Calibration of Hydraulic Roughness Using Supervised Classification

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INTRODUCTION

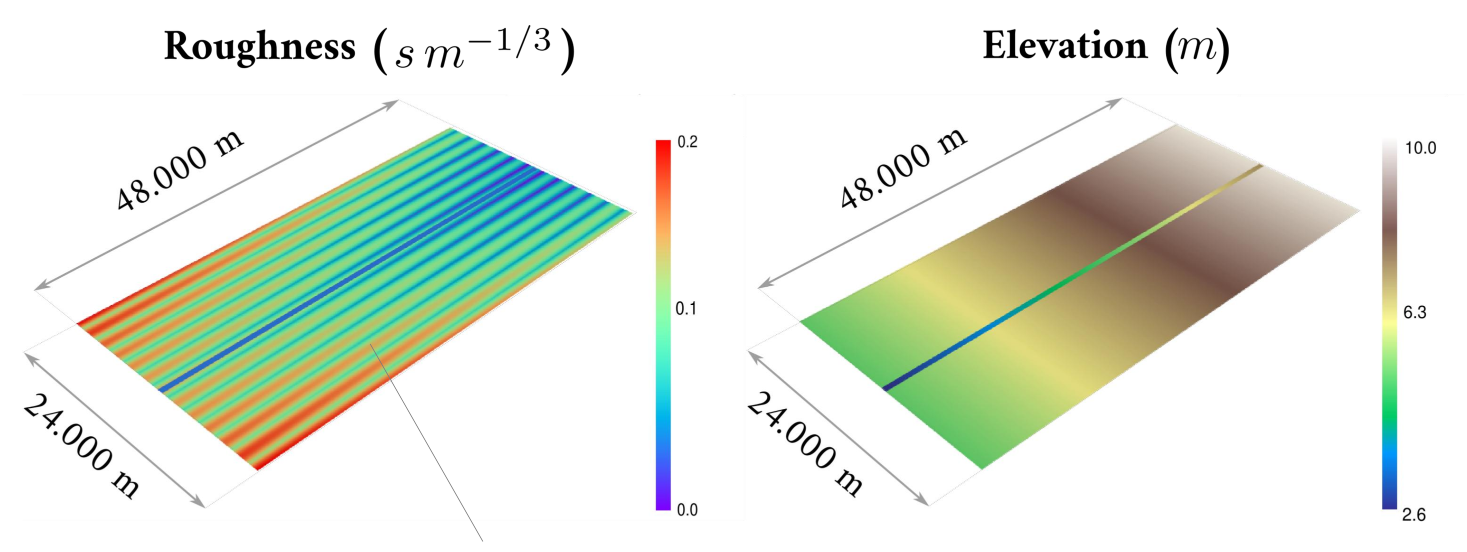
The predictive fidelity of hydrodynamic simulations is often compromised by the **uncertainty** [1] surrounding **Manning's roughness coefficient (n)**, which traditionally depends on the subjective expertise of the modeler. Conventional methods using static lookup tables introduce human bias and fail to capture the spatial complexity of natural floodplains. This research proposes an objective framework to determine spatially distributed Manning maps through parametric mathematical functions, significantly reducing the reliance on expert judgment.

TEST CASE

Idealized river reach with a **straight main channel** and adjacent floodplains. Topography with longitudinal and transversal gradients, Manning with a **parametric distribution**. The hydrodynamic behavior is modeled by solving the 2D Shallow Water Equations [3] over an unstructured triangular mesh. Simulations were conducted for high-flow regimes (1300 m³/s) until a steady-state condition.

Water depth · Discharge · Gravitational acceleration · Bed elevation · Velocity · Manning coeffcient

