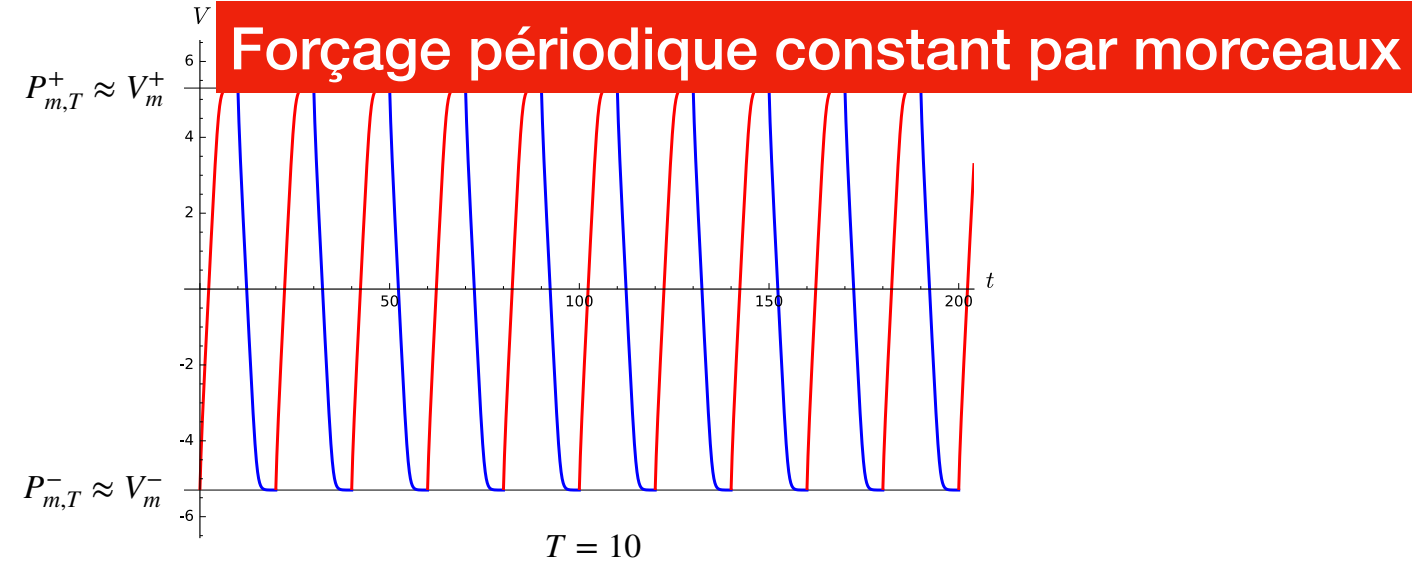
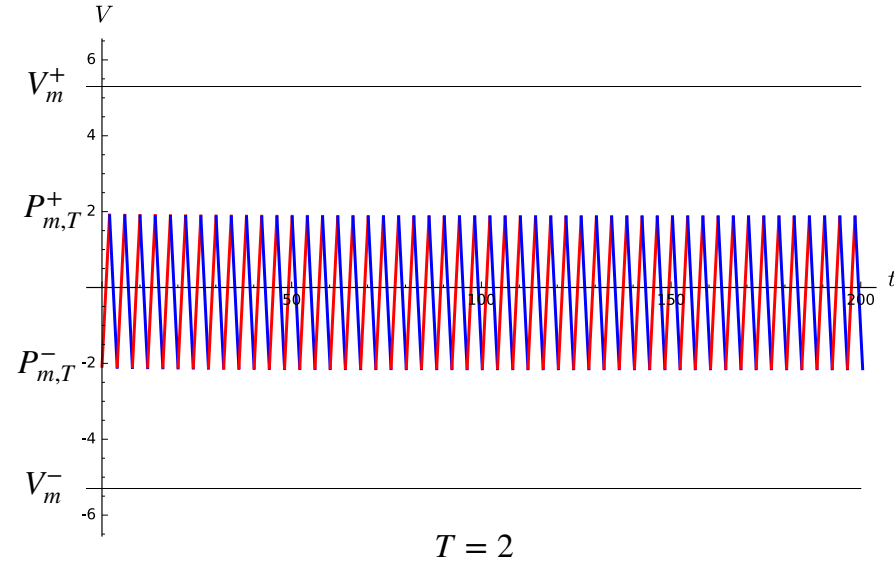


$$U(t) = U_0 + \int_0^t 2(m \cosh(V(s)) - m - \varepsilon) ds$$

$$A_{\varepsilon,m}^{\pm} = \operatorname{arccosh} \left( 1 - \frac{\varepsilon}{m} \right)$$

$$m < \frac{1 - \varepsilon^2}{2\varepsilon} \implies [A^-, A^+] \subset [V^-, V^+]$$

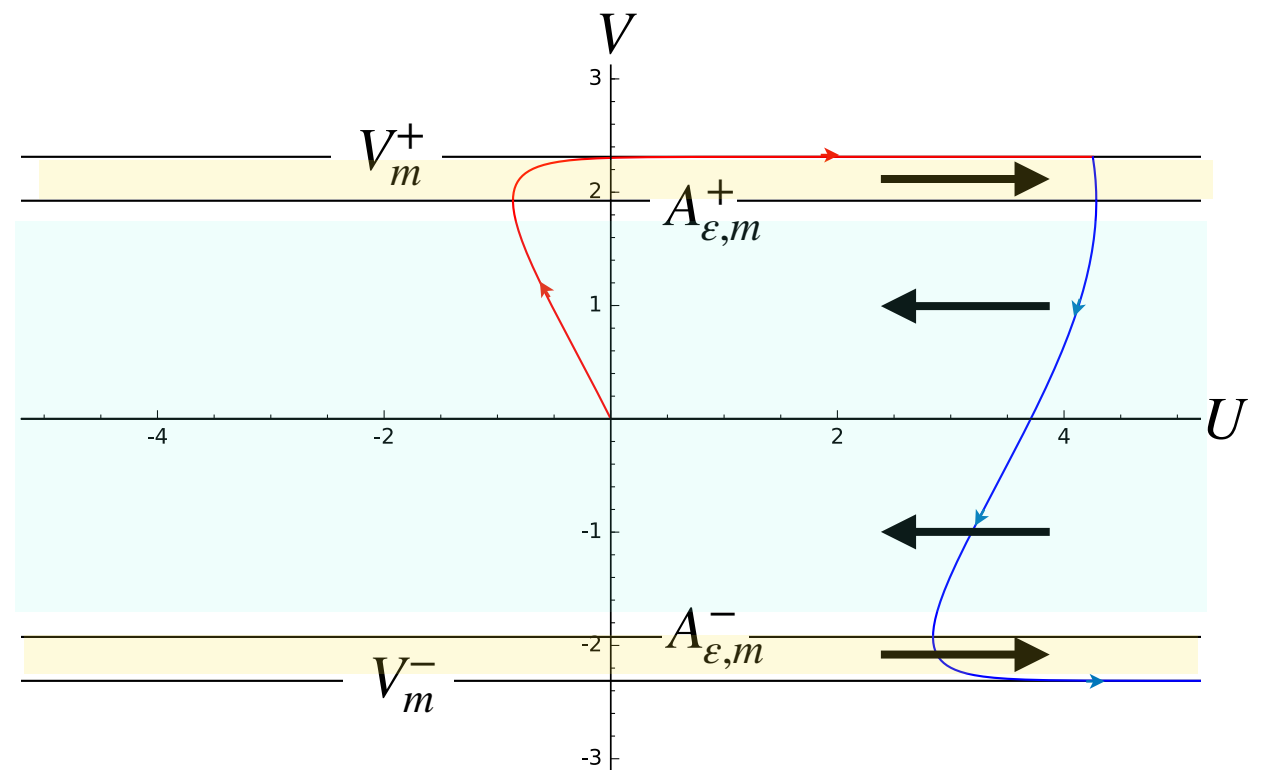
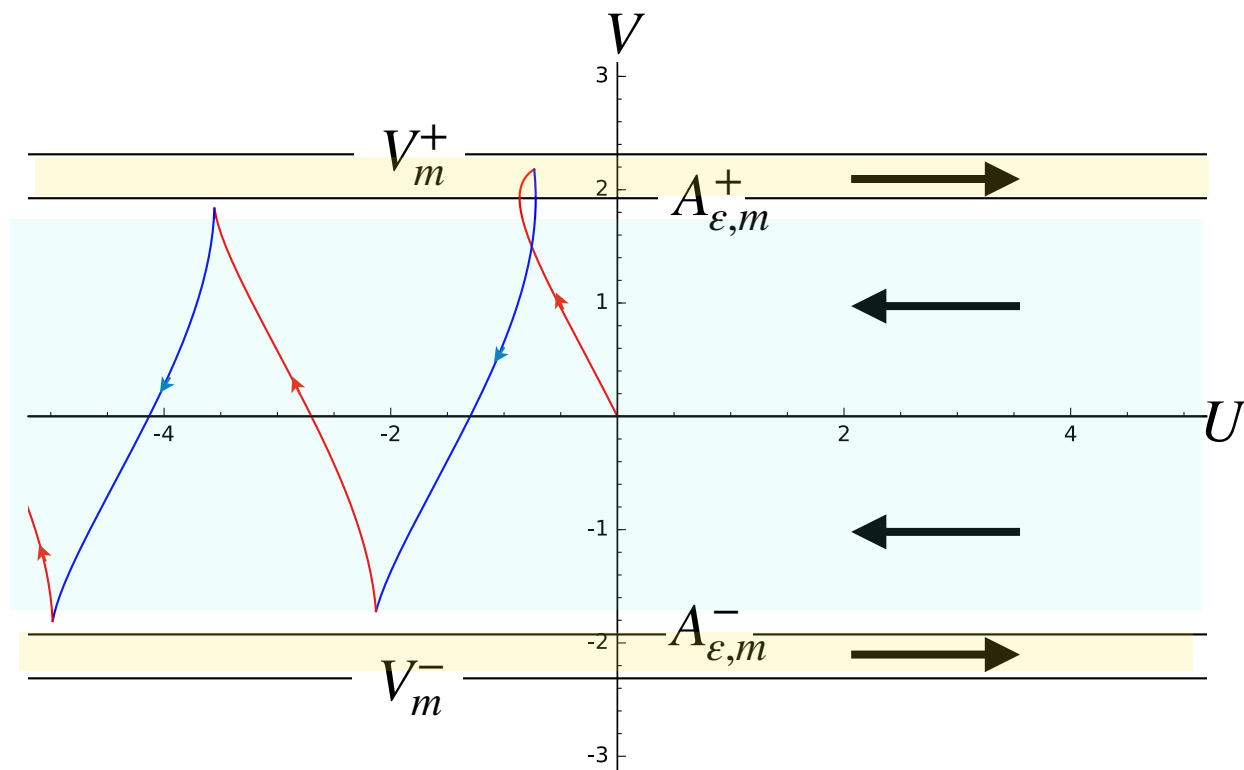




