

# Optimal management of stochastic shallow lakes

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# oligotrophic vs eutrophic lakes



# Modelling the nutrient content

The nutrient content is usually measured in terms of P concentration.

$$\begin{aligned}\dot{P}(t) &= L(t) && \text{(P loading by natural and human activity)} \\ &- sP(t) && \text{(sedimentation, outflow)} \\ &+ \Phi(P(t)) && \text{(recycling from sediments)}\end{aligned}$$

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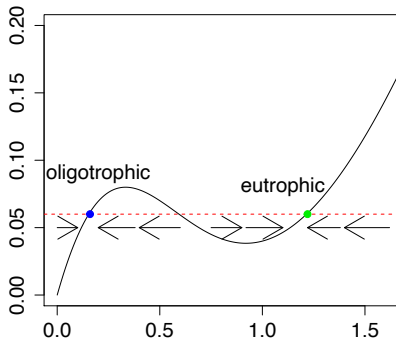
With a change of variables ( $x = \frac{P}{m}$ ,  $a = \frac{L}{r}$ ,  $b = \frac{sm}{r}$ ) the equation becomes

$$\dot{x}(t) = a(t) - bx(t) + \frac{x^2(t)}{1 + x^2(t)}.$$

# Equilibrium under constant load

$$\dot{x}(t) = a(t) - bx(t) + \frac{x^2(t)}{1 + x^2(t)}.$$

When  $b$  is not too high the lake may have 2 stable equilibria.



Solid black line:  $y = bx - \frac{x^2}{1+x^2}$ .

Dashed red line:  $y = a$ .

# A welfare function

Farmers or industry have an interest to increase P loading,  $a$ .

Visitors prefer a clean lake, i.e. small  $x$ .

Suppose a community balances these needs and assigns value to the state of the lake

$$U(a, x) = \ln a - cx^2.$$

Given the current P concentration  $x$ , we are interested in the optimal loading  $\{a(t) : t \geq 0\}$  to maximise the welfare function

$$J(x, a(\cdot)) = \int_0^{\infty} e^{-\rho t} U(a(t), x(t)) dt$$

where  $\{x(t) : t \geq 0\}$  solves

$$\dot{x}(t) = a(t) - bx(t) + \frac{x^2(t)}{1 + x^2(t)}, \quad x(0) = x.$$

# The problem

Add multiplicative noise

[Grass, Kiseleva, Wagener 2015]

$$\begin{cases} dx(t) = \left( u(t) - bx(t) + \frac{x^2(t)}{x^2(t) + 1} \right) dt + \sigma x(t) dW(t), \\ x(0) = x \end{cases} \quad (1)$$

and the value function

$$V(x) = \sup_{u \in \mathfrak{U}_x} \mathbb{E} \left[ \int_0^\infty e^{-\rho t} [\ln u(t) - cx^2(t)] dt \right].$$

Admissible controls  $u \in \mathfrak{U}_x$  should be positive, adapted processes in some filtered probability space such that

$$\mathbb{E} \left[ \int_0^\infty e^{-\rho t} \ln u(t) dt \right] < \infty$$

and (1) has a unique strong solution.



# DPP and HJB equation

The tool to characterise the value function  $V$  is the Dynamic Programming Principle (DPP):

$$V(x) = \sup_{u \in \mathcal{U}_x} \mathbb{E} \left[ \int_0^{\theta_u} e^{-\rho t} (\ln u(t) - cx^2(t)) dt + e^{-\rho \theta_u} V(x(\theta_u)) \right].$$

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- Unbounded controls, the Hamiltonian may be infinite.
- Boundary conditions at zero? at infinity?

# Elementary properties

Implicit formula

$$x(t) = xZ_t + \int_0^t \frac{Z_t}{Z_s} \left( u(s) + \frac{x^2(s)}{1 + x^2(s)} \right) ds,$$

where  $Z_t = e^{\sigma W_t - (b + \frac{\sigma^2}{2})t}$ .

## Elementary properties

- Any solution  $\{x(t) : t \geq 0\}$  with  $x(0) \geq 0$  remains positive at all times,  $\mathbb{P}$ -a.s.
- $\mathfrak{U}_x = \mathfrak{U}_y = \mathfrak{U}$  for all  $x, y \geq 0$
- If  $x_1(0) \leq x_2(0)$  and  $u_1(t) \leq u_2(t)$ ,  $\mathbb{P}$ -a.s., then  $x_2(t) - x_1(t) \geq (x_2(0) - x_1(0))Z_t$ ,  $\mathbb{P}$ -a.s.

