Simulation-Based Sensitivity Analysis of Check-Dam Height Effects on Downstream Debris-Flow Depth for Structural Countermeasure Scenarios

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Preprint status statement:

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Previous journal submission statement:

An earlier version of this manuscript was submitted to Natural Hazards Review for peer review.

Purpose of posting:

This preprint is shared as an open technical research output to support discussion, verification, and reuse of a simulation-derived scenario-screening workflow for preliminary interpretation of debris-flow mitigation scenarios.

Code and data statement:

The simulation-derived dataset and analysis scripts used for surrogate-model comparison, permutation-importance analysis, and figure generation will be deposited in Zenodo as a companion research package. The EarthArXiv preprint record will be updated with the Zenodo repository DOI after deposition.

Simulation-Based Sensitivity Analysis of Check-Dam Height Effects on Downstream Debris-Flow Depth for Structural Countermeasure Scenarios

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Abstract. Check dams can influence debris-flow propagation, but their effects may depend on location, height, and local topographic conditions. This study evaluates the sensitivity of downstream debris-flow depth to check-dam height scenarios using numerical simulations of a mountainous catchment in Atami, Japan. Six hypothetical check-dam locations were placed along the torrent, and 4,877 valid cases were generated by varying their heights. The maximum debris-flow depth at a downstream evaluation section was used as the response variable. A machine-learning surrogate model was used to summarize the simulation-derived relationship between dam-height combinations and downstream flow depth, and location-dependent sensitivity was evaluated using permutation importance. The highest sensitivity was found at a midstream check-dam location, while an adjacent downstream location also contributed substantially. Longitudinal topographic analysis suggests that this pattern may be related to local terrain modification and erosion–deposition tendencies between adjacent dam locations. These results indicate that check-dam height effects cannot be interpreted solely from downstream distance. The study provides a reproducible scenario-screening workflow for preliminary interpretation of debris-flow mitigation scenarios, distinct from event reproduction, design optimization, or design-criteria development.

1 Introduction

Rainfall-induced sediment-related disasters occur frequently worldwide. This study focuses on debris flows among various types of sediment-related disasters. In Japan, 578 sediment-related disasters were reported in 2025, of which 91 were classified as debris flows and related phenomena (Ministry of Land, Infrastructure, Transport and Tourism, 2026). Debris flows are high-concentration multiphase flows composed of water, sediment, boulders, woody debris, and other materials. They can travel rapidly along steep mountain torrents and cause severe damage to downstream residential areas and infrastructure.

One representative structural measure against debris flows is the installation of check dams along mountain torrents. Check dams can trap sediment and woody debris transported by debris flows. They can also influence sediment transport, bed erosion, and deposition processes during debris-flow propagation. Previous studies have reported that check dams and related open-type control structures contribute to sediment trapping, flow attenuation, and sediment-transport control in debris-flow channels (Mizuyama, 2008; Osanai et al., 2010; Shen et al., 2020b, a). For natural-hazard loss reduction, it is important to understand how structural countermeasure scenarios may alter downstream flow conditions before detailed site-specific design is considered. In debris-flow channels, check dams are often installed as part of structural countermeasures, but their effects may vary depending on local terrain and sediment dynamics. A simulation-based sensitivity analysis can provide a preliminary way to identify locations where changes in check-dam height are strongly associated with downstream response variables.

The effect of a check dam is not determined solely by its presence or height. It also depends on its location, channel gradient, local terrain changes, and erosion–deposition characteristics, as check dams, channel geometry, and prior bed conditions can strongly influence erosion and deposition patterns in debris-flow torrents (de Haas et al., 2020). When multiple check dams are arranged along a torrent, their effects on downstream flow depth are not necessarily uniform. The height of a check dam at one location may strongly affect downstream debris-flow depth, whereas the height of another check dam may have only a limited effect. Therefore, to understand debris-flow responses in channels containing multiple check dams, it is necessary to evaluate the sensitivity of downstream responses to the height of each check dam. It is also important to interpret such sensitivity in relation to local topographic conditions.

Numerical simulation using real terrain data is useful for this type of analysis. Two-dimensional depth-averaged models for debris flows and mudflows can account for topographic conditions, channel geometry, bed erosion, and deposition processes. These models allow spatial evaluation of flow depth, velocity, inundation extent, and terrain change. In recent years, various numerical simulation methods have been applied to evaluate debris-flow propagation, deposition processes, and interactions with control structures (Takebayashi et al., 2022; Takebayashi, 2020; Abraham et al., 2022; Cheon et al., 2020; Oh and Jun, 2023; Shi et al., 2022; Leonardi et al., 2021; Jang et al., 2025).

However, when the heights of multiple check dams are varied simultaneously, the number of possible input combinations increases rapidly. For example, if several dam heights are treated as continuous variables, the input space becomes multidimensional. It is therefore difficult to perform detailed numerical simulations for all possible conditions and to interpret each simulation result individually.