$$U(t) = U_0 + \int_0^t 2(m \cosh(V(s)) - m - \varepsilon) ds$$

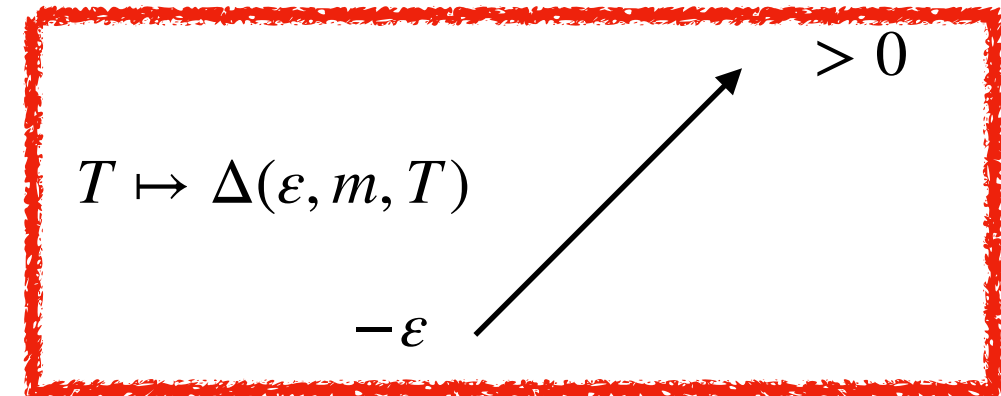
$$A_{\varepsilon,m}^{\pm} = \operatorname{arccosh} \left( 1 - \frac{\varepsilon}{m} \right)$$

$$m < \frac{1 - \varepsilon^2}{2\varepsilon} \implies [A^-, A^+] \subset [V^-, V^+]$$



$$2\Delta(\varepsilon, m, T) = \lim_{t \rightarrow \infty} \frac{U(t)}{t} = \int_0^{2T} 2(m \cosh(V_p(t)) - m - \varepsilon) dt$$

$$m < \frac{1 - \varepsilon^2}{2\varepsilon} \implies [A^-, A^+] \subset [V^-, V^+] \implies$$

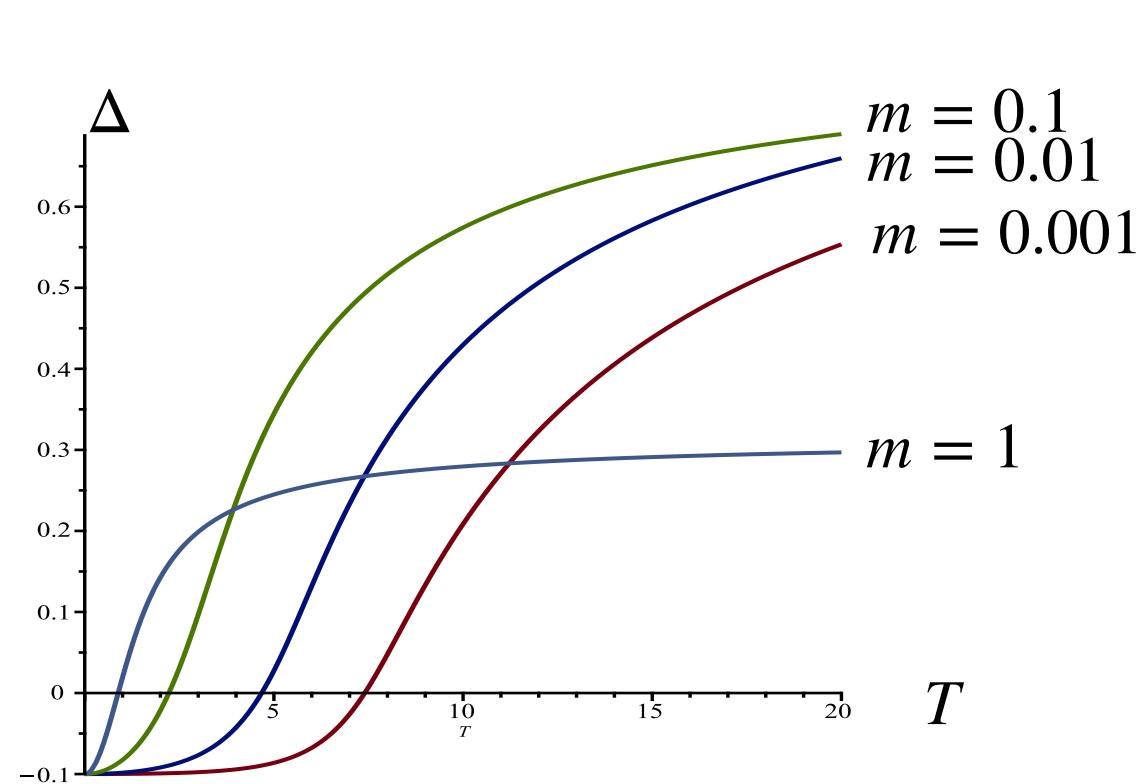
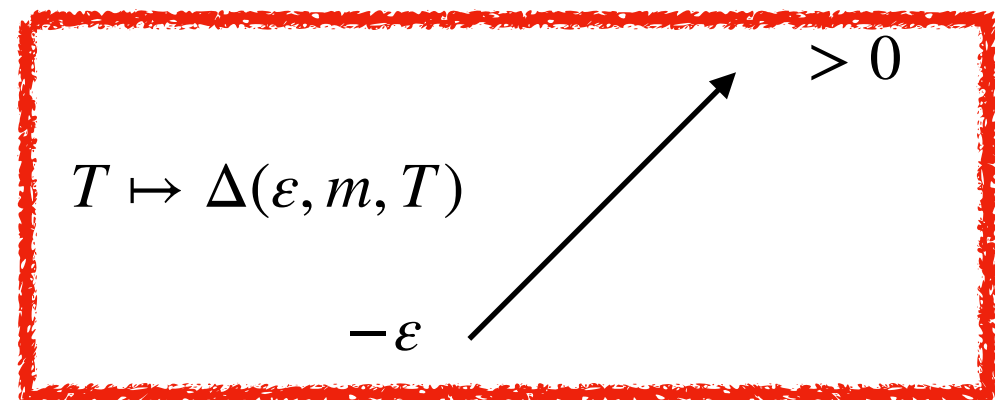


$$\Delta(\varepsilon, m, T^*(m)) = 0$$

**C'est un résultat que Katriel démontre de façon générale pour n sites**

$$\Delta(\varepsilon, m, T) = \lim_{t \rightarrow \infty} \frac{U(t)}{t} = \int_0^{2T} 2(m \cosh(V_p(t)) - m - \varepsilon) dt$$

$$m < \frac{1 - \varepsilon^2}{2\varepsilon} \implies [A^-, A^+] \subset [V^-, V^+] \implies$$



$$\Delta(\varepsilon, m, T^*(m)) = 0$$

m est de l'ordre de exp(-T)

