

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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Limnologists take Φ to be a sigmoid function, typically

$$\Phi(x) = r \frac{x^2}{m^2 + x^2}.$$

[Carpenter, Ludwig, Brock 1999]

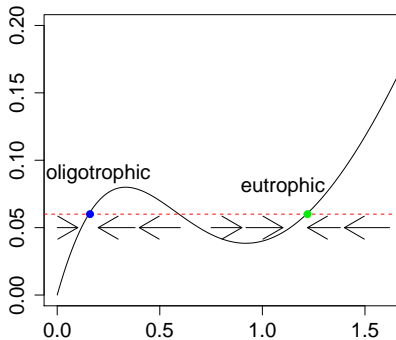
With a change of variables ($x = \frac{P}{m}$, $a = \frac{L}{r}$, $b = \frac{sm}{r}$) the equation becomes

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

Equilibrium under constant load

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

When b is not too large 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

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

Admissible controls $u \in \mathcal{U}_x$ 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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Issues

- Measurable selection problems in the proof of DPP
- No a priori regularity for V . In fact we do not even know if V takes finite values.
- Unbounded controls, the Hamiltonian may be infinite.
- Boundary conditions at zero? at infinity?

V as a constrained HJB v.s.

The value function V is a continuous constrained viscosity solution on $[0, \infty)$ to the HJB equation

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

- i) For every $\phi \in C^2[0, \infty)$ such that $V - \phi$ has a local maximum at $x \geq 0$:

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- ii) For any $\phi \in C^2(0, \infty)$ such that $V - \phi$ has a local minimum at $x > 0$:

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V as a constrained HJB v.s.

[Kossioris, L, Souganidis 2016; Koutsimpela, L 2022+]

The value function V is **the unique** continuous constrained viscosity solution on $[0, \infty)$ to

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satisfying:

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satisfying:

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

and

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

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

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For $\sigma = 0$, V' may have a jump discontinuity at one $x_* > 0$

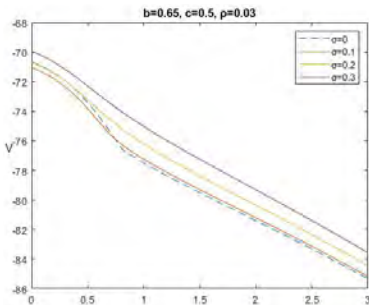
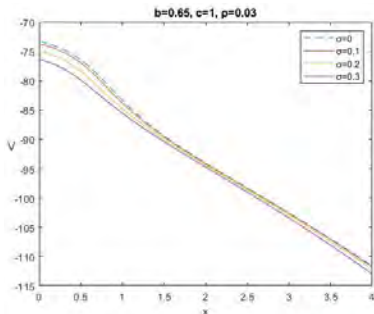
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$$V(x) + A \left(x + \frac{1}{b + \rho} \right)^2 + \frac{1}{\rho} \ln \left(x + \frac{1}{b + \rho} \right) \xrightarrow{x \rightarrow \infty} K$$



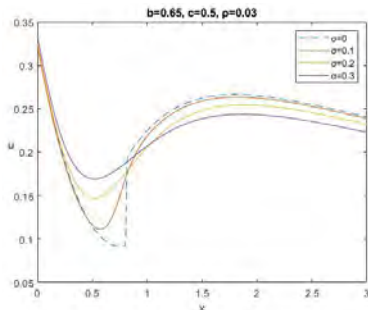
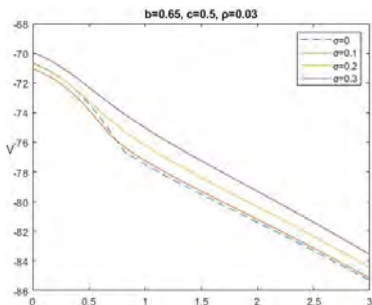
Optimally controlled process

A verification theorem gives the optimal control in feedback form

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

so the optimally controlled system satisfies

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



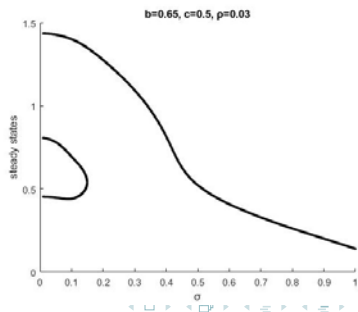
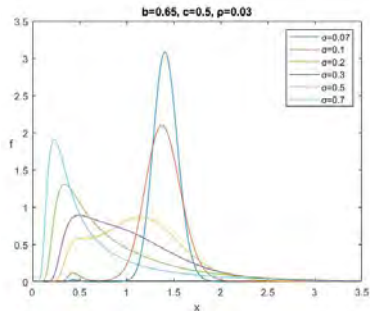
Invariant measure

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

The exponent Ψ_σ is explicitly given in terms of V'_σ and

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

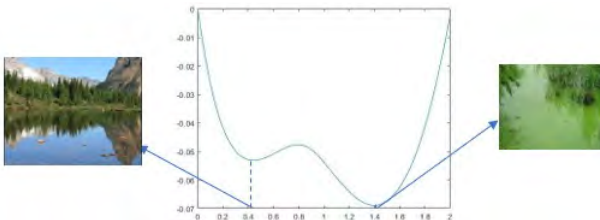
Polynomial tails at infinity get fatter as σ increases.



Oligotrophic vs Eutrophic

When σ 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 $\Phi_\sigma(y)$:

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



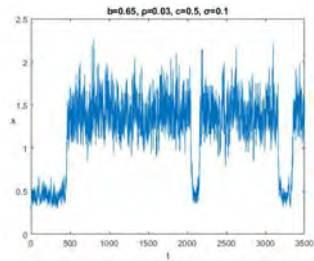
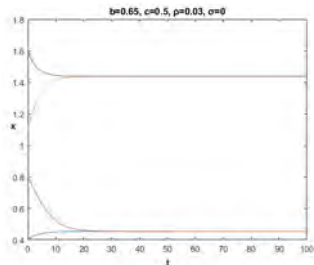
with invariant distribution for $\sigma > 0$

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

Deterministic vs Stochastic trajectories

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$\sigma \rightarrow 0$ asymptotics: metastability

V_σ semi-convex $\Rightarrow V'_\sigma \rightarrow V'_0$, as $\sigma \rightarrow 0$, $\forall x \neq x_*$

$\Rightarrow \Phi_\sigma \rightarrow \Phi_0$, uniformly on compact subsets of $(0, +\infty)$

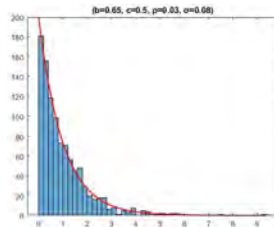
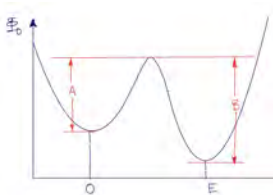
reduced to Freidlin-Wentzel theory.

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

[Sigura 1993, Bovier & den Hollander book 2014]

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

[Day 1983]



Ευχαριστούμε Μάκη.
Πάντα να εμπνέεις τους νεότερους!