Machine-learning-based surrogate models are useful for summarizing many repeated numerical simulations without replacing the physics-based model itself. Recent studies have combined numerical simulations and machine learning to improve the efficiency of debris-flow hazard assessment, barrier planning, and estimation of flow-depth or velocity-related quantities (Cheon et al., 2020; Gao et al., 2025). When multiple check-dam heights are treated as input variables, a surrogate model combined with feature-importance analysis can quantify how strongly each height variable contributes to the simulated downstream response. Here, permutation importance was used as a model-agnostic measure of the dependence of model performance on each input variable (Breiman, 2001; Fisher et al., 2019; Lundberg and Lee, 2017).

In this study, we use the catchment affected by the 2021 debris-flow event in Atami City, Shizuoka Prefecture, Japan, as a case study (Imaizumi et al., 2022). A debris-flow simulation model was constructed from publicly available three-dimensional topographic data provided by the Geospatial Information Authority of Japan and the Center for Spatial Information Science, The University of Tokyo (Geospatial Information Authority of Japan, 2025; Center for Spatial Information Science, The University of Tokyo, 2025). The debris-flow simulations were conducted using the Morpho2DH solver implemented in iRIC, which has been widely used in Japan for river and sediment-related numerical analyses (Takebayashi et al., 2022; iRIC Software, 2025).

In the numerical experiments, six hypothetical check-dam locations were placed along the torrent, and many simulation cases were generated by varying their heights. For each case, the maximum debris-flow depth at a downstream evaluation section was extracted, approximated using machine-learning models, and analyzed using feature importance. The objective is not to reproduce the Atami debris-flow event with high fidelity, determine optimal check-dam heights, or provide direct design criteria. The specific contribution is instead to demonstrate a reproducible screening workflow in which multiple check-dam heights are treated as simultaneous continuous scenario variables, simulation-derived input–output relationships are summarized by a surrogate model, and the resulting sensitivity ranking is interpreted together with longitudinal topographic change. This framing distinguishes the study from event-reproduction analyses, single-structure performance evaluations, and direct optimization studies, and focuses on how local terrain-controlled erosion–deposition tendencies may affect the relative importance of candidate check-dam locations.

2 Methods

2.1 Overview of the Analysis

Debris-flow simulations using real topographic data were combined with machine-learning-based surrogate modeling to evaluate the sensitivity of downstream debris-flow depth to check-dam height variations. The workflow consisted of four steps: construction of the numerical model for the Atami catchment, generation of multiple six-dam height scenarios, extraction of the maximum debris-flow depth at a downstream evaluation section, and surrogate-model-based feature-importance analysis. The surrogate model was used only to summarize the simulation-derived input–output relationship, not for optimization.

2.2 Study Area and Topographic Data

The study area is the mountainous catchment affected by the debris-flow event that occurred in Atami City, Shizuoka Prefecture, Japan, in July 2021 (Imaizumi et al., 2022). The event was initiated by slope failure in the upstream area during heavy rainfall and caused severe damage to the down-

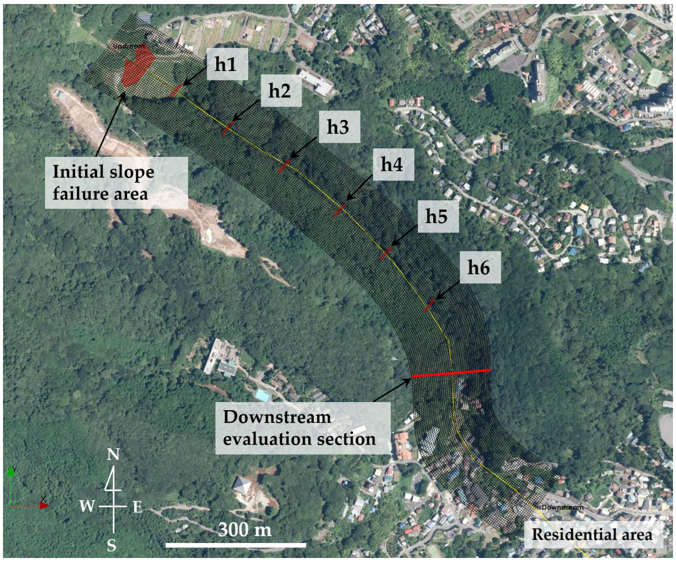

Figure 1. Study area and computational setup for the debris-flow simulations. The initial slope failure area, computational domain, six hypothetical check-dam locations (h_1–h_6), and downstream evaluation section are shown. The background map is from GSI Maps (Geospatial Information Authority of Japan, 2025); the failure-area delineation and terrain representation were based on the drone-based LiDAR dataset hosted by the G-Spatial Information Center (Center for Spatial Information Science, The University of Tokyo, 2025).

stream residential area. In the present study, this catchment was used as a case study with real topographic conditions.

