

Calibration of Hydraulic Roughness Using Supervised Classification

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Abstract

Flood prediction accuracy depends on properly calibrated hydraulic models and roughness parameters. This work proposes a machine learning-based framework trained on comparisons between reference and simulated solutions to predict error levels, evaluate Manning roughness configurations, and identify optimal parameterizations. The approach reduces computational costs while preserving hydraulic simulation reliability.

Introduction

Flooding events are among the natural phenomena with the most significant global impact, posing severe threats to human safety and resulting in massive economic losses [1]. Two-dimensional hydrodynamic modelling, based on the Shallow Water Equations (2D-SWE), has become a standard for flood prediction and fluvial simulations due to both its accuracy and optimized computational cost owing to high-performance GPU-accelerated implementations [4]. However, the reliability of these models depends critically on the quality of the input data defining the computational domain (topography data, roughness distribution map, etc.)

In particular, the estimation of hydraulic roughness is commonly based on land use and land cover (LULC) information, where predefined lookup tables are used to assign Manning's coefficients (n) to different surface types. This approach is rooted in classical hydraulic literature, where typical roughness values are associated with channel and floodplain characteristics [2]. More recently, the increasing availability of remote sensing data has enabled the spatially distributed estimation of Manning coefficients by linking LULC classifications with hydraulic parameters. Despite its widespread use, the assignment of Manning coefficients based on LULC classes presents important limitations. In particular, it assumes homogeneous roughness values within

each category, neglecting the inherent spatial variability of natural surfaces.

Methodology

This work explores a Supervised Classification-based approach that moves beyond traditional categorical LULC schemes. Unlike conventional methodologies, which rely on predefined land-cover classes or their direct refinement, the proposed framework does not aim to assign Manning coefficients from LULC maps nor to adjust a baseline roughness field derived from them. Instead, the objective is to enable the identification of spatially distributed roughness parameterizations directly from the hydraulic response of the model, allowing for a more flexible representation of flow resistance.

In particular, a Support Vector Machine (SVM) [3,5]-learning-based framework is proposed to support the calibration of hydraulic models by identifying roughness parameterizations that best reproduce a reference solution. The methodology is built upon a dataset generated from the comparison between a high-fidelity simulation, considered as the ground truth (GT), and an ensemble of simulations performed under different Manning roughness parameterizations (*Figure 1*).

For each simulation, hydraulic variables are sampled at predefined locations throughout the computational domain. The discrepancy between the sampled values and the corresponding GT values is quantified and transformed into a set of ordinal classes representing different levels of agreement with the reference solution.

The resulting dataset is used to train supervised classification models. Input features include spatial information, hydraulic state variables, and roughness descriptors, whereas the target variable corresponds to the error class. Prior to training, the data are standardized and divided into training and testing

subsets. Support Vector Machine classifiers are optimized through a combination of grid-search and Bayesian hyperparameter tuning, using cross-validation to maximize predictive accuracy.

Once trained, the classifier acts as a surrogate model capable of estimating the expected error class for new roughness configurations without requiring additional hydraulic simulations. This enables a rapid exploration of the parameter space and allows the evaluation of parameter combinations not explicitly included in the original dataset. To facilitate quantitative comparisons, predicted classes are transformed into a performance score through a weighting scheme that assigns higher values to lower-error classes. By aggregating these scores over the spatial domain and hydraulic scenarios, a global performance metric is obtained for each candidate roughness parameterization (Figure 2).

The optimal roughness configuration is then identified as the one maximizing the performance metric. Finally, a full hydraulic simulation is performed using the selected parameterization and directly compared against the GT solution to assess the capability of the proposed framework to recover the reference hydraulic behavior while significantly reducing computational requirements.

Conclusions

The results indicate that the reliability of the SVM-based surrogate model depends on both the quality and representativeness of the training dataset and the complexity of the Manning roughness distribution under consideration. While its predictive capability may decrease for highly heterogeneous or complex parameterizations, the proposed framework generally provides accurate and robust estimates for relatively simple roughness configurations. Therefore, it represents a valuable tool for accelerating hydraulic model calibration, reducing the number of computationally expensive simulations required while maintaining an acceptable level of accuracy in the identification of suitable roughness parameterizations.

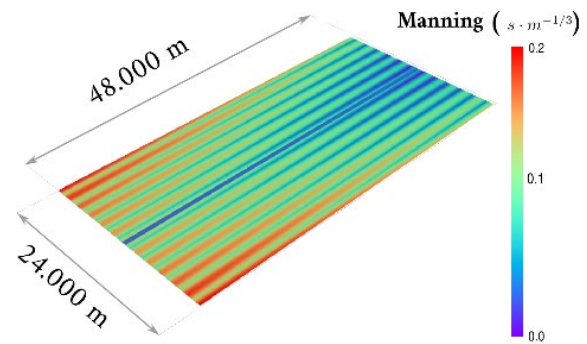


Figure 1: Schematic view of one roughness distribution.

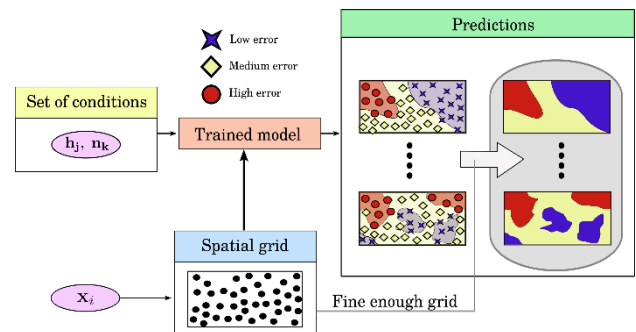


Figure 2: Methodology

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