# Forçage aléatoire P.D.M.P.

Piecewise Deterministic Markov Processes

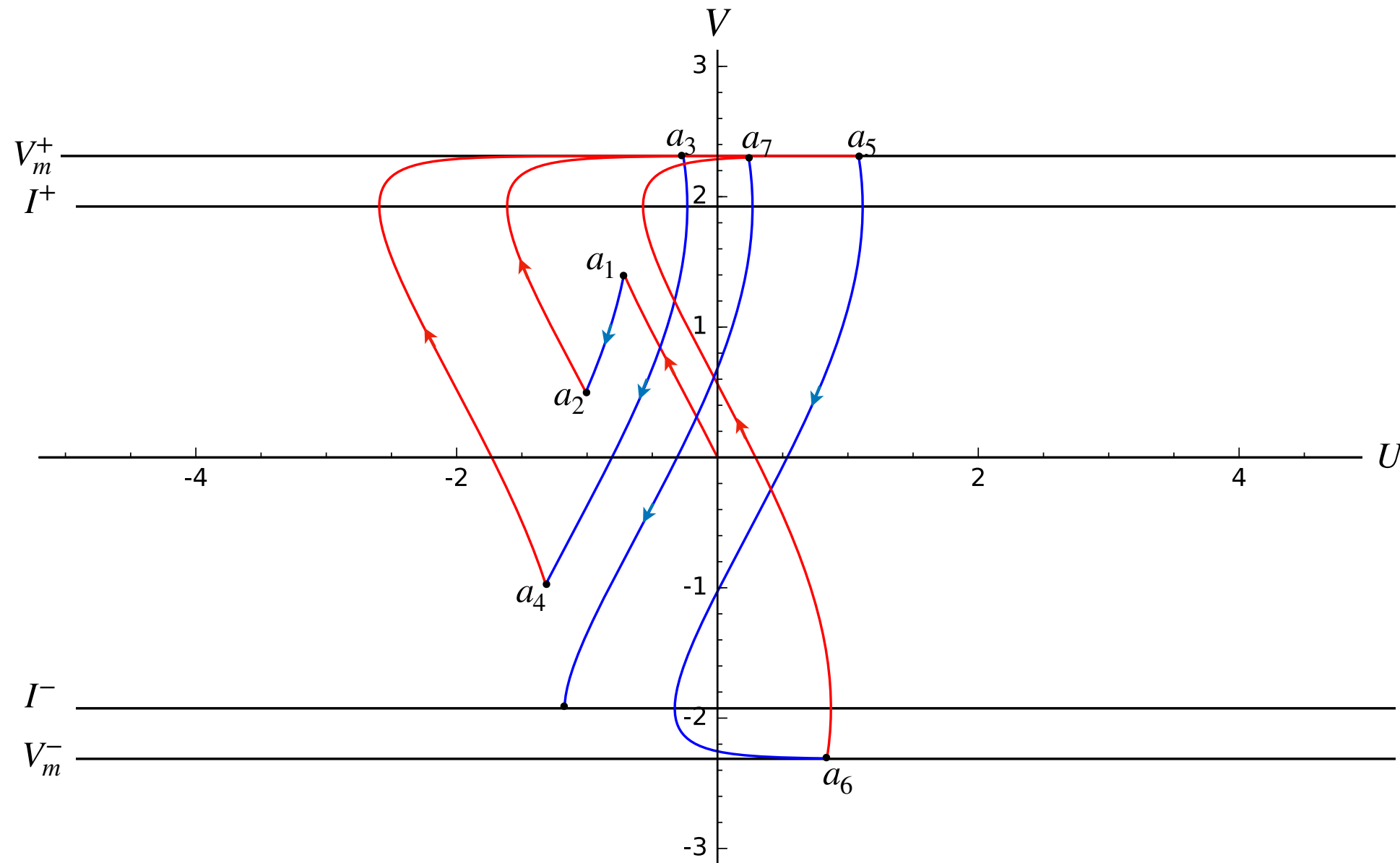
**Les PDMP ont été introduits par :**

- [8] Davis, M. H. *Piecewise deterministic Markov processes : a general class of non diffusion stochastic models*. Journal of the Royal Statistical Society : Series B (Methodological), 46(3), 353-376.(1984)

**Entre autres applications à la dynamique des populations:**

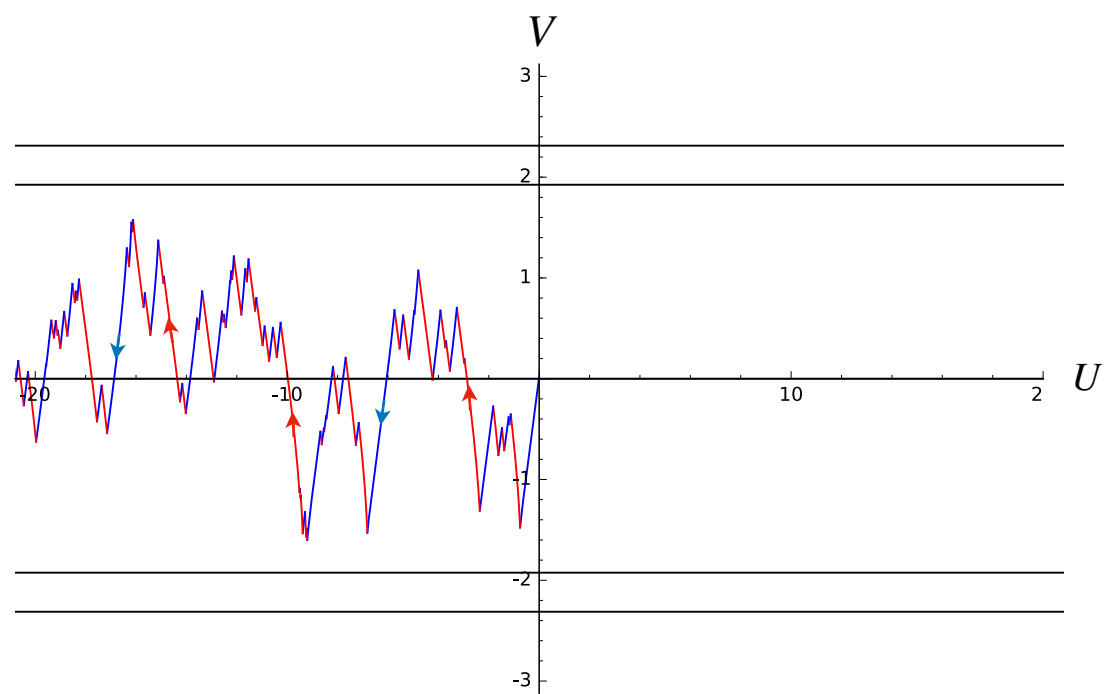
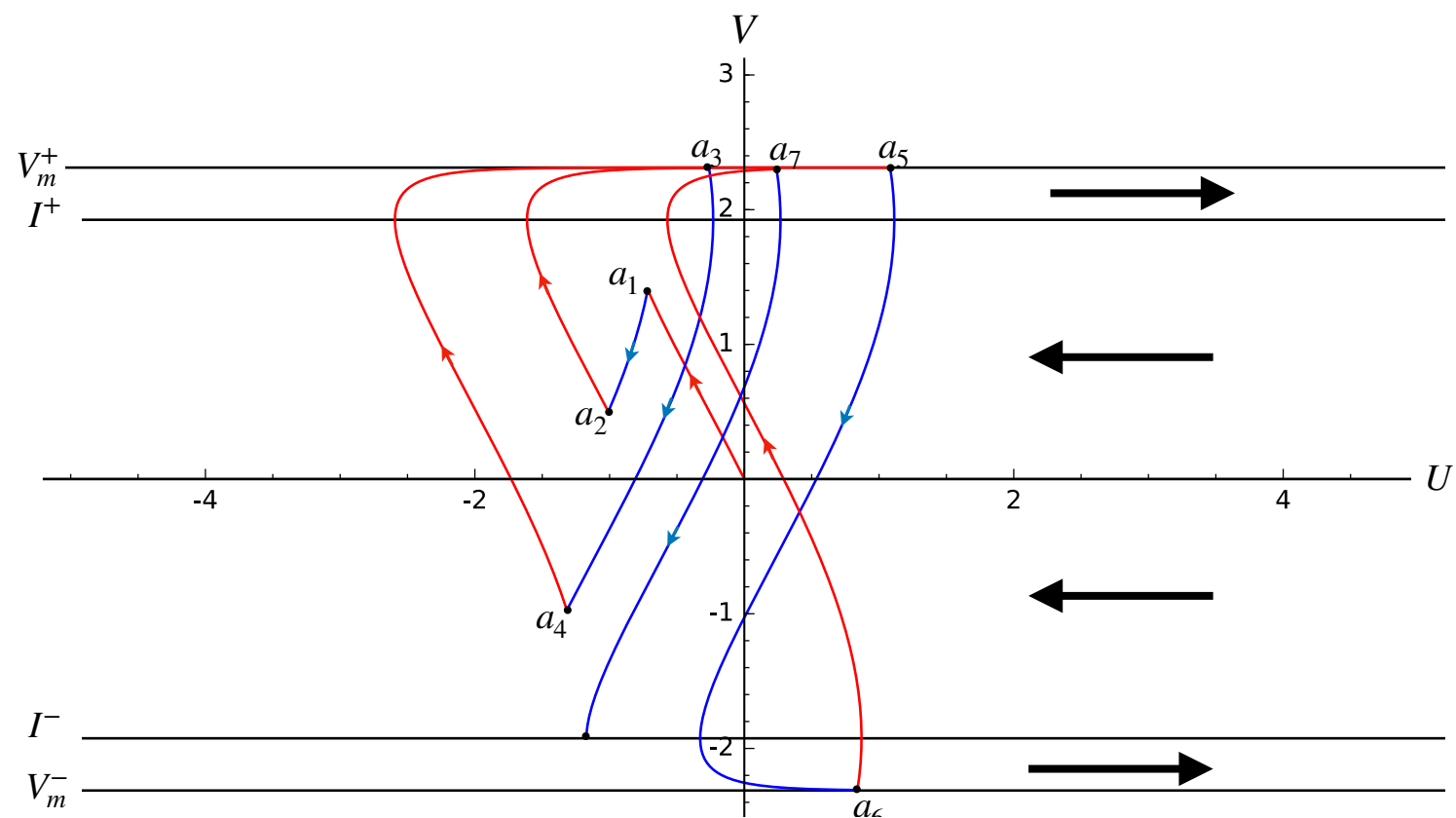
- [4] Benaïm, M. and Le Borgne, S. and Malrieu, F. and Zitt, P.- A. *Qualitative properties of certain piecewise deterministic Markov processes* = Ann. Inst. Henri Poincaré Probab. Stat. Annales de l'Institut Henri Poincaré, Probabilités et Statistiques, (2015)
- [5] Benaïm, M., & Lobry, C. *Lotka–Volterra with randomly fluctuating environments or “How switching between beneficial environments can make survival harder”*. The Annals of Applied Probability, 26(6), 3754-3785. (2016)
- [6] Benaïm, M. and Strickler, E. *Random Switching between Vector Fields Having a Common Zero* Ann. Appl. Probab., 29(1), 326-375 (2019)
- [12] Hening, Alexandru and Strickler, Edouard *On a predator-prey system with random switching that never converges to its equilibrium* SIAM Journal on Mathematical Analysis 51(5), 3625–3640 (2019)
- [13] Hurth, Tobias and Strickler, Edouard *Randomly Switched ODES with nonexponential switching times*. Preprint, 2021



