

# Multi-Level and Multi-Index Monte Carlo Discontinuous Galerkin Methods for Uncertainty Quantification of Nonlinear Hyperbolic Problems

Stanislav Polishchuk (Monash University), Hans De Sterck (University of Waterloo) and Tiangang Cui (Monash University)

## Introduction

Many physical phenomena are modelled by partial differential equations (PDEs). As a result of measurement noise and uncertainties in model-driven factors such as initial conditions, boundary conditions, domain geometry and other model inputs, it is required to quantify uncertainties in the solutions.

- Input uncertainty: quantified by some probability distribution of the model parameters,  $\pi(\omega)$ ;
- Quantity of interest:  $P(\omega)$ , requires solving PDEs;
- Uncertainty quantification:  $\mathbb{E}_\pi[P(\omega)]$  or some other statistics of QoI.

## Model problem

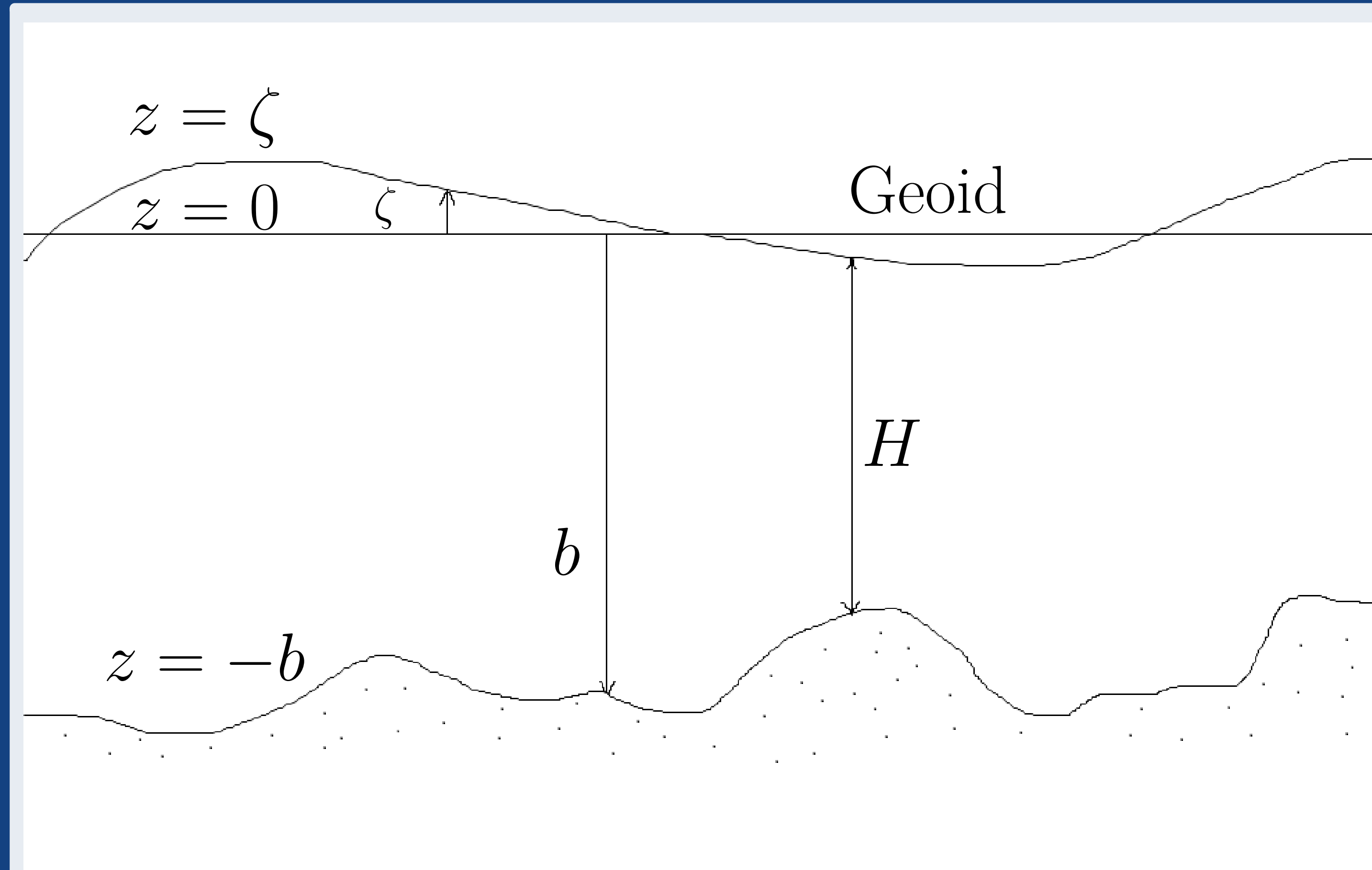


Figure – Shallow water model

Nonlinear shallow water equations in conservative form are

