

Multidimensional Hydro-Abrasion Modeling: Integrating Geometric-Hydraulic Parameters and Machine Learning for Enhanced Abrasion Prediction in Sediment Bypass Tunnel

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Dedication

My humble efforts are wholeheartedly dedicated

To my beloved Father and Mother

To my wife and children (Jana and Hoor)

Summary

Climate change has intensified extreme rainfall events, accelerated sediment transport, and posed serious challenges to hydraulic infrastructure, particularly Sediment Bypass Tunnels (SBTs). These structures divert sediment-laden flows around reservoirs, reducing sedimentation and preserving storage capacity. Due to their steep slopes, which minimize excavation costs and maintain effective flow dynamics, SBTs typically operate under supercritical flow conditions. While these flows enhance sediment transport, they expose tunnel surfaces to severe hydro-abrasion. Damage varies from minor surface wear to deep ones, sometimes threatening tunnel foundations and requiring frequent, costly repairs.

Field evidence shows that abrasion levels vary significantly even under similar hydrological conditions. For instance, Japan's Miwa SBT remains relatively undamaged due to the effective implementation of upstream sediment control measures. At the same time, the Koshiy SBT, despite being one of the most advanced designs, has experienced significant abrasion and prolonged downtime. This disparity raises concerns about how tunnel geometry, hydraulic conditions, and sediment load interact to influence abrasion and whether current design approaches adequately address these variables. Existing abrasion prediction models face two main limitations:

1. **Abrasion Coefficient Variability** – The abrasion coefficient is often considered a constant, but field data indicates it might change based on flow conditions and surface lining materials.
2. **Lack of Spatial Resolution** – All the existing models rely on average-based calculations, which fail to capture localized damage patterns and their underlying causes.

To overcome these limitations, this research utilizes high-resolution laser scanning data from the Koshiy SBT (with 2 cm × 2 cm resolution over a 4 km length) to analyze abrasion patterns. The study sets out to:

- Analyze observed abrasion damage and link it to findings from prior studies.

- Evaluate the variability of the abrasion coefficient across different damage zones.
- Develop multidimensional Machine Learning (ML) models (1D, 2D, and 3D) to predict abrasion with improved accuracy and spatial resolution.

The study enhances current modeling approaches by integrating geometric-hydraulic dynamics with spatiotemporal field data and ML techniques. The result is a multidimensional, data-driven framework that delivers more accurate and actionable abrasion predictions for tunnel designers and infrastructure managers. The following sections outline the thesis chapters, detailing the methodology and key research contributions.

1. Introduction

The thesis starts with a thorough introduction that outlines the study's background, motivation, and significance. Reservoir sedimentation is a common issue affecting dam operations and water storage efficiency. SBTs have emerged as a sustainable solution; however, during flood events, high-velocity flows (ranging from 10 to 15 m/s) carrying coarse sediments apply significant mechanical forces on tunnel floors, leading to severe hydro-abrasion damage. The motivation for this work stems from the inherent limitations of existing abrasion models, which typically average damage in a single dimension, and the need for models that account for spatial variability in damage. Clear research objectives are established, focusing on enhancing predictive accuracy and providing actionable insights for maintenance and design purposes.

2. Literature Review (Gaps and State-of-Art Analysis)

The literature review critically examines the challenge of reservoir sedimentation and explores current sustainable management practices for addressing this issue. It begins with an overview of sedimentation issues and the ecological and operational consequences for reservoirs. A section is dedicated to countermeasures, with particular emphasis on SBTs. This review addresses multiple aspects of SBT performance, including bypass efficiency, ecomorphological impacts, and hydro-abrasion mechanisms. Recent studies, which involve experimental work, numerical validation, and field investigations, highlight shortcomings in existing abrasion prediction models. These models fail to account for localized variations in hydraulic

conditions and material responses. The review identifies significant knowledge gaps, particularly the lack of localized modeling approaches, which justifies the scope of the current study and frames the subsequent research contributions.