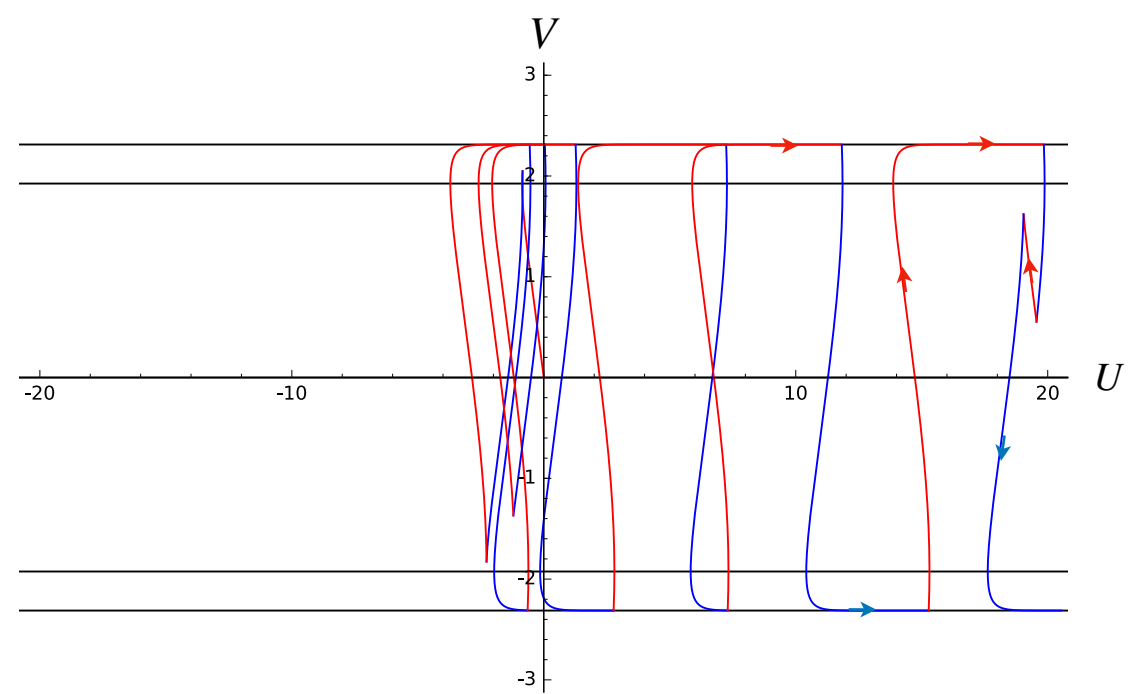


## Piecewise Deterministic Markov Processes (PDMP) :

Des variables aléatoires indépendantes  $T_1, T_2, \dots, T_n, \dots$  suivant une loi exponentielle  
 Définissent un processus de Markov  $U_t, V_t$



$T = 0.2$



$T = 5$

$$T_i \sim \mathcal{E}(\mu) \iff P(T_i \leq x) = \frac{1}{\mu} \int_0^x e^{-\mu s} ds \quad E(T_i) = \frac{1}{\mu}$$

$$T_i \sim \mathcal{E}\left(\frac{1}{T}\right) \iff P(T_i \leq x) = T \int_0^x e^{-\frac{1}{T}s} ds \quad E(T_i) = T$$

„Périodique en moyenne T”

Le processus  $V_t$  a une unique probabilité stationnaire  $\mu$  définie sur  $[V_m^-, V_m^+]$  qui est calculable explicitement telle que pour toute fonction, p. s.  $\Phi$

$$\lim_{t \rightarrow +\infty} \frac{\int_0^t \Phi(V_t) dt}{t} = \int_{[V_m^-, V_m^+]} \phi(s) d\mu(s) \quad a.s.$$

$$\bar{\Delta}(\varepsilon, m, T) = \lim_{t \rightarrow \infty} \frac{U_t}{t} = \frac{1}{t} \int_0^t 2(m \cosh(V_t) - m - \varepsilon) dt = \int_{[V_m^-, V_m^+]} 2(m \cosh(s) - m - \varepsilon) d\mu(s)$$

$$\bar{\Delta}(\varepsilon, m, T) = \frac{1}{t} \int_0^t 2(m \cosh(V_t) - m - \varepsilon) dt = \int_{[V_m^-, V_m^+]} 2(m \cosh(s) - m - \varepsilon) d\mu(s)$$

$$\rho_{m,T}^h(v) = \frac{C(m)}{|F_m^h(v)|} \left( \frac{e^{V_m^+} - e^v}{e^v + e^{V_m^-}} \frac{e^v - e^{V_m^-}}{e^v + e^{V_m^+}} \right)^{\frac{1}{2T\sqrt{m^2+1}}}$$

$$\int_{V_m^-}^{V_m^+} \rho_m^+(v) + \rho_m^-(v) dv = 1.$$

formules explicites pour

$$\Rightarrow \bar{\Delta}(\varepsilon, m, T)$$

étude asymptotique

Le processus  $V_t$  a une unique probabilité stationnaire  $\mu$  définie sur  $[V_m^-, V_m^+]$  qui est calculable explicitement telle que pour toute fonction, p. s.  $\Phi$

**Cas déterministe**

$$\overline{\Delta}(\varepsilon, m, T) = \lim_{t \rightarrow \infty} \frac{U(t)}{t} = \int_0^{2T} 2(m \cosh(V_p(t)) - m - \varepsilon) dt$$

$$\overline{\Delta}(\varepsilon, m, T) = \frac{1}{t} \int_0^t 2(m \cosh(V_t) - m - \varepsilon) dt = \int_{[V_m^-, V_m^+]} 2(m \cosh(s) - m - \varepsilon) d\mu(s)$$

$$\rho_{m,T}^h(v) = \frac{C(m)}{|F_m^h(v)|} \left( \frac{e^{V_m^+} - e^v}{e^v + e^{V_m^-}} \frac{e^v - e^{V_m^-}}{e^v + e^{V_m^+}} \right)^{\frac{1}{2T\sqrt{m^2+1}}}$$

$$\int_{V_m^-}^{V_m^+} \rho_m^+(v) + \rho_m^-(v) dv = 1.$$

formules explicites pour

$$\Rightarrow \overline{\Delta}(\varepsilon, m, T)$$

étude asymptotique

## Theorem

1. Pour tout  $m > 0$ ,

$$\lim_{T \rightarrow 0} \bar{\Delta}(\varepsilon, m, T) = -2\varepsilon < 0.$$

2. Pour tout  $m > 0$ ,

$$\lim_{T \rightarrow \infty} \bar{\Delta}(\varepsilon, m, T) = 2 \left( \sqrt{m^2 + 1} - m - \varepsilon \right).$$

*en particulier*

Existence de l'inflation pour T grand

$$\lim_{T \rightarrow \infty} \bar{\Delta}(\varepsilon, m, T) > 0 \quad \Leftrightarrow \quad m < \frac{1 - \varepsilon^2}{2\varepsilon}.$$