The study area, computational domain, hypothetical check-dam locations, and downstream evaluation section are shown in Figure 1. The numerical simulation model was constructed using publicly available three-dimensional topographic data. Digital elevation data provided by the Geospatial Information Authority of Japan and the Center for Spatial Information Science, The University of Tokyo, were used to represent the terrain of the target catchment (Geospatial Information Authority of Japan, 2025; Center for Spatial Information Science, The University of Tokyo, 2025). The initial failure area was defined with reference to pre- and post-event elevation differences so that the model represented the real terrain of the target mountainous catchment.

2.3 Debris-Flow Simulation Model and Computational Conditions

Debris-flow simulations were conducted using the Morpho2DH solver implemented in iRIC. iRIC is an integrated numerical simulation environment used for analyses of river flow, flooding, sediment transport, and debris-flow-related processes (Kimura, 2021). Morpho2DH is a two-dimensional depth-averaged numerical solver for debris flows and mudflows. By depth-averaging the flow field, the solver can simulate debris-flow propagation, erosion, deposition, and associated terrain changes (Takebayashi et al., 2022; Takebayashi, 2023; iRIC Software, 2025).

Morpho2DH was used to calculate debris-flow propagation from the initial failure area to the downstream evaluation section. Because this study focuses on scenario comparison rather than solver development or validation, only the model settings relevant to the sensitivity analysis are described here; details of the governing equations and numerical implementation are available in previous studies and in the official solver manual (Takebayashi et al., 2022; iRIC Software, 2025).

The computational domain was defined along the torrent from the vicinity of the initial failure area to the downstream residential area. A curved centerline was traced along the main flow path, and a computational grid was generated around this centerline. The longitudinal length of the centerline was approximately 1279 m. The grid spacing was set to approximately 4 m in both the longitudinal and transverse directions, resulting in 13,398 grid cells. All boundaries were treated as free-outflow boundaries.

The total simulation time was set to 100 s, and the time step was set to 0.004 s. These values were determined by considering numerical stability and computational efficiency. As the initial condition, a prescribed sediment thickness was assigned to the mapped initial failure area. The failure area was delineated from pre- and post-event elevation differences in the G-Spatial Information Center dataset (Center for Spatial Information Science, The University of Tokyo, 2025); its mapped area was approximately 2715 m^2. The initial sediment thickness was prescribed as a model input and set to 0.1 m for numerical stability and controlled scenario comparison, corresponding to an initial sediment volume of approximately 272 m^3. Preliminary trial simulations indicated that both the prescribed source volume and the maximum erosion depth could affect downstream flow-depth responses. In the present study, the prescribed source volume was fixed, whereas the maximum erosion depth was examined only for three supplementary cases, as described later. A systematic parametric evaluation of these two settings is left for future work.

The main simulation parameters are summarized in Table 1. Other parameters were set to values commonly used in Morpho2DH.

Geological heterogeneity, woody debris, large boulders, structural failure, and blockage by bridges or other structures were not explicitly considered in the simulations. Therefore, the results should be interpreted as relative comparisons of downstream responses under the same numerical model conditions, rather than as an attempt to reproduce actual debris-flow damage at a specific location.

Table 1. Simulation parameters used in debris-flow simulation

Parameter	Value	Unit
Simulation time	100	s
Time step	0.004	s
Density of water	1,000	kg/m^3
Density of sediment	2,650	kg/m^3
Static sediment concentration	0.6	–
Fraction of sediment behaving as fluid	0.2	–
Minimum flow depth	0.01	m
Internal friction angle	34	deg
Laminar-layer thickness	constant	–
Ratio of laminar-layer thickness	0.4	–
Resistance coefficient	72	–
Bed material type	uniform sand	–
Mean grain size	0.01	m
Maximum erosion depth	2	m
Thickness of initial failure area	0.1	m

2.4 Hypothetical Check-Dam Height Scenarios

Six check-dam locations were defined along the target torrent. These locations are denoted as h_1 to h_6 from upstream to downstream, as shown in Figure 1. The six locations were defined as hypothetical check-dam positions along the torrent, with reference to the existing check-dam location in the study area.

The height of each check dam was varied from 0 to 12 m. In the numerical model, each check dam was represented as an impermeable rectangular topographic obstacle placed across the channel, with an approximate transverse width of 31 m and a streamwise thickness of 4.6 m. This simplified geometry was adopted for controlled numerical trials and is not intended to represent design-level structural details.

The dam height was defined as the additional elevation relative to the original local terrain. Therefore, a height of 0 m corresponds to the original terrain elevation at the dam location. However, even in the 0 m case, the dam cells were treated as non-erodible impermeable cells in the numerical model. Thus, the 0 m case should be interpreted as the zero-height member of this controlled obstacle-height experiment, not as a fully erodible no-dam baseline.

Because erosion and deposition were included in the debris-flow simulation, the effective overflow condition changed during the calculation. When deposited sediment accumulated upstream of a dam, the local bed elevation increased. Accordingly, overflow could occur when the simulated flow depth exceeded the remaining height difference between the dam crest and the locally aggraded bed surface. Thus, the dams did not represent fully blocking boundaries throughout the simulation, but rather impermeable topographic obstacles over which flow could pass when the local flow and deposition conditions allowed overflow.