3. Topographic and Hydraulic Analysis of the Koshiu SBT

Focusing on the Koshiu SBT in Japan, a prominent example of modern SBT implementation, Chapter 3 provides a detailed case study on high-resolution laser scanning to capture the tunnel topography at a spatial resolution of 2 cm. Two separate topographic datasets (topography-I and topography-II) are created by scanning after different flood events, allowing for comparative analysis. Comprehensive data analysis is conducted to derive detailed representations of the tunnel floor, whereas hydraulic measurements from various flood events facilitate a correlation between flow dynamics and observed abrasion patterns. This analysis is crucial for quantifying the impact of water depth, velocity, and tunnel geometry on the distribution of damage. The extensive dataset, comprising over one million data points, establishes a solid foundation for recalibrating the traditional abrasion model and serves as a benchmark for subsequent ML approaches.

4. Calibration of the Existing Mechanistic Abrasion Model (Resolving the Abrasion Coefficient Issue)

Chapter 4 addresses the limitations of traditional mechanistic abrasion models by determining the abrasion coefficient (K_v). Historically, K_v has been considered a constant parameter; however, recent field studies suggest it may display quasi-constant behavior. This chapter systematically documents the challenges posed by conventional abrasion prediction. It provides an in-depth description of the field-scale setup, including laser scanning protocols, SBT discharge measurements, sediment transport dynamics, and material properties. This chapter recalibrates the existing saltation abrasion model using the collected data by quantifying hydraulics and sediment transport dynamics across various tunnel sections. The analysis distinguishes among different abrasion patterns (scatter, edged, and skewed), demonstrating that the recalibrated K_v accurately reflects the spatially heterogeneous nature of the damage. These findings are crucial for refining existing models and enhancing their predictive performance under realistic operating conditions.

5. Advanced Abrasion Susceptibility Mapping [ASM Model] (Machine Learning in Action)

Chapter 5 presents the Advanced Abrasion Susceptibility Mapping (ASM) model, an academic contribution that utilizes ML techniques to overcome the limitations of traditional methods. In this study, the ASM model employs the Extreme Gradient Boosting (XGBoost) algorithm to forecast the spatial distribution of abrasion damage within the tunnel. It incorporates extensive data on flood events, hydraulic features, and tunnel characteristics, including geometry, laser scan data, and a thorough abrasion inventory as inputs for the model. The chapter considers three experiments (the entire tunnel, the straight section, and the curved section) and explains how each segment is analyzed separately. The XGBoost model is rigorously trained and validated using a 50/50 ratio, achieving high accuracy levels as shown by accuracy assessments. The results not only highlight the overall effectiveness of the ASM model, which attained an accuracy of 0.864 and exceeded 0.9 in certain sections, but also reveal the impact of specific input features on predicting abrasion susceptibility. This contribution emphasizes the potential of advanced data-driven methods to revolutionize damage assessment in hydraulic structures.

This work has been peer-reviewed and published as:

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6. Advanced Abrasion Susceptibility and Depth Mapping [ASDM Model] (A Comprehensive Approach to Abrasion Prediction)

Chapter 6 enhances accuracy and applicability by introducing the Advanced Abrasion Susceptibility and Depth Mapping (ASDM) model. This model offers a comprehensive approach that extends beyond susceptibility mapping to predict the depth of abrasion damage. The ASDM model builds on the methodological framework established in the previous chapter by adding an extra layer of data: the detailed abrasion damage depth derived from laser scanning and abrasion inventory mapping.

The application of XGBoost is further refined to statistically evaluate abrasion damage's quantitative and qualitative aspects. The chapter describes the segmentation of the tunnel into comprehensive and localized (straight and curved) sections, providing a nuanced perspective on how various factors influence the extent and severity of damage. The results from the ASDM model show strong correlations between predicted and observed abrasion depths, with a correlation coefficient of 0.861 and a Nash-Sutcliffe efficiency of 0.748 across the tunnel's length, with specific sections reaching values of 0.93 and 0.87, respectively. This highlights its accuracy while addressing limitations and areas for further improvement. The model's comprehensive nature makes it a valuable tool for researchers and practitioners in the field.