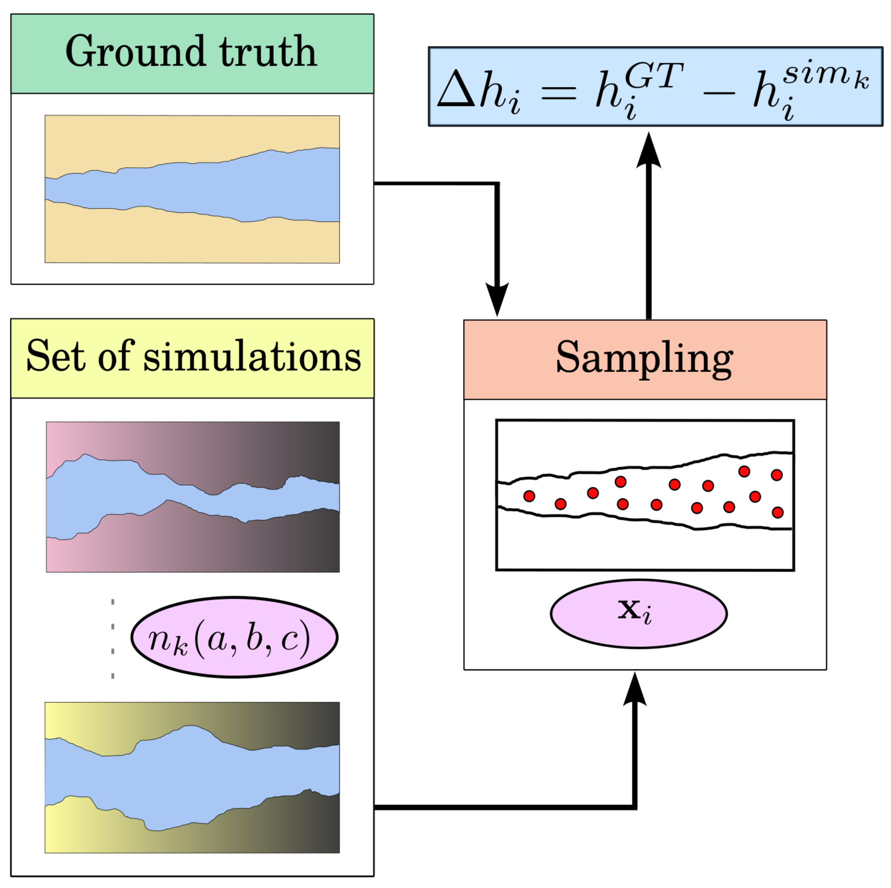
$$\frac{\partial}{\partial t}\begin{pmatrix} h \\ q_x \\ q_y \end{pmatrix} + \frac{\partial}{\partial x}\begin{pmatrix} q_x \\ \frac{q_x^2}{h} + \frac{gh^2}{2} \\ \frac{q_x q_y}{h} \end{pmatrix} + \frac{\partial}{\partial y}\begin{pmatrix} q_y \\ \frac{q_x q_y}{h} \\ \frac{q_y^2}{h} + \frac{gh^2}{2} \end{pmatrix} = \begin{pmatrix} 0 \\ -gh\left(\frac{\partial z_b}{\partial x} + \frac{n^2 u\|\mathbf{u}\|}{h^{4/3}}\right) \\ -gh\left(\frac{\partial z_b}{\partial y} + \frac{n^2 v\|\mathbf{u}\|}{h^{4/3}}\right) \end{pmatrix}$$



$$n(x,y) = 0.005 + a\cdot\exp\left(\left(\frac{2|y - L_y/2|}{L_y}\right)^{1.5} - 1\right) + b\cdot x + |2\cdot c\cdot\cos(2\pi y/4000)|$$

SAMPLING PROCESS

A Sobol sequence was employed to generate **k roughness distributions** across the floodplains, inducing diverse flow behaviors in the domain. A synthetic high-resolution **Ground Truth (GT)** simulation is established as a benchmark, allowing for a comparison of **water depth discrepancies** (Δh) between the the GT and the rest of simulations.

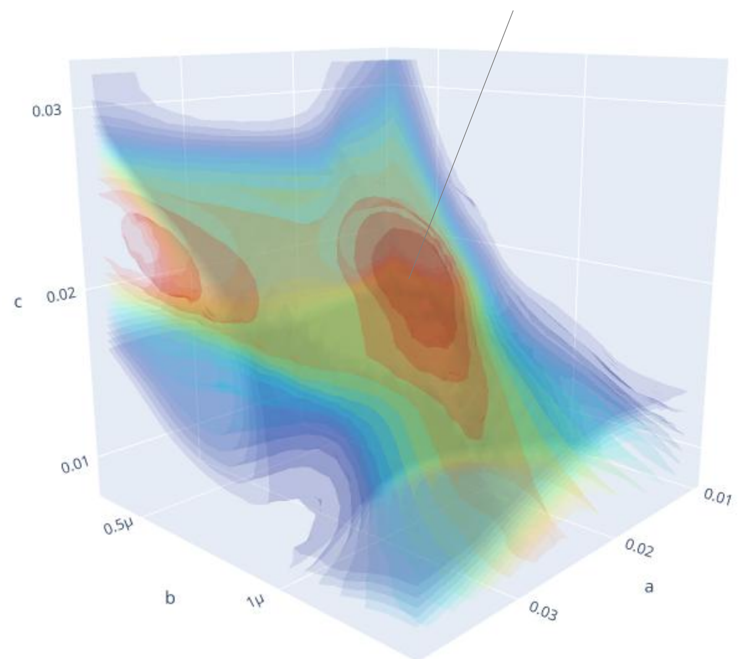


PERFORMANCE METRIC

The function $\phi(a,b,c)$ evaluates the classifier across several points (x_i) of the domain. Each predicted error class (E_i^q) is assigned a specific weight (w_i^q), with higher weights allocated to classes representing smaller discrepancies to prioritize accuracy.