$$\begin{aligned} \frac{\partial H}{\partial t} + \frac{\partial}{\partial x}(Hu) + \frac{\partial}{\partial y}(Hv) &= 0 \\ \frac{\partial Hu}{\partial t} + \frac{\partial}{\partial x}(Hu^2 + \frac{1}{2}g(H^2 - h^2)) + \frac{\partial}{\partial y}(Huv) &= -gH \frac{\partial \zeta}{\partial x} \\ \frac{\partial Hv}{\partial t} + \frac{\partial}{\partial x}(Huv) + \frac{\partial}{\partial y}(Hv^2 + \frac{1}{2}g(H^2 - h^2)) &= -gH \frac{\partial \zeta}{\partial y} \end{aligned}$$

- $D = [-1000; 1000] \times [-1000; 1000]$  and  $T = [0; 10]$ ;
- $\zeta = \zeta(t, x, y)$ : the elevation of the free surface relative to the geoid;
- $b = b(x, y; \omega)$ : the bathymetry modelled as a lognormal random field;
- $H(t, x, y; \omega) = b + \zeta$  is the total depth of the water column.
- QoI: the average total depth over the region  $[-500; 500] \times [-500; 500]$ :

$$P(\omega) = D^{-1} \int_D H(t = 10, x, y; \omega) dD.$$

## Discontinuous Galerkin method

$$(U_t, v)_{D_k} = (A(U), \nabla v)_{D_k} + (A^* \cdot n, v)_{\partial D}$$

- $(\cdot, \cdot)_{D_k}$  is the scalar product in  $L_2$ -space;
- $A(U)$  is the flux matrix;
- the function  $v$  is the test function in some test space.