The existing check dam corresponding to h_2 was also treated as a variable-height dam in the same manner as the other hypothetical dams. Thus, all six dam-height variables, including h_2, were varied within the range of 0–12 m for the sensitivity analysis. Each check-dam height was treated as a continuous input variable.

Latin hypercube sampling was used to efficiently generate combinations of the six check-dam heights. A total of 5,000 input cases were generated, and debris-flow simulations were performed for each case. Some simulations did not provide valid outputs because of numerical instability or output-processing problems. After excluding these cases, 4,877 valid simulation results were obtained. These scenarios were not intended to represent finalized engineering designs, but to provide controlled variations for evaluating how check-dam height changes influence the simulated downstream response.

For each valid simulation case, the maximum debris-flow depth at the downstream evaluation section was extracted. This maximum depth was used as the response variable in the subsequent surrogate modeling and sensitivity analysis. Thus, the surrogate model does not directly predict the spatial distribution of flow depth over the entire catchment.

2.5 Machine-Learning Approximation of Simulation Responses

The 4,877 valid simulation results were used to approximate the relationship between the check-dam height vector $(h_1, h_2, \ldots, h_6)$ and the maximum downstream debris-flow depth, $D_{\max}$. Here, $D_{\max}$ was defined as the maximum value of the debris-flow depth at the downstream evaluation section shown in Figure 1. The six dam heights were used as input variables, and $D_{\max}$ was used as the output variable.

Several regression models were examined to approximate the simulation-derived input–output relationship. The candidate models were support vector regression (SVR), Gaussian process regression (GPR), multilayer perceptron regression (MLP), XGBoost, and LightGBM. All models were implemented in Python using scikit-learn and related libraries (Pedregosa et al., 2011; Chen and Guestrin, 2016; Ke et al., 2017). For each model, input standardization was performed using `StandardScaler`, and the scaler and regressor were combined into a single `Pipeline` to avoid data leakage during cross-validation.

Model performance was evaluated using four-fold cross-validation with shuffled splits and a fixed random seed of 42. The predictive performance was quantified using the root mean squared error (RMSE) and coefficient of determination (R^2). SVR and GPR were used with the default settings of the corresponding Python implementations. The MLP model was trained with a maximum of 1000 iterations and a random seed of 0. XGBoost and LightGBM were trained with

100 estimators and a random seed of 0. Because the objective of this study was not algorithm benchmarking, extensive hyperparameter optimization was not performed. Instead, the same cross-validation procedure was applied to all models to compare their ability to summarize the simulation-derived response relationship.

Based on the cross-validation results, the model with the best predictive performance was selected for the subsequent sensitivity analysis. The selected model was used as a surrogate model that approximated $D_{\max}$ from the six check-dam heights. The model performance should therefore be interpreted as approximation accuracy for numerical simulation outputs, rather than as predictive accuracy for actual debris-flow behavior.

2.6 Sensitivity Analysis Using Feature Importance

In this study, the term "sensitivity" refers to model-based sensitivity evaluated from feature importance, not to local derivative-based physical sensitivity. Thus, the importance values quantify how strongly each input variable contributes to the surrogate-model prediction of $D_{\max}$ under the given dataset and model conditions.

Feature-importance analysis was performed using permutation importance (Fisher et al., 2019). Permutation importance evaluates the contribution of an input variable by randomly permuting its values among samples and measuring the resulting decrease in model performance. In this study, the decrease in R^2 was used as the importance measure.

Permutation importance was evaluated using the same MLP setting as that used in the model-comparison step. The model consisted of a `StandardScaler` and an `MLPRegressor` with a maximum of 1000 iterations and a random seed of 0. The dataset was divided into training and test subsets using an 80/20 split with a random seed of 42. The model was trained on the training subset, and permutation importance was evaluated on the test subset.

For each input variable, the permutation procedure was repeated 30 times. The importance value was calculated as the mean decrease in R^2 caused by permuting the corresponding input variable. The error bars in Figure 4 indicate the standard deviation over the repeated permutations.

A high importance value indicates that the height of the corresponding check-dam location is strongly associated with the surrogate-model prediction of $D_{\max}$ under the dataset and model conditions considered here. Conversely, a low importance value indicates a relatively small contribution to the prediction of $D_{\max}$ under the same conditions. The resulting importance values are interpreted as model-based sensitivity indicators, rather than as direct physical sensitivities or causal effects.