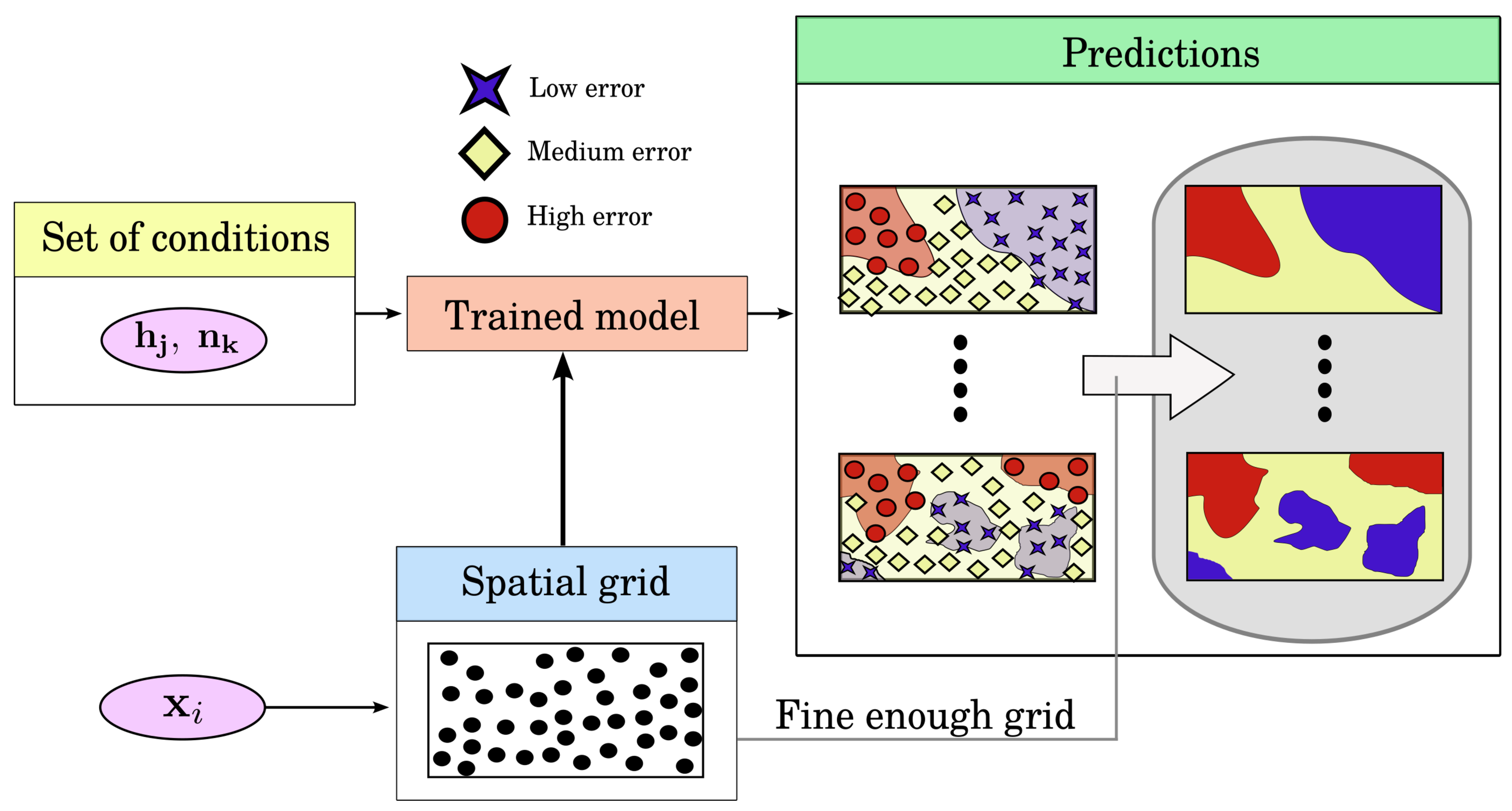
$$\phi(a,b,c) = \sum_{i}^{N_{points}} w_i^q \cdot E_i^q$$