# Estimates for $V$ from the SDE

- $\sigma^2 \geq \rho + 2b \Rightarrow V(x) = -\infty, \forall x \geq 0.$   
 $\sigma^2 < \rho + 2b \Rightarrow V(x) \in \mathbb{R}, \forall x \geq 0$  (assume hereafter).

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- If  $0 \leq x < y \leq K$ , there exist constants  $C_1(K), C_2 > 0$  such that

$$-C_1(K) \leq \frac{V(y) - V(x)}{y - x} \leq -C_2.$$

In particular  $V$  is **strictly decreasing and locally Lipschitz**.

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- Set  $A = c(\rho + 2b - \sigma^2)^{-1}$ . There exist constants  $K_1, K_2$  s.t.

$$K_1 \leq V(x) + A \left( x + \frac{1}{b + \rho} \right)^2 + \frac{1}{\rho} \ln \left( x + \frac{1}{b + \rho} \right) \leq K_2,$$

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$$\rho V = \underbrace{\left( \frac{x^2}{x^2 + 1} - bx \right) V' - (\ln(-V') + cx^2 + 1) + \frac{1}{2} \sigma^2 x^2 V''}_{H(x, V', V'')}$$

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Note: Boundary condition at  $x = 0 \rightarrow$  HJB is satisfied at  $x = 0$ .

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# Definition

[Soner 1986, Lasry, Lions 1989,...]

Let  $v : [0, \infty) \rightarrow \mathbb{R}$  a continuous function. We say that

- i)  $v$  is a *viscosity subsolution* of the HJB on  $[0, \infty)$ , if for every  $\phi \in C^2[0, \infty)$  such that  $v - \phi$  has a local maximum at  $x \geq 0$

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- iii)  $v$  is a *constrained viscosity solution* of the HJB on  $[0, \infty)$ , if it is both a viscosity supersolution on  $(0, \infty)$  and a viscosity subsolution on  $[0, \infty)$ .

# $V$ is the unique constrained v.s. to the HJB

By the DPP and the boundary condition at  $x = 0$ , the value function  $V$  is a constrained viscosity solution to

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**Comparison principle:** Let

$u$  be a continuous viscosity subsolution of the HJB on  $[0, \infty)$  s.t.

$$\frac{u(y) - u(x)}{y - x} \leq -\frac{1}{c_*} < 0, \quad \forall x, y \in [0, \infty)$$

$v$  be a continuous, strictly decreasing viscosity supersolution of the HJB on  $(0, \infty)$  such that

$$\liminf_{x \rightarrow \infty} \frac{v(x)}{1 + x^2} > -\infty.$$

Then,  $u \leq v$  on  $[0, \infty)$ .

# Properties of the value function ( $\sigma^2 < 2b + \rho$ )

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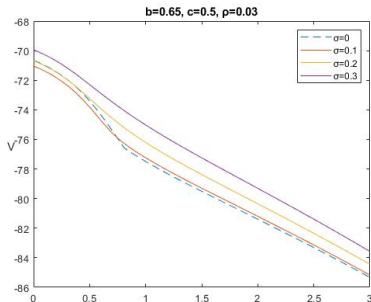
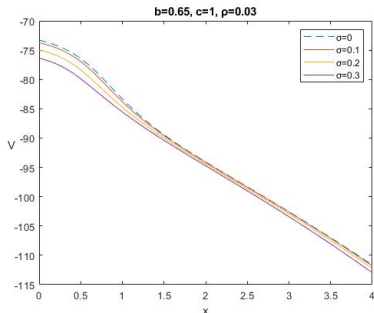
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$$V(x) + A \left( x + \frac{1}{b + \rho} \right)^2 + \frac{1}{\rho} \ln \left( x + \frac{1}{b + \rho} \right) \xrightarrow{x \rightarrow \infty} K$$



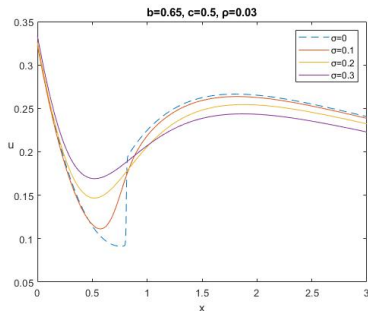
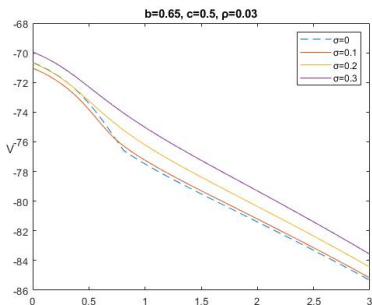
# Optimally controlled process