3. Pour tout  $T > 0$ ,

mais pour m ni trop grand ni trop petit

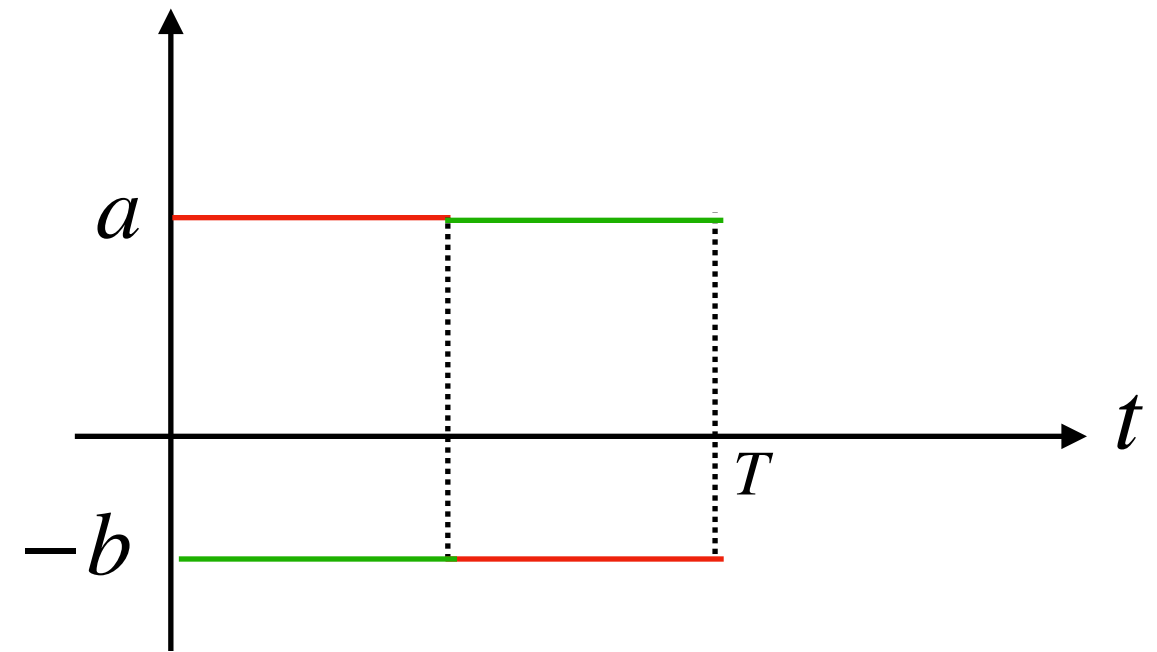
$$\lim_{m \rightarrow 0} \bar{\Delta}(\varepsilon, m, T) = \lim_{m \rightarrow \infty} \bar{\Delta}(\varepsilon, m, T) = -2\varepsilon.$$

On retrouve la même conclusion que dans le cas déterministe

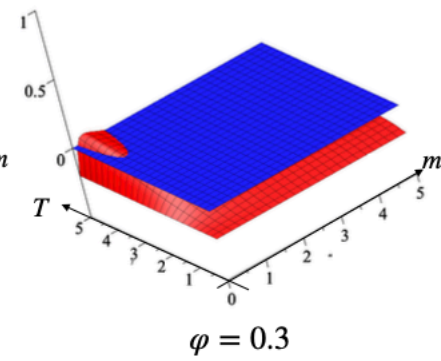
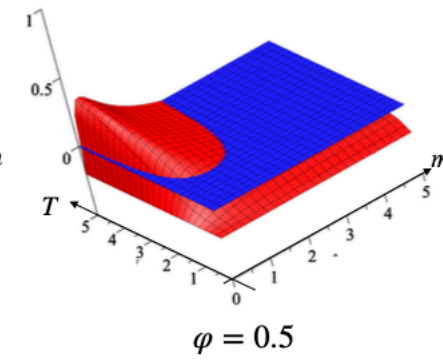
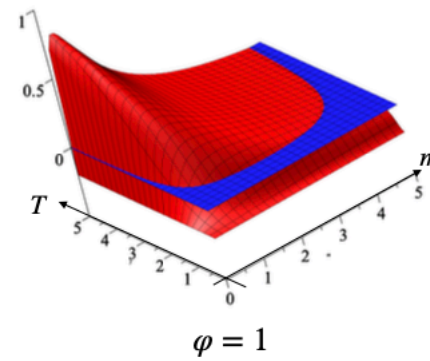
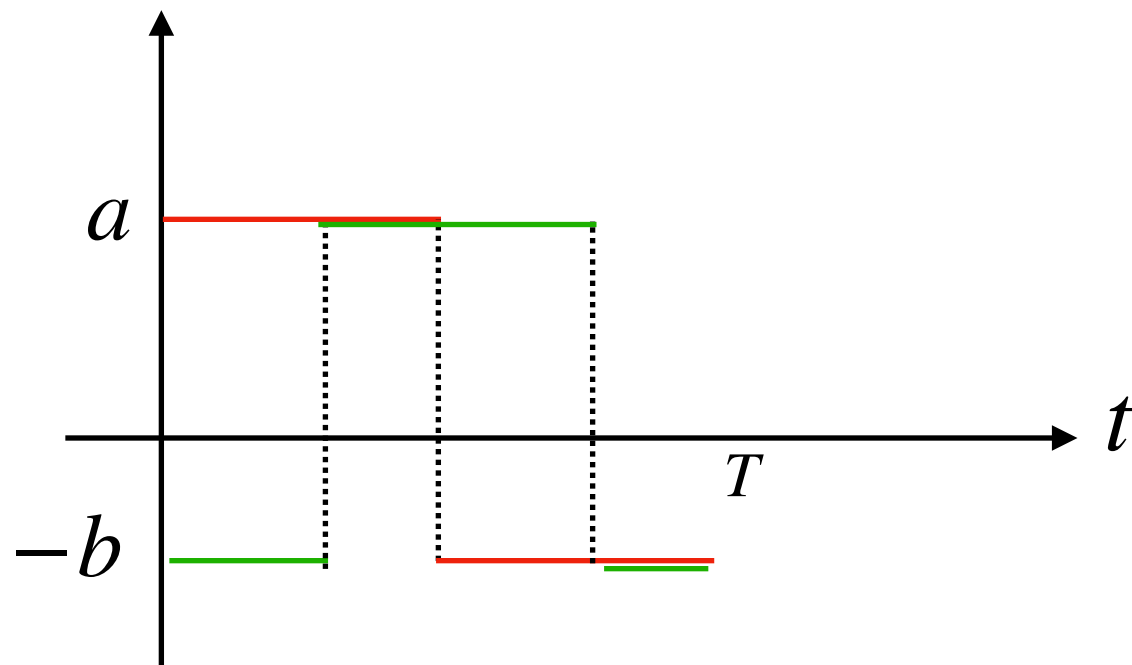
# Extensions

## Le modèle (+a-b)

Opposition de phase



Déphasage partiel



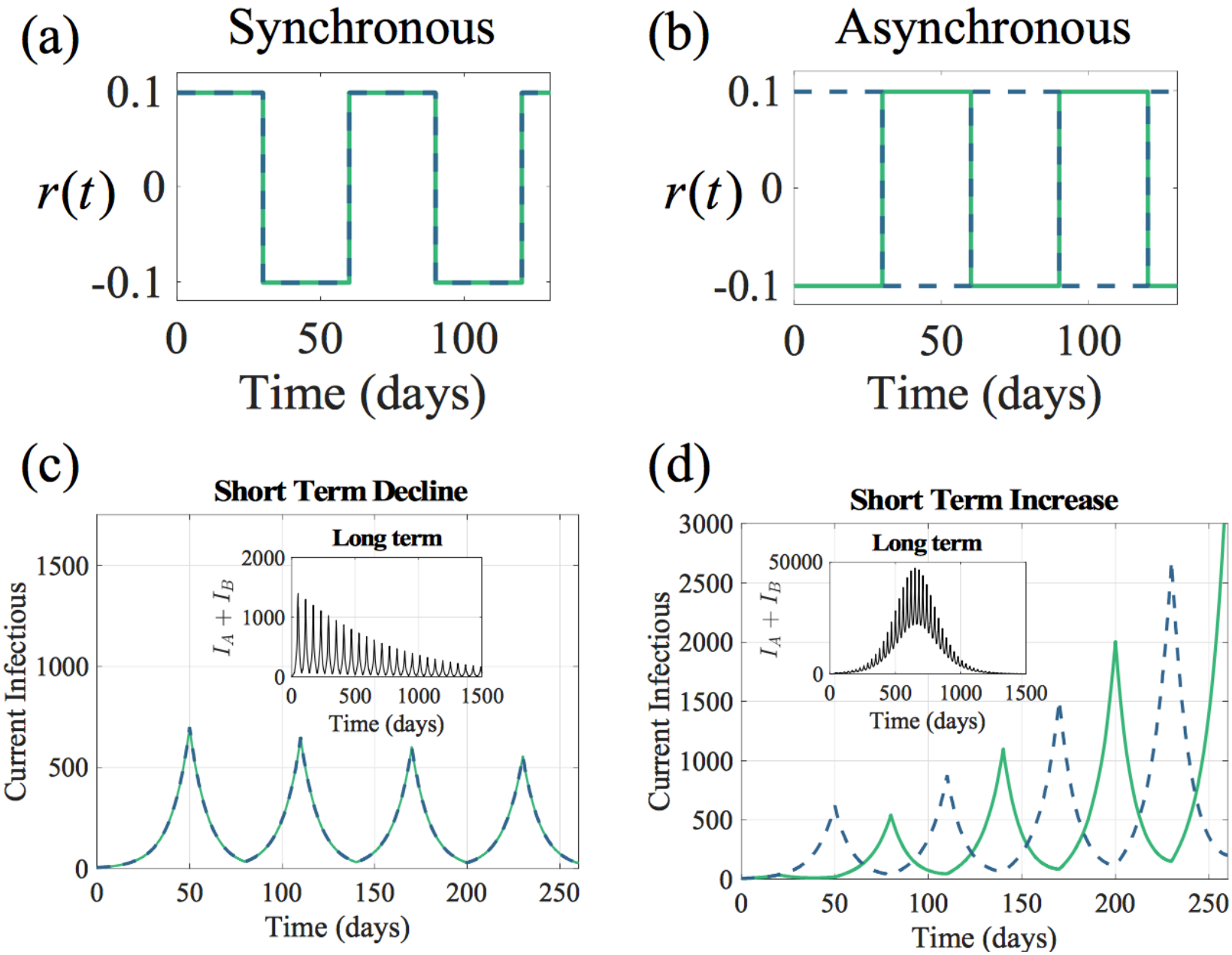
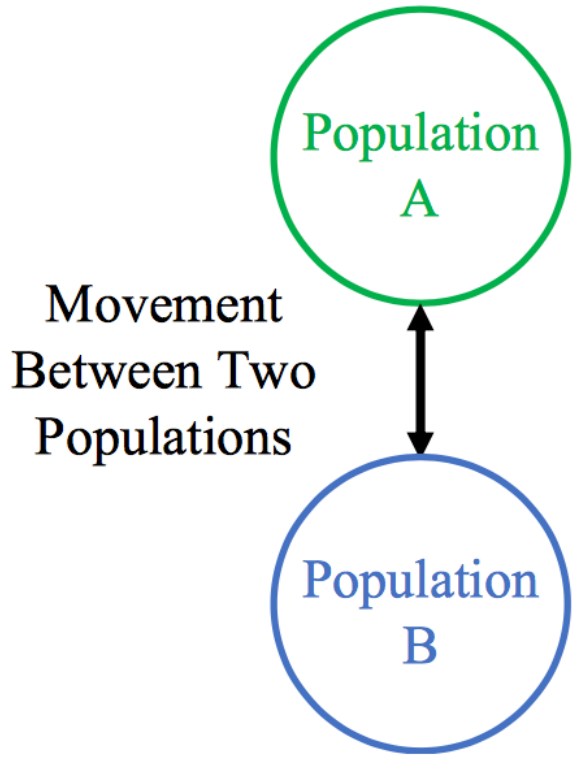