$$(a,b,c)^* = \operatorname{argmax} \phi(a,b,c)$$



SUPERVISED CLASSIFICATION

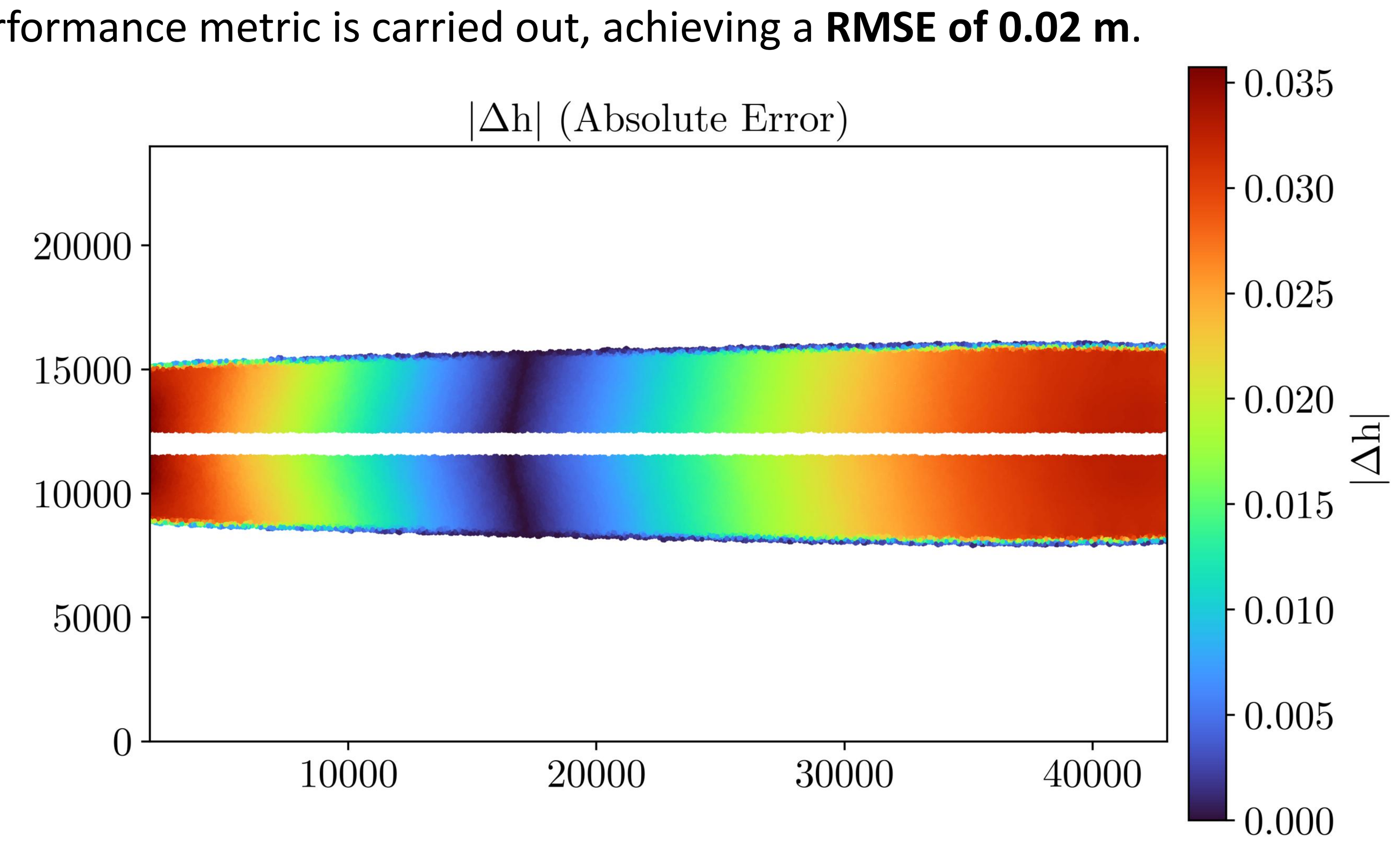
The distribution of $|\Delta h|$ is discretized into **categorical** percentile-based **classes** (E^q) representing varying error magnitudes—ranging from low to high residuals, serving as the target for a **Support Vector Machine (SVM)** algorithm [2], which uses the parametric coefficients (a,b,c) and spatial coordinates (x,y) as input features to predict the expected error level.



For a 5-class scheme, the model achieves an **accuracy and F1-score of 0.96**, providing a highly reliable framework for identifying discrepancies in hypothetical hydrodynamic scenarios.

RESULTS

A complete simulation using the **optimal parameters** $(a,b,c)^*$ identified by the performance metric is carried out, achieving a **RMSE of 0.02 m**.



CONCLUSIONS AND FUTURE WORK

The proposed framework succesfully **minimizes** local water depth **discrepancies** without relying on subjective manual tuning. Future research will explore alternative approaches, specifically transitioning towards regression-based algorithms, looking for continuous error estimations in complex hydraulic environments.

References

[1] Brandimarte, L., and Di Baldassarre, G. (2012). Uncertainty in design floodprofiles derived by hydraulic modelling. *Hydrology Research*, 43(6), 753–761.
[2] Cortes, C., and Vapnik, V. (1995). Support-vector networks. *Machine Learning*, 20(3), 273–297.
[3] García-Navarro, P., Murillo, J., Fernández-Pato, J., Echeverribar, I., and Morales-Hernández, M. (2019). The shallow water equations and their application to realistic cases, *Environmental Fluid Mechanics,* 19(1–2), 1235–1252.