This work has been peer-reviewed and published as:

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7. Conclusion and Outlook (Key Findings and Future Directions)

In the final chapter, the thesis synthesizes the key findings and contributions of the research. This finding demonstrates that advanced ML techniques can significantly enhance hydro-abrasion prediction in SBTs when combined with high-resolution field data and thorough topographic analysis. The recalibrated and innovative ASM and ASDM models provide a powerful toolkit for assessing both the spatial distribution and severity of abrasion damage. These advancements have direct practical implications for the maintenance and design of SBTs, resulting in enhanced operational safety and a longer lifespan for the tunnel. The conclusion also outlines future research directions, including the integration of additional data sources, the exploration of hybrid modeling approaches, and the extension of the methodology to other hydraulic structures affected by sediment transport and abrasion.

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CHAPTER 1

Introduction (Setting the Outline)

1.1. Background

Sediment transport and deposition pose major challenges to the operation and longevity of reservoirs worldwide. As rivers carry sediment loads downstream, reservoirs accumulate these materials, leading to reduced storage capacity, impaired flood control, and degraded water quality. Among the countermeasures developed to address reservoir sedimentation, Sediment Bypass Tunnels (SBTs) have proven highly effective. By diverting sediment-laden flood flows around the reservoir body, SBTs maintain storage volume without the need for frequent dredging. These tunnels are typically constructed with steep slopes to sustain supercritical flow regimes—flow conditions that optimize sediment conveyance; however, these high-speed, sediment-laden flows cause hydro-abrasion—the progressive removal of material from the tunnel lining by impacting sediment particles—at rates that can severely compromise tunnel integrity. Although hydro-abrasion also occurs in high-gradient bedrock rivers and other hydraulic structure outlets, in SBTs, and due to its elongated shape, the

combination of flow energy and sediment load creates localized abrasion patterns that challenge any existing prediction method.

1.2. Motivation

Despite their operational success, SBTs frequently demand costly maintenance due to hydro-abrasion damage. Field observations reveal that even tunnels with similar hydrological inputs can exhibit markedly different abrasion patterns. Such variability underscores that current design approaches (especially in abrasion prediction)—which largely assume uniform abrasion resistance and rely on zero-dimensional, average-based models—are insufficient for predicting localized damage. Furthermore, traditional models often treat the abrasion coefficient as a spatially and temporally constant parameter, whereas recent field investigations suggest a quasi-constant value for this parameter. Recent advances in high-resolution surveying and data-driven modeling have paved the way for more nuanced analyses. Detailed topographic scans can capture high-resolution-scale damage features, and Machine Learning (ML) techniques can discern complex, nonlinear relationships among hydraulic, geometric, and sedimentological variables. This convergence of technology motivates a comprehensive re-examination of abrasion prediction in SBTs.

1.3. Research Objectives and Significance

This thesis aims to transcend the limitations of existing abrasion models by integrating high-resolution field data with advanced computational methods. The specific objectives are to:

1. Characterize spatial abrasion patterns in a steeply sloped SBT using 2 cm × 2 cm laser scan data collected before and after flood events.
2. Quantify the variability of the abrasion coefficient across different tunnel sections and damage regimes.

3. Develop and validate one-, two-, and three-dimensional (1D, 2D,3D) ML models capable of predicting both the susceptibility and depth of abrasion damage at high spatial resolution.

By achieving these objectives, the study provides a data-driven framework that enhances predictive accuracy, informs targeted maintenance, and informs the design of abrasion-resistant tunnel linings. The resulting models provide practitioners with actionable insights into the interactions among flow dynamics and tunnel geometry, advancing the state of the art in sustainable sediment management and resilient hydraulic infrastructure design.