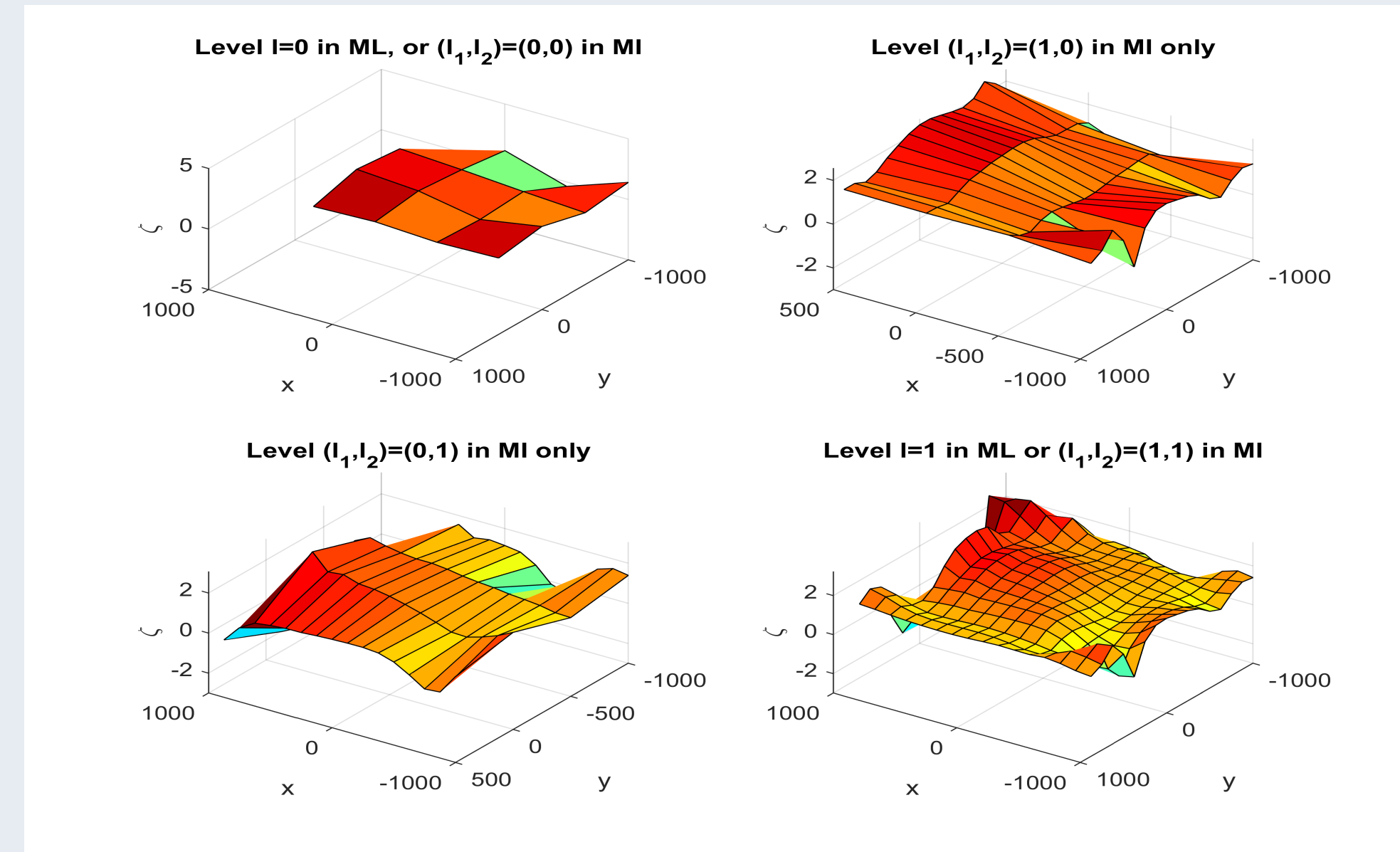


Figure – Free surface elevation,  $\zeta(x, y, t = 1.14)$

## Multi-level Monte Carlo

Given a sequence of QoIs  $P_0, \dots, P_L$

$$\mathbb{E}[P] \approx \mathbb{E}[P_L] = \mathbb{E}[P_0] + \sum_{l=1}^L \mathbb{E}[P_l - P_{l-1}]$$

The ML estimator

$$N_0^{-1} \sum_{n=1}^{N_0} P_0^{(0,n)} + \sum_{\ell=1}^L \left( N_\ell^{(-1)} \sum_{n=1}^{N_\ell} (P_\ell^{(\ell,n)} - P_{\ell-1}^{(\ell,n)}) \right).$$

$$N_\ell = 2\epsilon^{-2} \sqrt{V_\ell / C_\ell} \sum_{i=0}^L \sqrt{V_i C_i}$$

## Multi-index Monte Carlo

Level  $\ell$  is now a vector of indices  $\ell = (\ell_1, \ell_2, \dots, \ell_M)$  and we define a backward difference operator in one particular dimension,

$$\Delta_m P_\ell \equiv P_\ell - P_{\ell - e_m}$$

Then defining the cross-difference

$$\Delta P_\ell \equiv \left( \prod_{m=1}^M \Delta_m \right) P_\ell,$$

where  $\mathcal{L}$  is some index set.