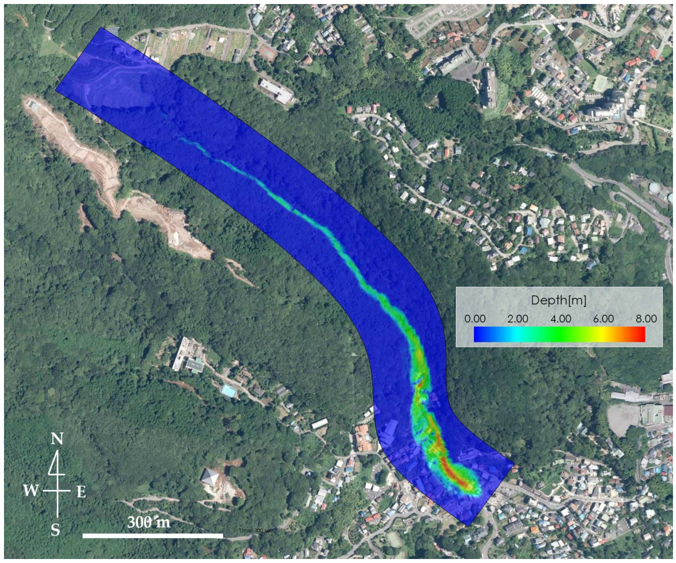

Figure 2. Representative result of the debris-flow simulation. The figure shows the spatial distribution of debris-flow depth at the final simulation time. The background map is from GSI Maps (Geospatial Information Authority of Japan, 2025).

2.7 Evaluation of Topographic Implications

Longitudinal elevation profiles and post-simulation terrain changes were examined to interpret the feature-importance results in relation to local topographic conditions. Particular attention was paid to the midstream reach between adjacent check-dam locations. This evaluation was not intended to prove a strict causal mechanism, but to assess whether distance alone was sufficient to interpret the location-dependent sensitivity or whether terrain-controlled erosion–deposition tendencies also needed to be considered.

3 Results and Discussion

3.1 Representative Debris-Flow Simulation Result

Figure 2 shows a representative result of the debris-flow simulation used in this study. The figure presents an example of the spatial distribution of debris-flow depth at the final simulation time. Sediment released from the initial failure area propagated downstream along the torrent and formed zones of relatively large flow depth within and around the channel.

3.2 Performance of Surrogate Models

Table 2 summarizes the cross-validation results for the five regression models examined in this study. The model performance was evaluated using the root mean squared error (RMSE) and the coefficient of determination (R^2). The compared models were support vector regression (SVR), Gaus-

Table 2. Cross-validation results of the surrogate models.

Model	RMSE	R^2
SVR	1.026	0.709
GPR	1.996	-0.103
MLP	0.990	0.729
XGBoost	1.126	0.649
LightGBM	1.061	0.688

sian process regression (GPR), multilayer perceptron regression (MLP), XGBoost, and LightGBM.

The MLP model showed the lowest RMSE and the highest R^2 among the tested models, with values of 0.990 and 0.729, respectively. SVR showed similar but slightly lower performance, whereas GPR performed poorly and XGBoost and LightGBM showed lower R^2 values than the MLP. Based on these results, the MLP was used for the subsequent sensitivity analysis. Because the obtained R^2 was approximately 0.7, the model should be regarded as an auxiliary surrogate for summarizing simulation outputs rather than as a high-accuracy predictor of actual debris-flow behavior.

3.3 Response under Uniform-Height Scenarios

To examine how well the surrogate model captured the response tendency to changes in check-dam height, additional cases were prepared in which all six check dams had the same height. Specifically, the height of each dam was increased uniformly from 0 m to 11.5 m at intervals of 0.25 m. For these cases, direct numerical simulation results were compared with predictions obtained from the machine-learning models. The results are shown in Figure 3.

The simulation results showed a non-monotonic response when the total check-dam height was small; within an approximate total-height range of 0–10 m, the maximum downstream flow depth locally increased with increasing height. For larger total heights, the downstream flow depth decreased markedly, indicating that the height effect is nonlinear and depends on the propagation and deposition processes. Among the tested models, the MLP reproduced this overall trend relatively smoothly, whereas SVR and GPR showed larger deviations and XGBoost and LightGBM showed local fluctuations. The uniform-height scenarios were limited validation cases outside the Latin hypercube training design, so the result should be interpreted as a check of broad response tendency rather than a comprehensive validation.

3.4 Sensitivity of Downstream Debris-Flow Depth to Check-Dam Heights

The MLP surrogate model was used to evaluate the influence of the six check-dam heights on the maximum downstream debris-flow depth. Permutation importance was used as the model-based sensitivity index (Fisher et al., 2019). The results are shown in Figure 4. The check-dam locations in the figure are arranged from upstream (h_1) to downstream (h_6).

The permutation-importance values were strongly location dependent. The highest importance value was obtained for the midstream location h_3, and the adjacent downstream location h_4 also showed a relatively large value. The upstream locations h_1 and h_2 showed smaller values, whereas h_5 and h_6 showed intermediate contributions. This pattern cannot be explained by downstream distance alone, because the importance did not increase monotonically toward the downstream side. It suggests that local topographic conditions and erosion–deposition processes may influence the downstream response to check-dam height variations.