1.4. Thesis Structure

Figure 1 illustrates the methodological framework and overall structure of this thesis. The research is organized into seven chapters, beginning with background and motivation, progressing through data acquisition and model development, and culminating in conclusions and perspectives for future work. The chapters are structured as follows:

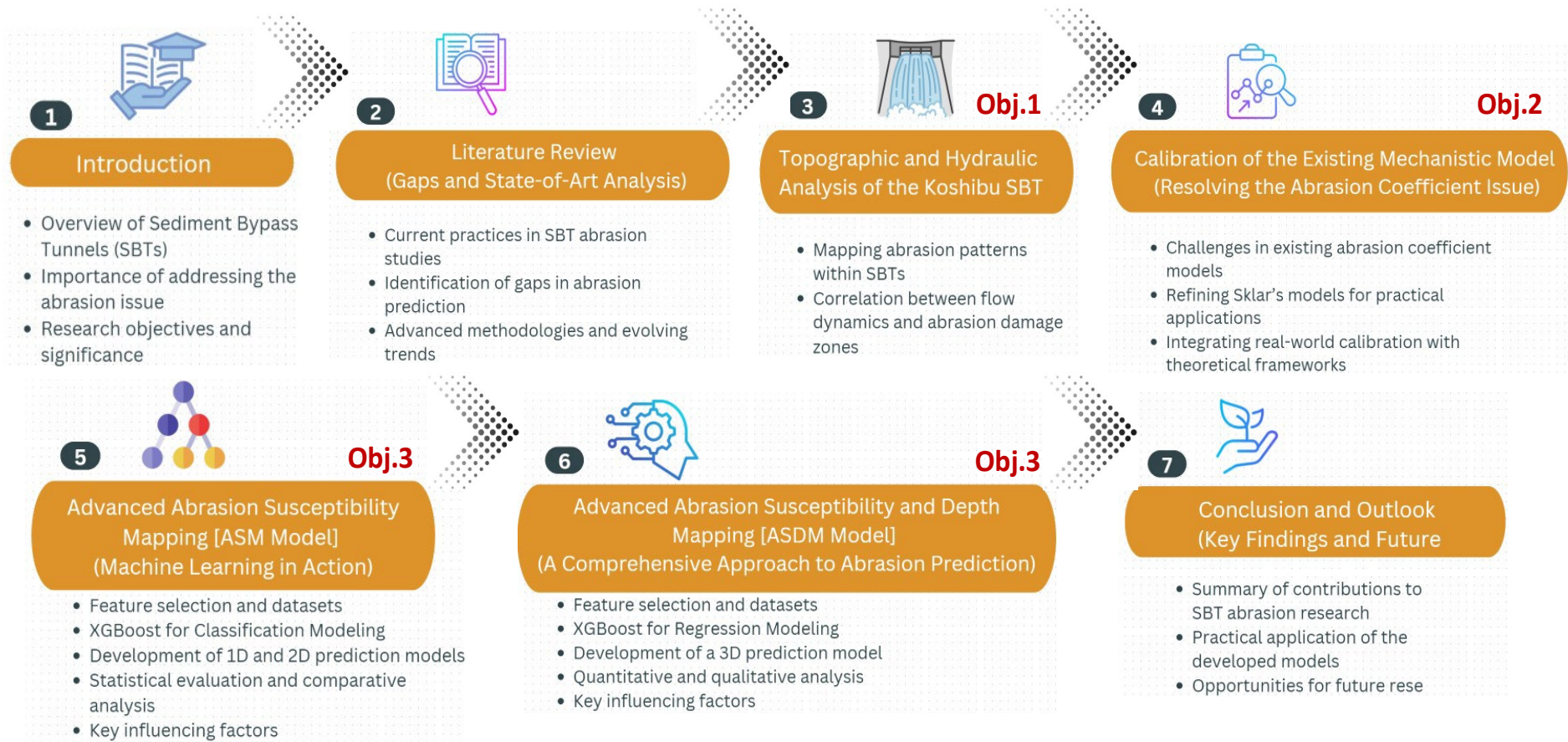


Figure 1: Research Methodology.