The MI telescopic sum

$$\mathbb{E}[P] = \sum_{\ell \in \mathcal{L}} \mathbb{E}[\Delta P_\ell].$$

The estimator  $Y$  for  $\mathbb{E}[P]$

$$Y = \sum_{\ell \in \mathcal{L}} Y_\ell, \quad Y_\ell = \frac{1}{N_\ell} \sum_{n=1}^{N_\ell} \Delta P_\ell^{(\ell,n)}.$$

## Results

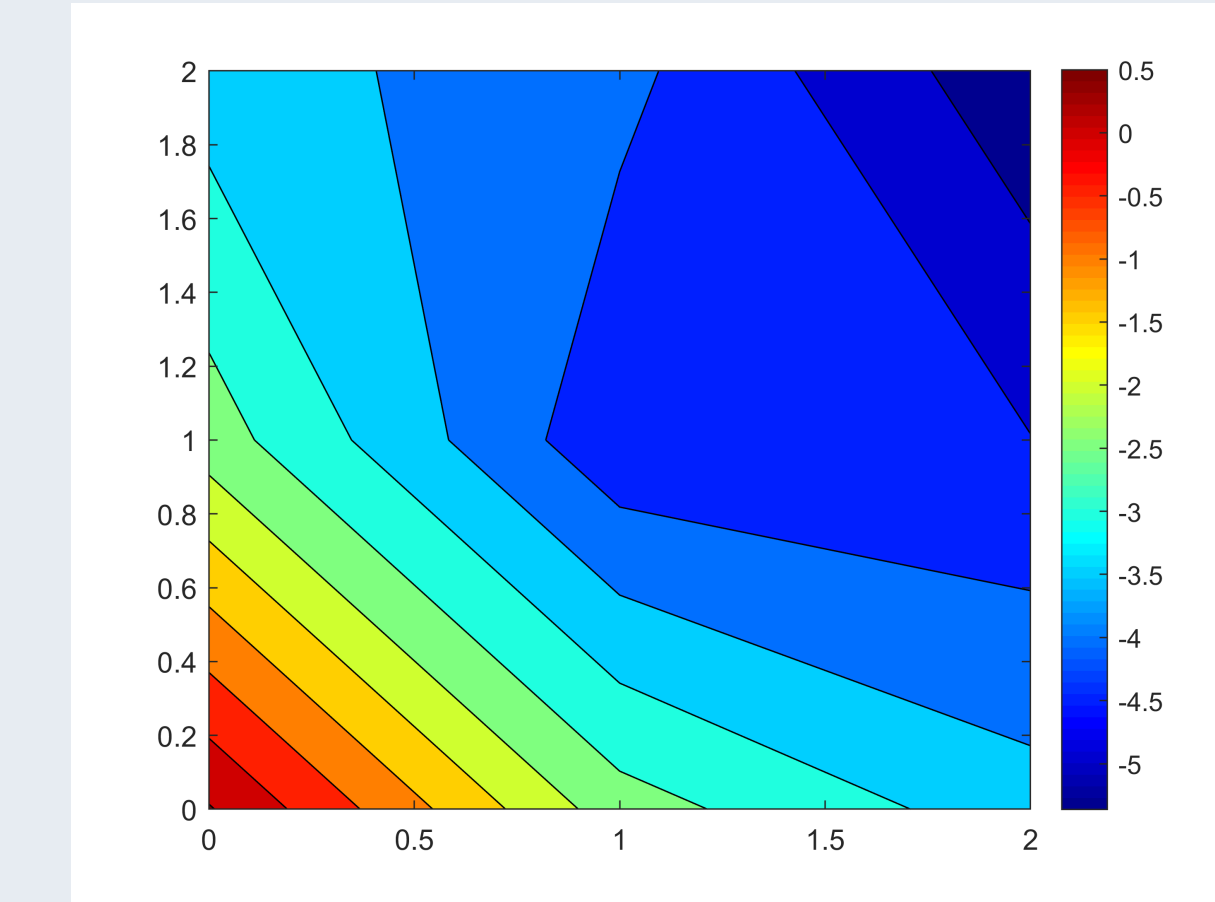


Figure – MI mean,  $\log(\mathbb{E}_\ell)$

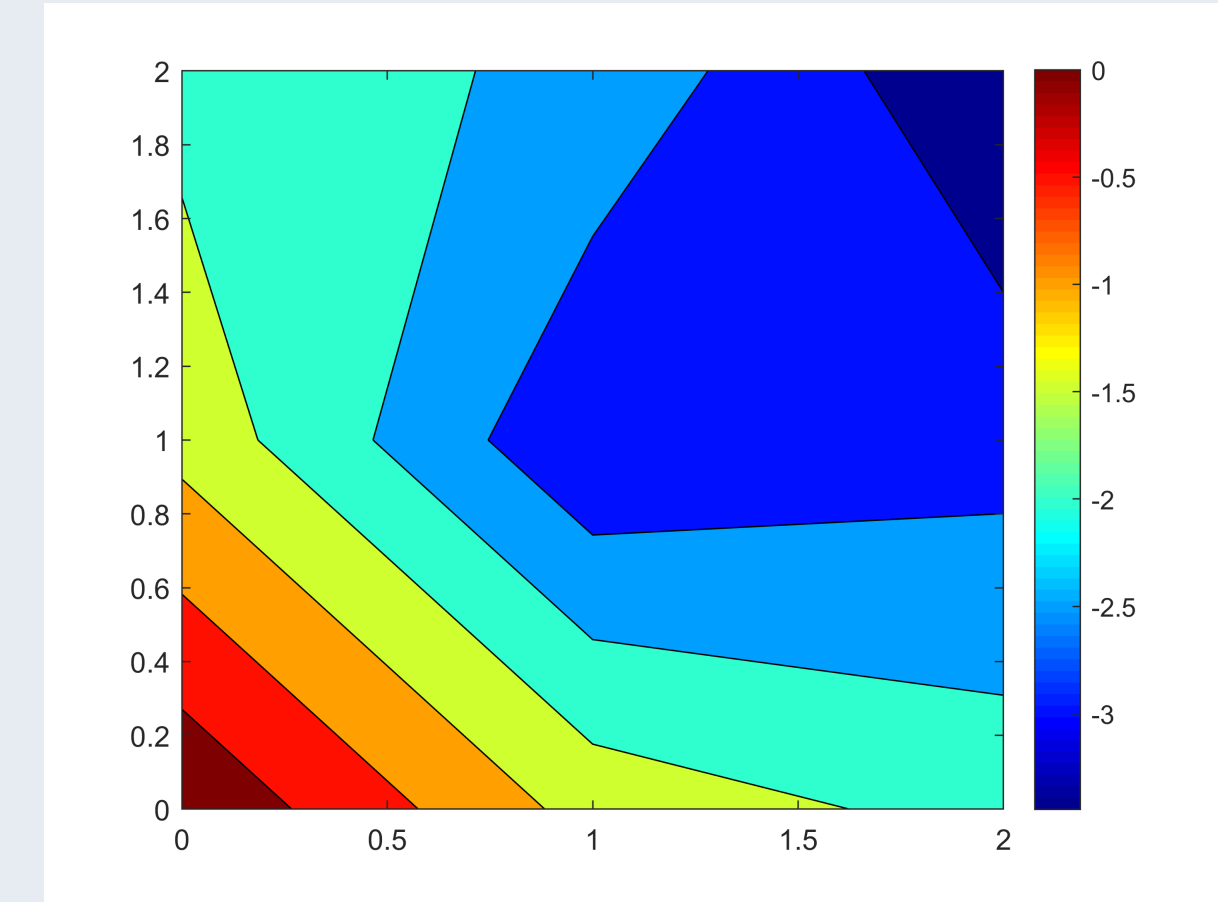


Figure – Profits,  $\log \mathbb{P}_\ell = \log \frac{\mathbb{E}_\ell}{\sqrt{V_\ell} C_\ell}$