The importance values obtained here should not be interpreted as direct physical sensitivities or causal effects. Permutation importance indicates how strongly the selected machine-learning model relies on each input variable for predicting $D_{\max}$. Therefore, a check-dam location with high importance should be interpreted as a location whose height is strongly associated with the maximum downstream debris-flow depth within the simulation-derived input–output relationship.

3.5 Topographic Implications of the High-Sensitivity Midstream Reach

To examine why the midstream locations showed high importance, the longitudinal elevation profile and post-simulation terrain changes were analyzed. The results are shown in Figure 5. Figure 5a shows the longitudinal profiles of the initial terrain and the terrain after simulation. Figure 5b provides an enlarged view of the terrain changes around the reach between h_2 and h_3.

The longitudinal profile shows a relatively steep upstream reach followed by a change in channel gradient. A local topographic high existed in the initial terrain around the reach from h_2 to h_3, and this high was lowered after the simulation, suggesting erosion or terrain lowering under the assumed conditions. This interpretation is consistent with studies showing that check dams, channel geometry, bed conditions, and flow conditions can control erosion, deposition, and bulking in debris-flow torrents (de Haas et al., 2020, 2022). Because h_3 is located immediately downstream of this terrain-changing reach, variations in the height of h_3 may have influenced downstream propagation and the maximum flow depth at the evaluation section. The relatively large importance of h_4 may also reflect downstream propagation of the modified flow conditions, although this interpretation remains qualitative.

Figure 5b also shows terrain changes under different maximum erosion-depth conditions. When the maximum erosion depth was set to 0 m, erosion did not occur, and the post-simulation terrain coincided with the initial terrain. When the maximum erosion depth was set to 1 m, the local to-

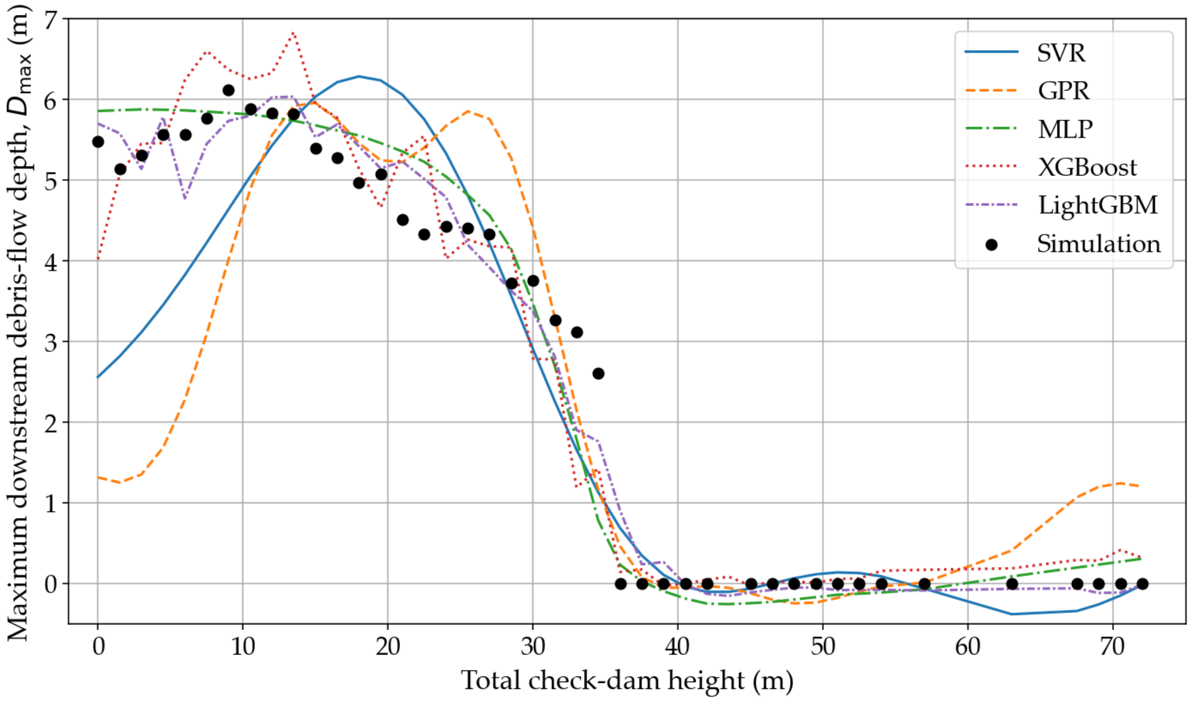

Figure 3. Response of the maximum downstream debris-flow depth under uniform-height scenarios and corresponding model predictions. All six check-dam heights were increased uniformly from 0 m to 11.5 m.