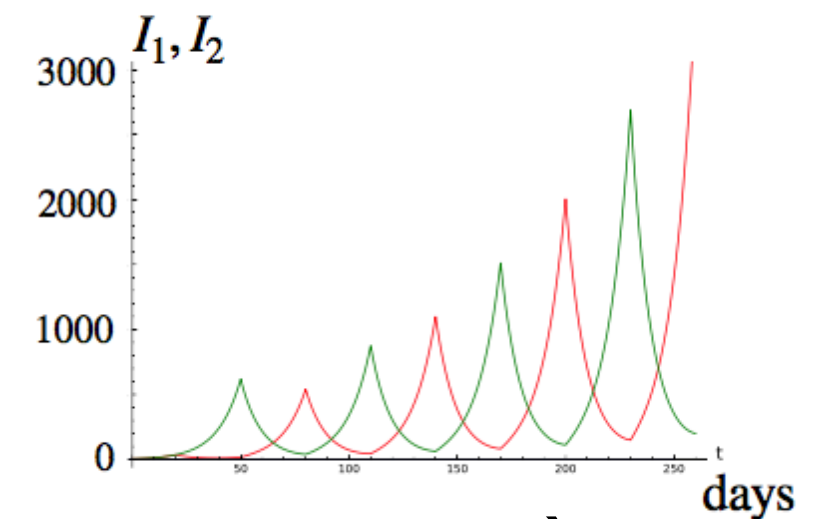
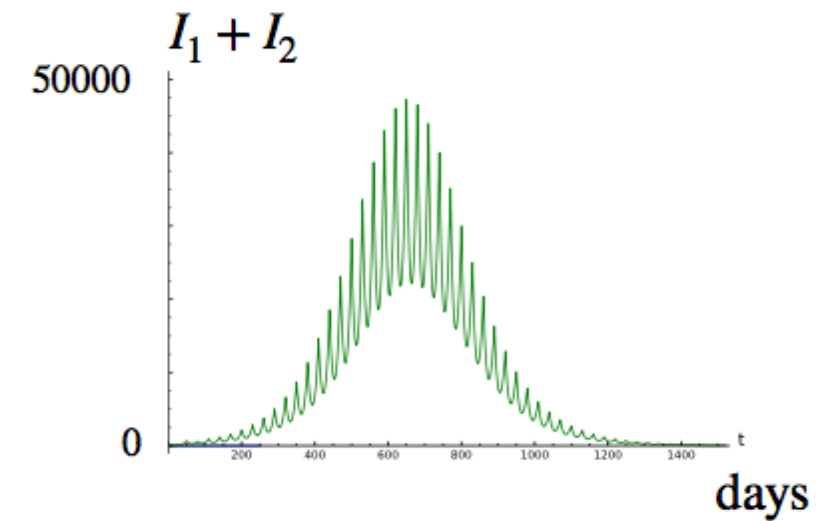
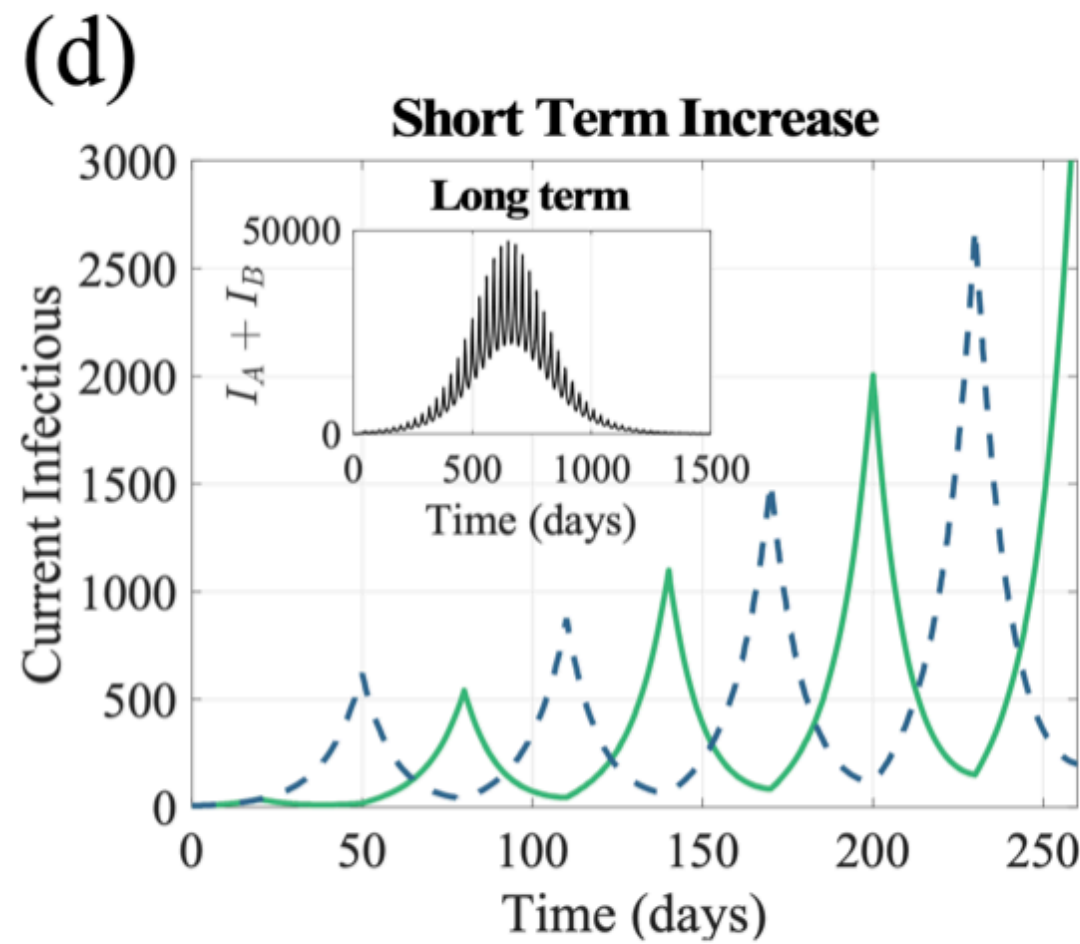
Figures

Staggering Disease Mitigation Strategies Can Fail

Time-Varying  
Transmission Dynamics

$$r_i(t) = \underbrace{N_i \beta_i(t)}_{\text{Transmission}} - \underbrace{\gamma_i(t)}_{\text{Recovery}} - \underbrace{\mu}_{\text{Mortality}}$$





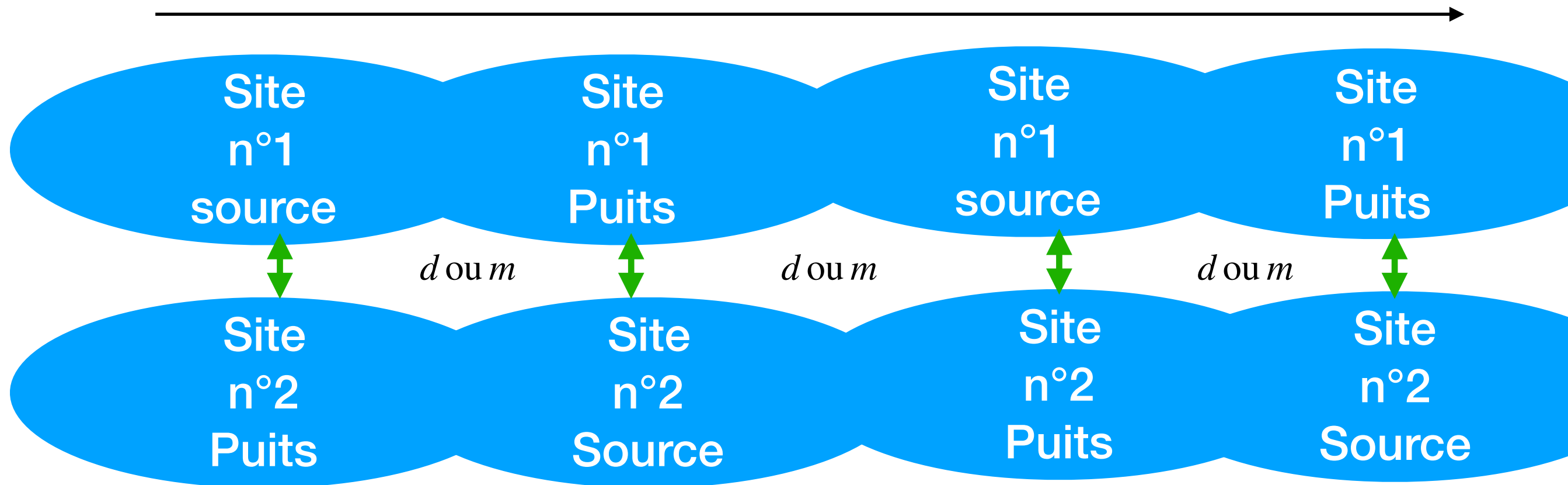
**Même modèle  
simulé par nous**

$\beta_n N = 0.1988$	$\gamma_n = 0.098$	$\mu_n = 0.002$
$\beta_s N = 0.0288$	$\gamma_s = 0.128$	$\mu_s = 0.002$