1. **Chapter 1: Introduction.** Presents the background, motivation, research objectives, significance, and an overview of the thesis organization.
2. **Chapter 2: Literature Review.** Critically examines sedimentation challenges, SBT design principles, hydro-abrasion mechanisms, and existing prediction models, identifying key gaps.
3. **Chapter 3: Topographic and Hydraulic Analysis.** Describes high-resolution laser scanning at the Koshiu SBT, data processing methods, and hydraulic measurements, establishing the empirical foundation.
4. **Chapter 4: Mechanistic Model Calibration.** Recalibrates the traditional abrasion model by analyzing spatial abrasion patterns and determining variable abrasion coefficients.
5. **Chapter 5: Advanced Abrasion Susceptibility Mapping (ASM).** Develops and assesses ML models for 1D and 2D abrasion susceptibility forecasting.
6. **Chapter 6: Advanced Abrasion Susceptibility and Depth Mapping (ASDM).** Extends the ASM framework to 3D depth predictions, evaluating model performance and practical implications.
7. **Chapter 7: Conclusions and Future Work.** Synthesizes findings, discusses contributions to theory and practice, and outlines opportunities for extending the methodology to other hydraulic structures.

CHAPTER 2

Literature Review (Gaps and State-of-the-art Analysis)

2.1. Reservoir Sedimentation Issue

Transverse hydraulic structures, such as dams and weirs, constructed across natural streams decelerate the approach flow and create a stagnant water pool. This environment fosters sediment deposition upstream of these structures, thereby reducing the storage capacity of reservoirs. This capacity reduction impacts various uses, including water supply, urban applications, agriculture, and hydropower generation. Additionally, reservoir sediment accumulation decreases flood retention volume, heightens the risk of blockages in outlet structures, and causes abrasion to hydromechanical equipment (R. Boes et al., 2014; Sumi, 2006). The disruption of sediment continuity affects downstream channel morphology, erosion mechanisms, ecosystem balance, and the habitats of aquatic organisms. Over recent decades, factors such as climate change, land use practices, deforestation, frequent flash floods, and

increased human activities have escalated sediment inflow (Walling, 2009), accelerating sediment entrapment within reservoirs and shortening their operational lifespan.

Numerous researchers globally have determined that the mean annual rate of reservoir sedimentation ranges between 0.5% and 2.0% of the storage capacity. Specifically, Anari et al. (2020) and Schleiss et al. (2016) report a 0.5% to 1% range. However, this rate is highly site-specific and influenced by soil erosion, transportation, and deposition factors. Reservoir sedimentation has significantly impacted global and per capita reservoir storage volumes over the past few decades, according to (Annandale et al., 2016; Morris, 2020). Future projections indicate increasingly challenging scenarios for upcoming generations, driven by reservoir sedimentation, population growth, climate change, fewer new projects, and inadequate implementation of sustainable reservoir management strategies. On a positive note, active sediment management has gained traction as a viable alternative to traditional dead storage and decommissioning of reservoirs to extend their lifespans. Fan & Morris (1998) introduced the idea of sustainable sediment management, stressing that while the twentieth century was centered around building new dams, the focus in the twenty-first century must shift to addressing sedimentation to enhance the longevity of existing infrastructure. Sustainability aims to balance sediment inflow and outflow, restore the continuity of downstream sediment, maximize both storage lifespan and water efficiency, and reduce environmental impacts.

2.2. Overview of Countermeasures

Reservoir sediment management strategies are generally classified into three main categories: (a) reducing sediment yield at the catchment level, (b) routing sediment-laden flow around or through the reservoir, and (c) removing already deposited sediments (Anari et al., 2020; Auel, 2018; Kondolf et al., 2014; Morris, 2020; Sumi, 2006) as illustrated in **Figure 2**. Müller-Hagmann (2018) also discussed a preventive measure involving the optimization of dam and reservoir locations during project planning. The selection of a

strategy or combination of strategies is highly site-specific and influenced by various technical, design, hydrological, hydraulic, geological, environmental, financial, governance, and legal factors. The following sections provide a brief overview of these strategies.