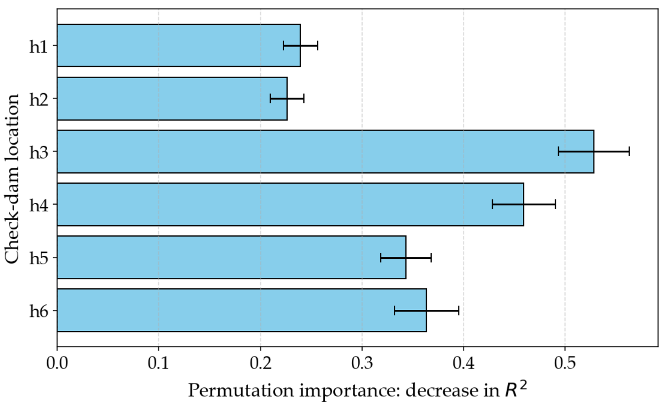

Figure 4. Permutation importance of each check-dam height for predicting the maximum downstream debris-flow depth. The check-dam locations are arranged from upstream (h_1) to downstream (h_6). Bars indicate the mean decrease in R^2, and error bars indicate the standard deviation over 30 repeated permutations.

pographic high partially remained, and sediment deposition was observed around it. Under the reference condition with a maximum erosion depth of 2 m, the local topographic high was more strongly lowered. These results indicate that terrain changes in the reach between h_2 and h_3 were sensitive to the erosion condition.

The high sensitivity around the midstream locations, especially h_3, may therefore be related not simply to distance from the downstream evaluation section, but also to local terrain changes and erosion–deposition tendencies in the reach between h_2 and h_3. However, this study did not explicitly consider ground strength, detailed soil properties, woody debris, or large boulders. Therefore, the detailed physical mechanism that produced the high importance of the midstream locations cannot be fully identified from the present analysis. This result should therefore be interpreted as a possible topographic implication under the target catchment and numerical model conditions, rather than as a quantitatively identified causal mechanism.

3.6 Implications and Limitations for Structural Countermeasure Scenarios

The results show that the response of the maximum downstream debris-flow depth to multiple hypothetical check-dam heights was strongly location dependent. The midstream locations, especially h_3 and h_4, showed relatively high sensitivity, whereas the upstream locations h_1 and h_2 showed smaller contributions. Thus, preliminary countermeasure evaluations should not rely only on downstream distance; local topography and erosion–deposition processes should also be considered when interpreting check-dam height effects.

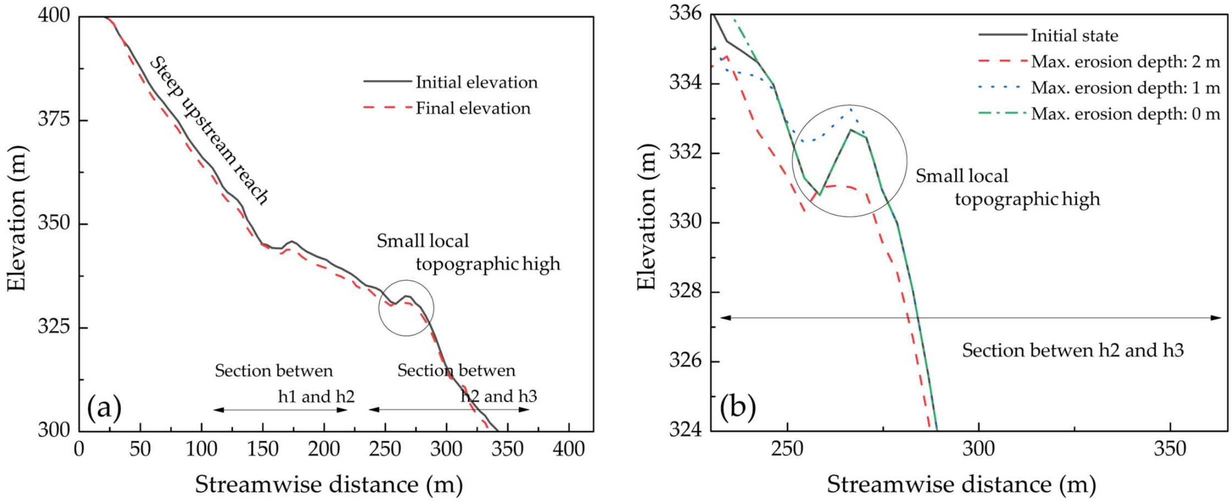

Figure 5. Longitudinal topographic profiles and comparison of terrain changes under different erosion-depth conditions. Panel (a) shows the initial and post-simulation longitudinal terrain profiles. Panel (b) shows an enlarged view around the reach between h_2 and h_3. The profiles were derived from the topographic datasets described in the text (Geospatial Information Authority of Japan, 2025; Center for Spatial Information Science, The University of Tokyo, 2025).