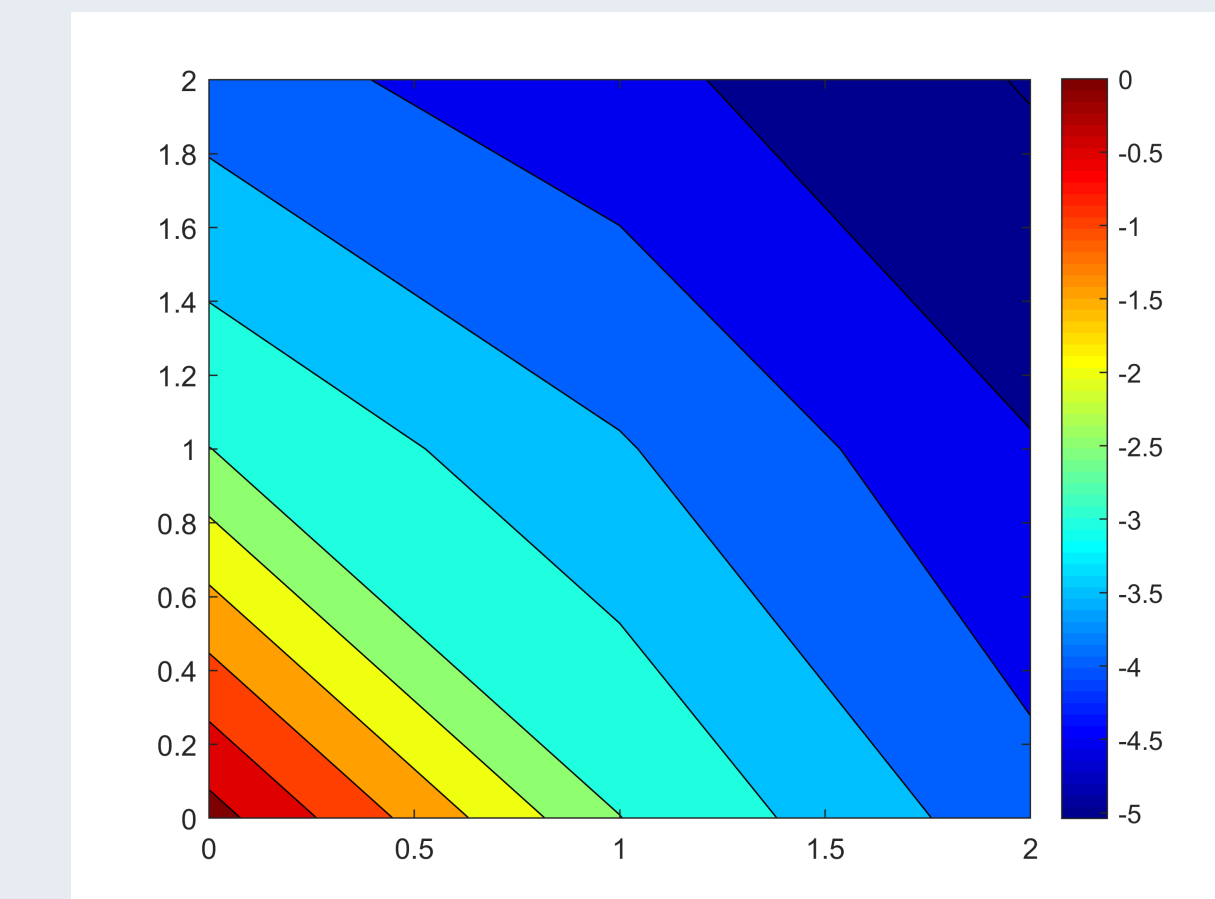


Figure – MI variance,  $\log V_\ell$

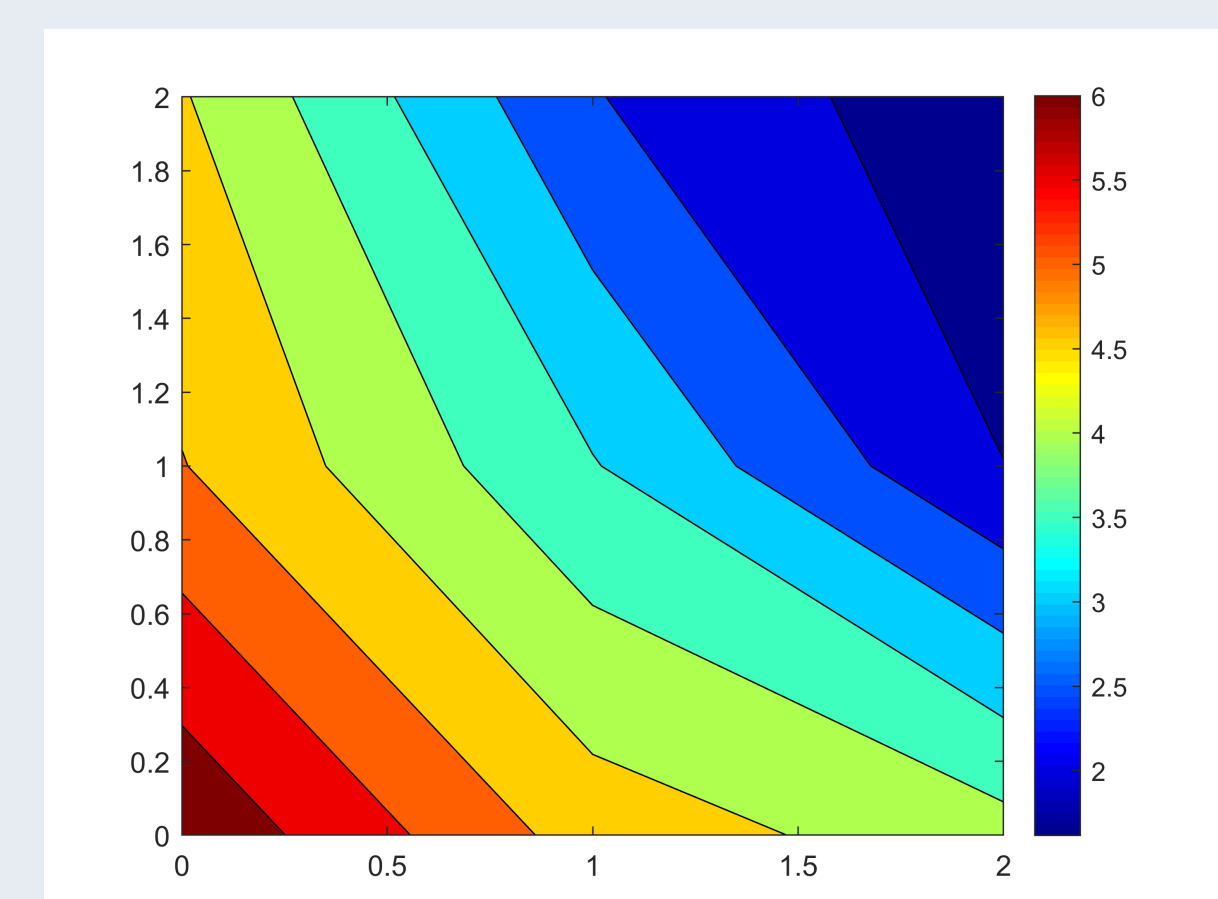


Figure – MI number of samples,  $\log N_\ell$

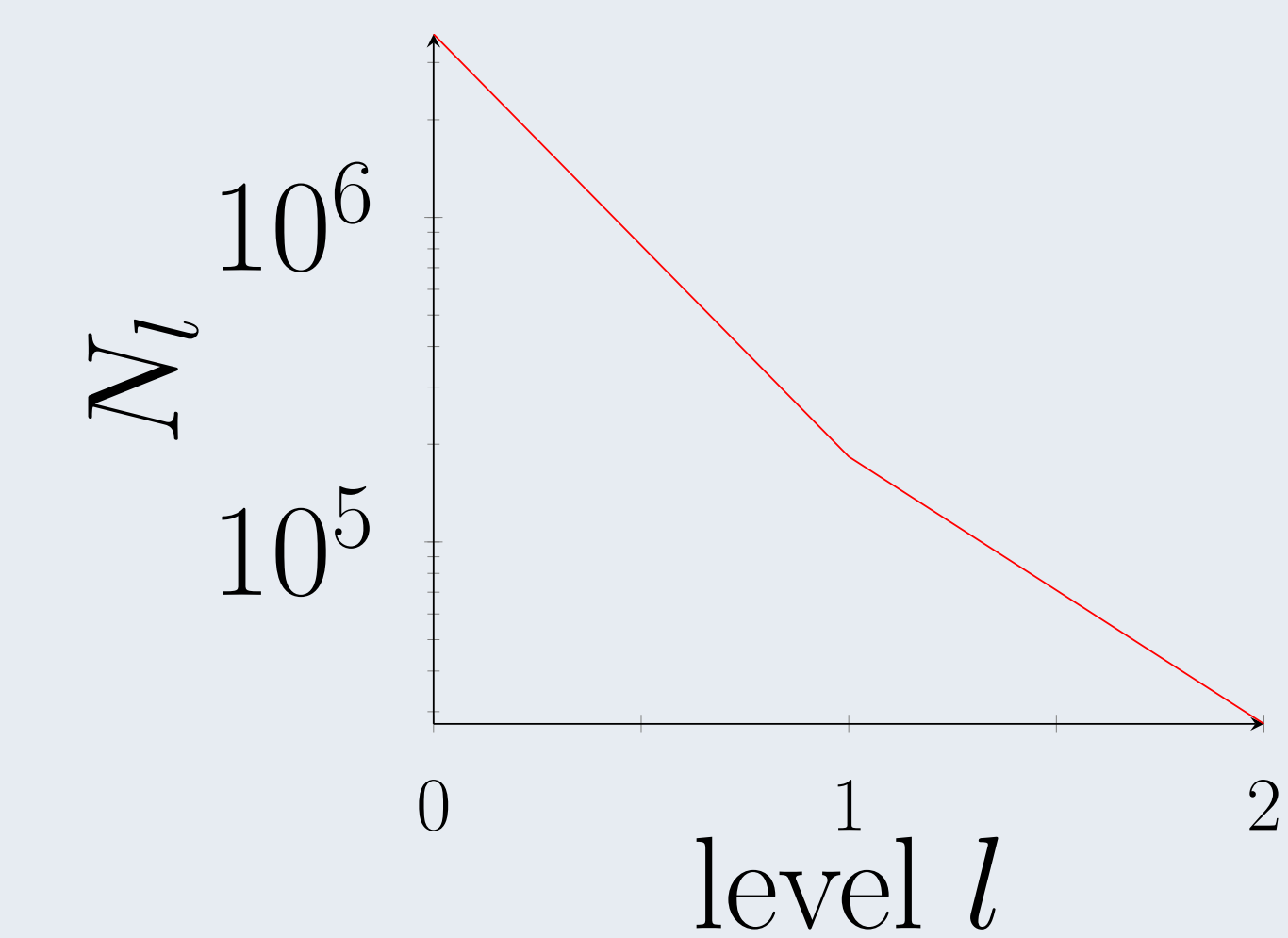


Figure – ML number of samples

	MC	MLMC	MIMC
Complexity	$O(\epsilon^{-5})$	$O(\epsilon^{-2})$	$O(\epsilon^{-2})$
Computational time	17 hours (estimated)	1.03 h	1.05 h

Table – Computational cost,  $\epsilon = 1e-3$

## References

- [1] M.B. Giles. Multilevel Monte Carlo methods. *Acta Numerica*, 24:259–328, 2015.
- [2] J.S. Hesthaven and T. Warburton. *Nodal Discontinuous Galerkin Methods Algorithms, Analysis, and Applications*. Springer, 2007.
- [3] Abdul-Lateef Haji-Ali, Fabio Nobile, and Raúl Tempone. Multi-index Monte Carlo: when sparsity meets sampling. *Numerische Mathematik*, 132:767–806, 2016.