$\beta_n N - (\gamma_n + \mu_n) = 0.0988$
$\beta_s N - (\gamma_s + \mu_s) = -0.1012$

**Le secret**

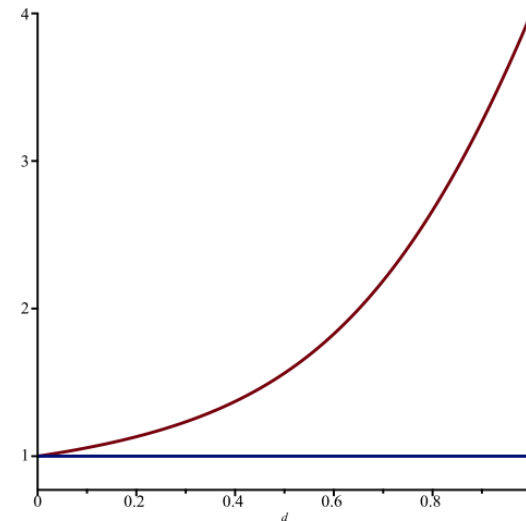
## Globalement neutre



$$x_1(n+1) = [f(x_1(n), x_2(n))](1-d)$$

$$x_2(n+1) = [f(x_1(n), x_2(n))]d$$

$$d \in [0,1]$$



$$\frac{dx_1}{dt} = f(x_1, x_2) + m(x_2 - x_1)$$

$$\frac{dx_2}{dt} = f(x_1, x_2) + m(x_1 - x_2)$$

$$m \in [0, +\infty)$$

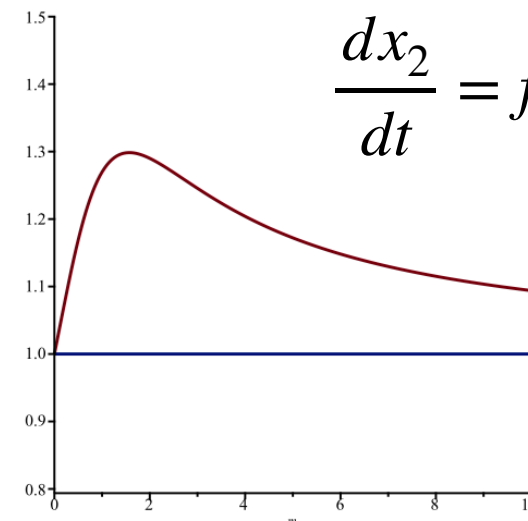
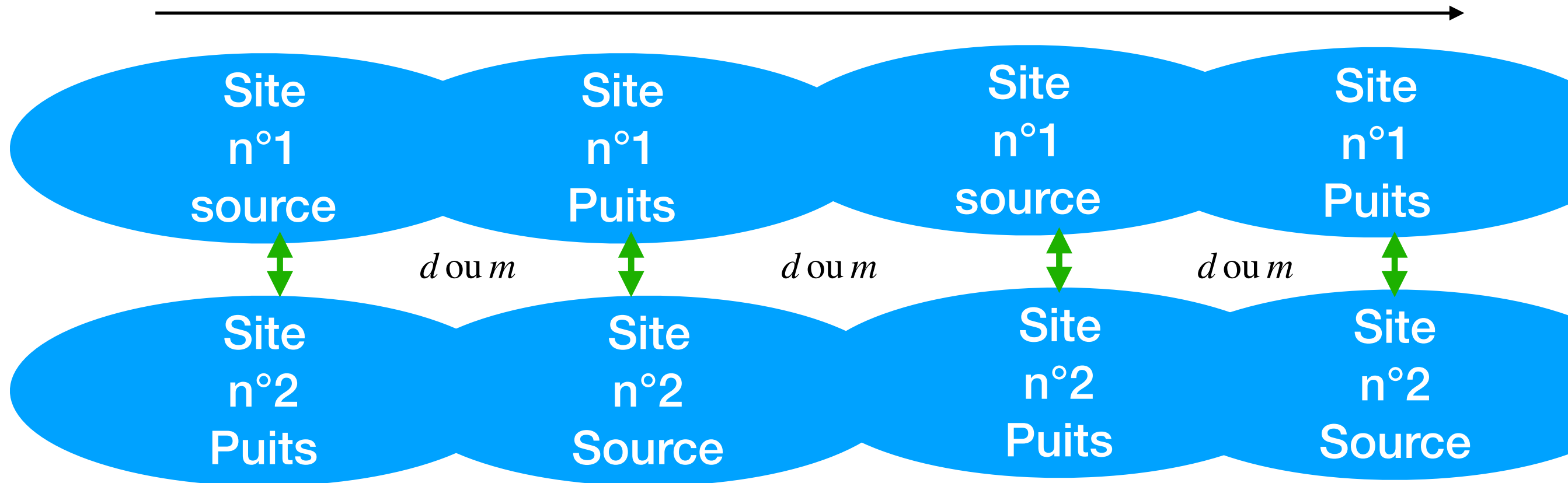


FIGURE 4 – Modèle "alternatif" : Discret (à gauche), continu (à droite)