A verification theorem gives the optimal control in feedback form

$$u_*(x(t)) = -\frac{1}{V'(x(t))} \leq \frac{1}{c_*}$$

so the optimally controlled system satisfies

$$dx(t) = \left( -\frac{1}{V'(x(t))} - bx(t) + \frac{x^2(t)}{x^2(t) + 1} \right) dt + \sigma x(t) dW(t).$$



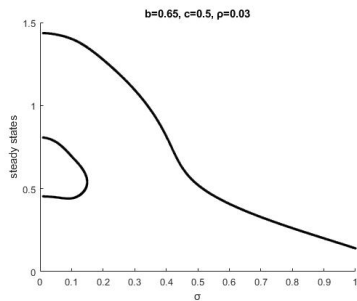
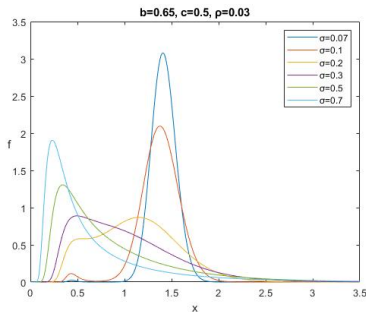
# Invariant measure

$$\mathcal{L}^* \mu = 0 \implies d\mu(x) = \frac{1}{Z} x^{-2(1+\frac{b}{\sigma^2})} e^{-\Psi_\sigma(x)} dx.$$

The exponent  $\Psi_\sigma$  is explicitly given in terms of  $V'$  and

$$\Psi_\sigma(x) \simeq \frac{2}{\sigma^2 |V'(0)| x}, \quad x \rightarrow 0 \quad \text{and} \quad \Psi_\sigma(x) \simeq \frac{2}{\sigma^2 x}, \quad x \rightarrow \infty.$$

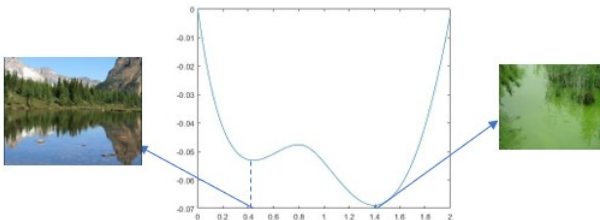
Polynomial tails at infinity get fatter as  $\sigma$  increases.



# Oligotrophic vs Eutrophic

When  $\sigma$  is small and other parameters are suitable, the invariant distribution may be bimodal. The process  $y(t) = \ln(x(t))$  is a diffusion in a double-well potential  $\Phi_\sigma(y)$ :

$$dy(t) = -\Phi'_\sigma(y(t))dt + \sigma dW(t).$$



with invariant distribution for  $\sigma > 0$

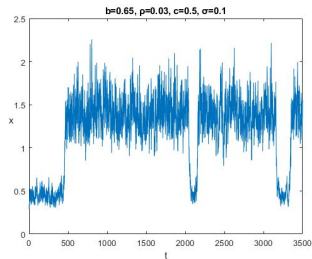
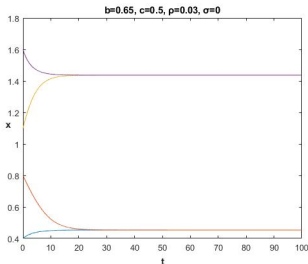
$$d\mu_\sigma(x) = \frac{1}{Z_\sigma} \exp\left(-\frac{2}{\sigma^2}\Phi_\sigma(x)\right)dx.$$



# Deterministic vs Stochastic trajectories

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# $\sigma \rightarrow 0$ asymptotics: metastability

For a diffusion in a double well potential

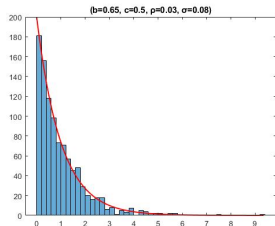
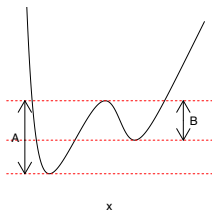
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Arrhenius law :  $\frac{\sigma^2}{2} \log \mathbb{E}[\tau_{O \rightarrow E}] \rightarrow A, \quad \frac{\sigma^2}{2} \log \mathbb{E}[\tau_{E \rightarrow O}] \rightarrow B$

[Siguira 1993, Bovier & den Hollander book 2014]

$$\frac{\tau_{O \rightarrow E}}{\mathbb{E}[\tau_{O \rightarrow E}]} \xrightarrow{d} \text{Exp}(1)$$

[Day 1983]



**Thank you for your attention**