Several limitations should be noted. First, the surrogate model is an auxiliary approximation of numerical simulation outputs, and its R^2 value of approximately 0.7 is not sufficient for high-accuracy quantitative prediction. Second, this study used only the maximum debris-flow depth at the downstream evaluation section as the output variable, although debris-flow responses can also be characterized by velocity, deposition thickness, arrival time, inundation extent, and impact force. Third, the prescribed source volume and maximum erosion depth can affect downstream flow-depth responses; here, the source volume was fixed and the maximum erosion depth was examined only in three supplementary cases. Future work should systematically vary these settings to evaluate how they affect the sensitivity ranking of check-dam locations, because debris-flow erosion, bulking, and bed interaction can depend on flow conditions, bed conditions, and material composition (de Haas et al., 2022; Roelofs et al., 2022).

The proposed workflow does not replace detailed hydraulic, geotechnical, structural, or socio-economic assessments required for practical countermeasure planning. For design-level applications, more detailed analyses of debris-flow interaction with countermeasure structures, including impact-force evaluation and structural response, may be required (Leonardi et al., 2016, 2021; Jang et al., 2025). The simplified rectangular dam geometry and the non-erodible treatment of the dam cells should also be considered when interpreting the results. In particular, the 0 m cases are not equivalent to fully erodible no-dam cases. The scenarios should therefore be regarded as controlled computational trials for comparing dam-height effects, rather than as site-specific representations of actual or proposed check-dam structures.

4 Conclusions

This study used the catchment affected by the 2021 debris-flow event in Atami, Japan, as a real-terrain case study to evaluate the sensitivity of maximum downstream debris-flow depth to the heights of multiple hypothetical check dams. Using 4,877 valid simulation results, the relationship between six check-dam heights and the maximum downstream flow depth was approximated by machine-learning models, and feature-importance analysis was used to evaluate location-dependent sensitivity. The main contribution is not a new numerical solver or machine-learning algorithm, but a screening framework that combines real-terrain debris-flow simulation, surrogate modeling, and topographic interpretation to compare multiple structural countermeasure scenarios.

The main findings of this study are summarized as follows:

– Among the tested regression models, the MLP model showed the best cross-validation performance. However, its coefficient of determination was approximately 0.7, indicating that the model should be regarded as a surrogate model for summarizing broad input–output trends rather than as a high-accuracy predictor.

– Under uniform-height scenarios, the maximum downstream debris-flow depth did not decrease monotonically with increasing check-dam height. This suggests that low-height check-dam scenarios may produce non-monotonic downstream responses by modifying flow propagation and deposition patterns.

- The permutation-importance analysis showed that the influence of check-dam height was strongly location dependent. The highest importance was obtained for the midstream location h_3, and the adjacent downstream location h_4 also showed a relatively large contribution. This indicates that the dam-height effect cannot be explained solely by distance from the downstream evaluation section.
- Comparison of longitudinal terrain profiles showed that a local topographic high between h_2 and h_3 was lowered after the simulation. This suggests that erosion may have occurred in this reach.
- Simulations with different maximum erosion-depth conditions showed that terrain changes around the reach between h_2 and h_3 depended on the erosion condition. The high sensitivity around the midstream locations, especially h_3, may therefore be related to local terrain changes and erosion–deposition tendencies in this reach.

These results indicate that debris-flow simulation, surrogate modeling, and feature-importance analysis can help organize the location-dependent sensitivity of downstream flow depth to multiple hypothetical check-dam heights. They do not provide practical design criteria or damage predictions, but they offer model-based insight for identifying check-dam locations that warrant closer examination in subsequent engineering and hazard-loss-reduction studies.

Future work should extend the analysis to response variables other than maximum flow depth, including velocity, deposition thickness, arrival time, inundation extent, and impact force. The prescribed source volume and maximum erosion-depth settings should also be examined through systematic parameter sweeps, because these settings may affect erosion–deposition processes and the resulting sensitivity ranking. Applications to additional catchments are needed to evaluate the generality of the location-dependent sensitivity and topographic implications observed in this study.

Code and data availability. The topographic dataset used in this study is available from the Center for Spatial Information Science, The University of Tokyo, as cited in the References. The iRIC software and Morpho2DH solver are available from the iRIC project website. The simulation-derived input–output dataset, Latin hypercube sampling table, uniform-height scenario dataset, and Python scripts used for surrogate-model comparison, permutation-importance analysis, and figure generation will be deposited in Zenodo as a companion research package, and the preprint record will be updated with the repository DOI after deposition. The internal scripts used to automate individual iRIC/Morpho2DH simulation runs will not be redistributed because they include environment-specific file paths, local case-management procedures, and workflow-specific implementation details that are not required to reproduce the surrogate modelling and sensitivity analyses presented here.

The topographic dataset used in this study is available from the Center for Spatial Information Science, The University of Tokyo, as cited in the References. The iRIC software and Morpho2DH solver are available from the iRIC project website.

Author contributions. JK designed the study, performed the simulations and surrogate analyses, prepared the figures, and wrote the initial manuscript draft. HS and TS contributed to the interpretation of the results and revised the manuscript. All authors reviewed and approved the final version of the manuscript.

Competing interests. The authors declare that they have no conflict of interest.

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