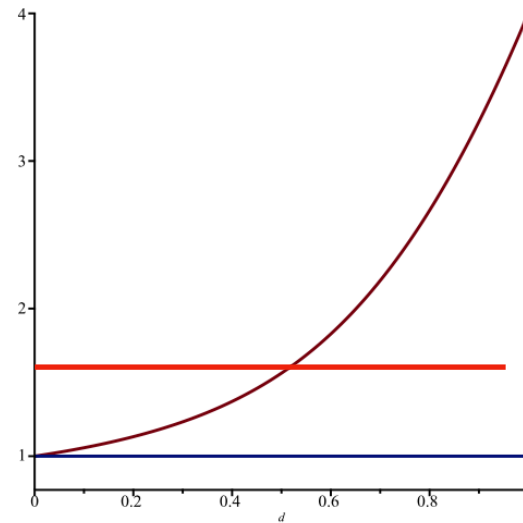
## Globalement puits



$$x_1(n+1) = [f(x_1(n), x_2(n))](1-d)$$

$$x_2(n+1) = [f(x_1(n), x_2(n))]d$$

$$d \in [0, 1]$$



$$\frac{dx_1}{dt} = f(x_1, x_2) + m(x_2 - x_1)$$

$$\frac{dx_2}{dt} = f(x_1, x_2) + m(x_1 - x_2)$$

$$m \in [0, +\infty)$$

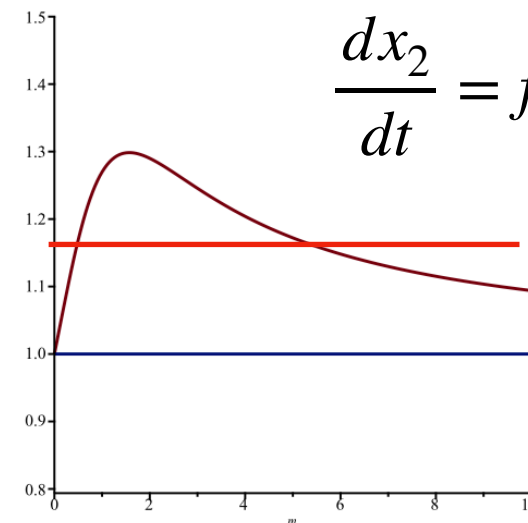
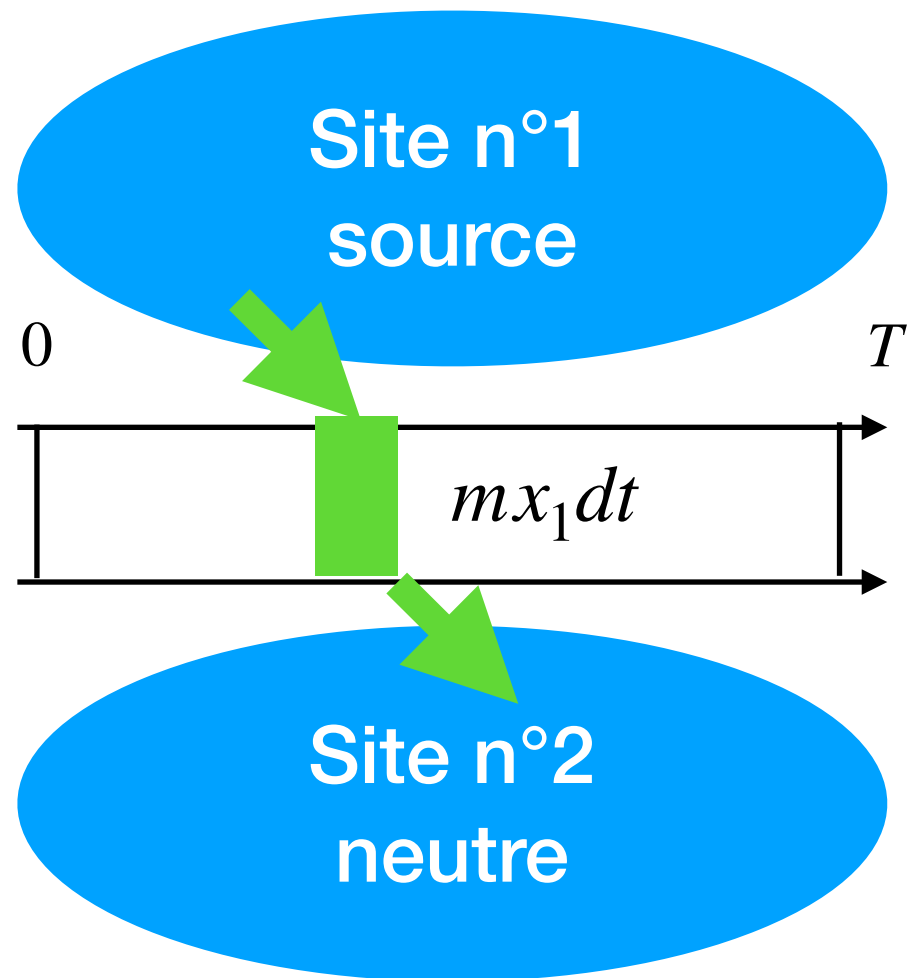
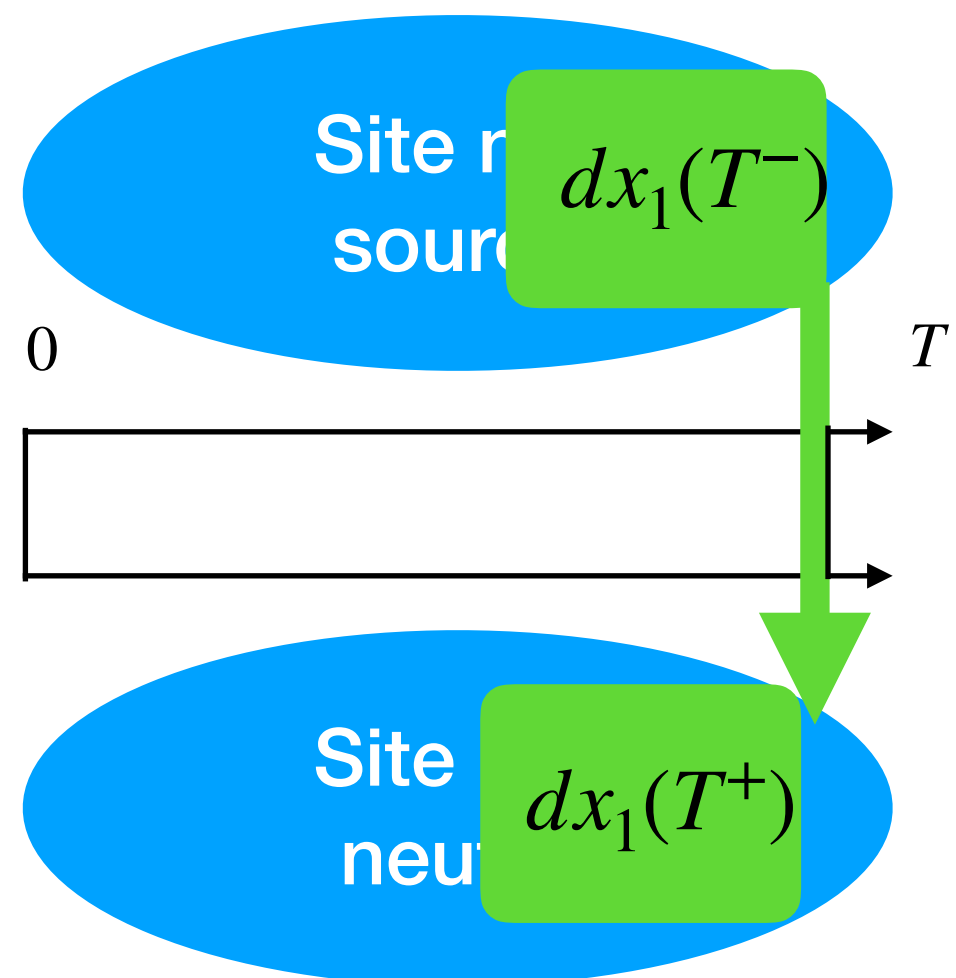


FIGURE 4 – Modèle "alternatif" : Discret (à gauche), continu (à droite)

$$\frac{dx_1}{dt} = (r - m)x_1, \quad r > 0$$



$$\frac{dx_1}{dt} = rx_1, \quad r > 0 \quad x_1(T) = x_1(0)e^{rT}$$





$$x_1(t) = x_1(0)e^{(r-m)t}$$

$$x_2(T) = \int_0^T mx_1(0)e^{(r-m)t} dt$$

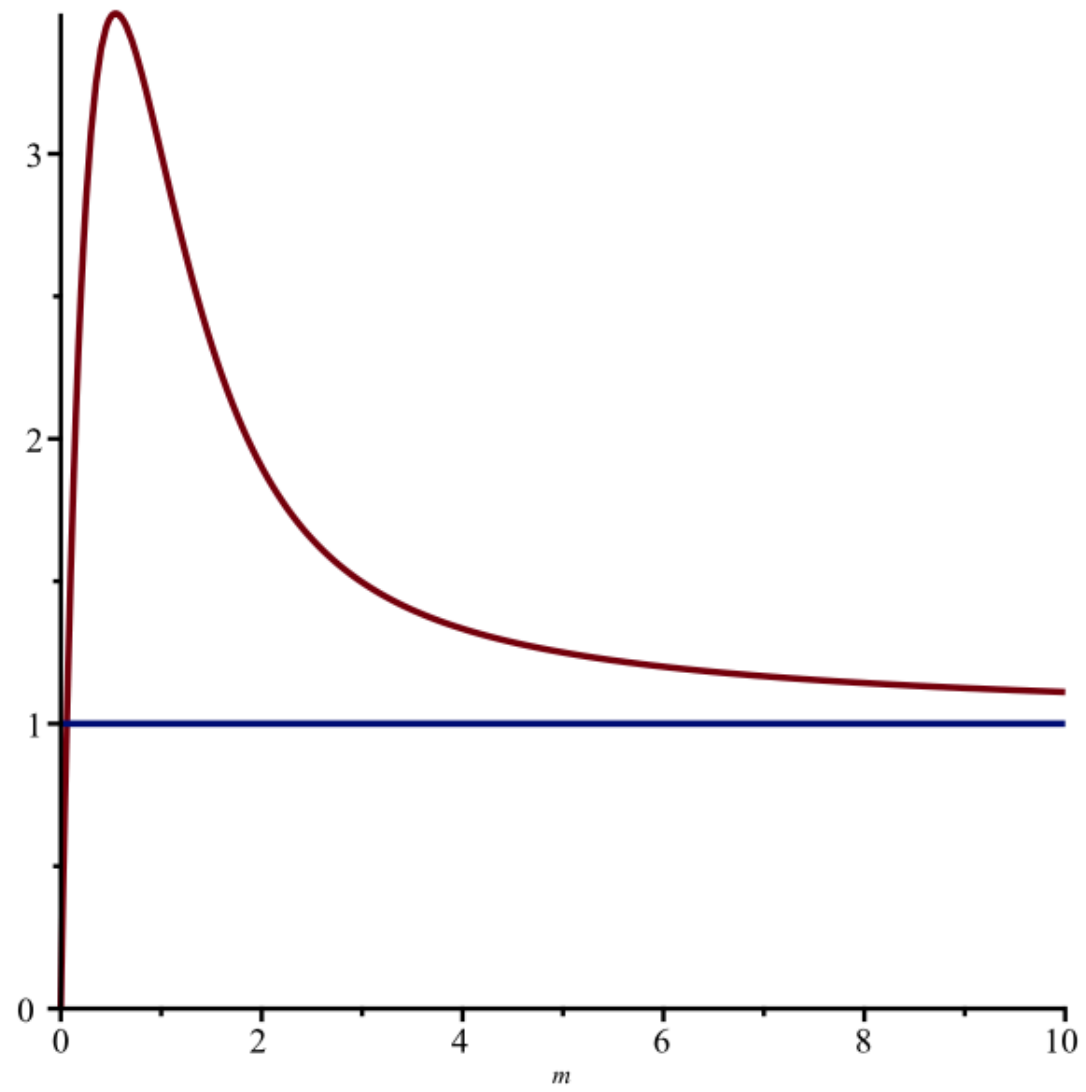
$$x_2(T) = \frac{m}{r-m} (e^{(r-m)T} - 1)$$



$$x_1(T) = x_1(0)e^{rt}(1-d)$$

$$x_2(T) = x_1(0)e^{rt}d$$

**La disperstion ne change pas**  
**La population totale**



$$x_2(T) = \frac{m}{r - m} \left( e^{(r-m)T} - 1 \right)$$