Sedimentation Countermeasures

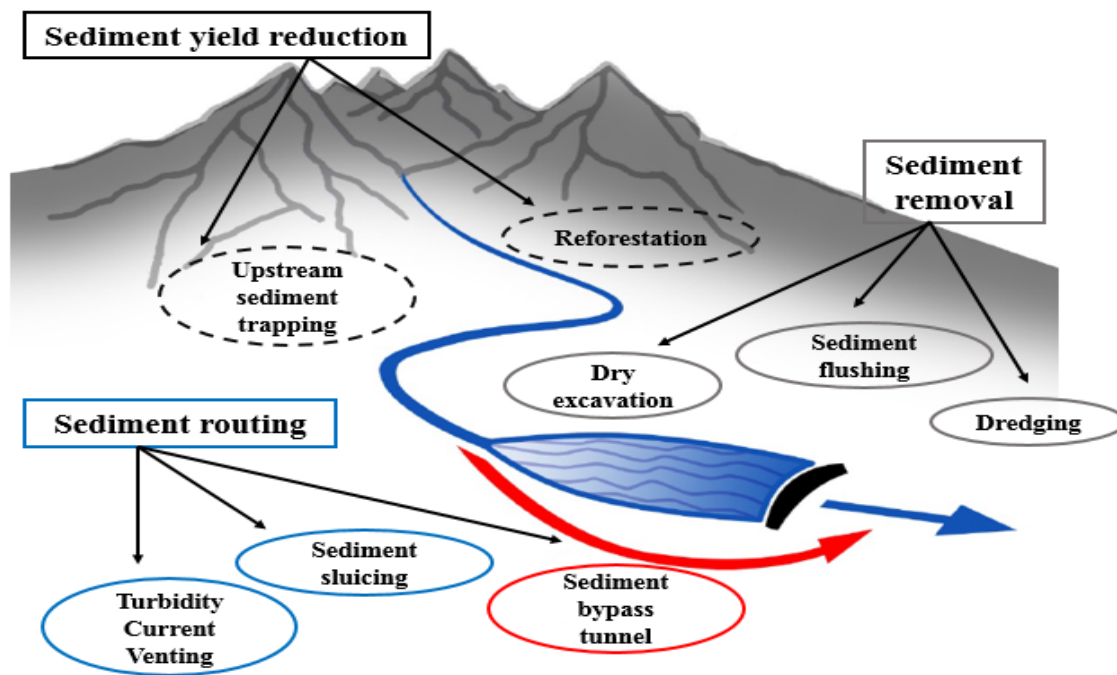


Figure 2: Categories of sedimentation countermeasures.

At the catchment level, sediment yield into streams can be reduced through afforestation, soil erosion control, channel improvement, and sediment trapping. Sediment routing around the reservoir, discharging into the tailwater channel, and enhancing the reservoir's live storage capacity can be accomplished using off-stream reservoirs, flood bypass channels, sediment bypass tunnels, venting turbid density currents (vertical separation) under favorable conditions, sluicing sediments through dam outlet structures, and guiding sediment-laden flows through compartmented reservoirs (horizontal separation).

Additionally, sediments deposited in the reservoir can be removed through pressure flushing, empty flushing (including drawdown, empty, and refill stages), dry excavation, and dredging (mechanical and hydraulic). Each strategy has advantages and disadvantages, and selecting a particular plan or combination of strategies depends on the factors mentioned earlier. This research primarily focuses on the detailed hydraulics of sediment-laden flows routed around the reservoir through SBTs.

2.3. Sediment Bypass Tunnels

Sediment bypass tunnels (SBTs) are a sediment routing technique designed to mitigate or entirely prevent sedimentation by diverting incoming sediment-laden flows around the dam, thereby maintaining sediment continuity between upstream and downstream river reaches (**Figure 2**) (R. Boes et al., 2014; Kondolf et al., 2014). Ensuring sediment continuity is crucial as it enhances habitat quality and morphological variability in the downstream reach of the reservoir (R. Boes et al., 2019; Facchini et al., 2015).

Typically, an SBT comprises a guiding structure, a tunnel intake, an acceleration section with a steep slope, a tunnel section with a milder slope, and an outlet structure (**Figure 3**). The guiding structure directs the incoming sediment-laden flow to the intake structure, which is discharged through the bypass tunnel section. To prevent sediment accumulation in the reservoir system, the guiding structure should not be overtopped unless the design discharge of the SBT is exceeded (Auel, 2014). In cases where the design discharge is surpassed, the guiding structure should either be overtopped, or the excess flow should be conveyed to the dam outlet structures via an opening at the downstream end of the guiding structure.

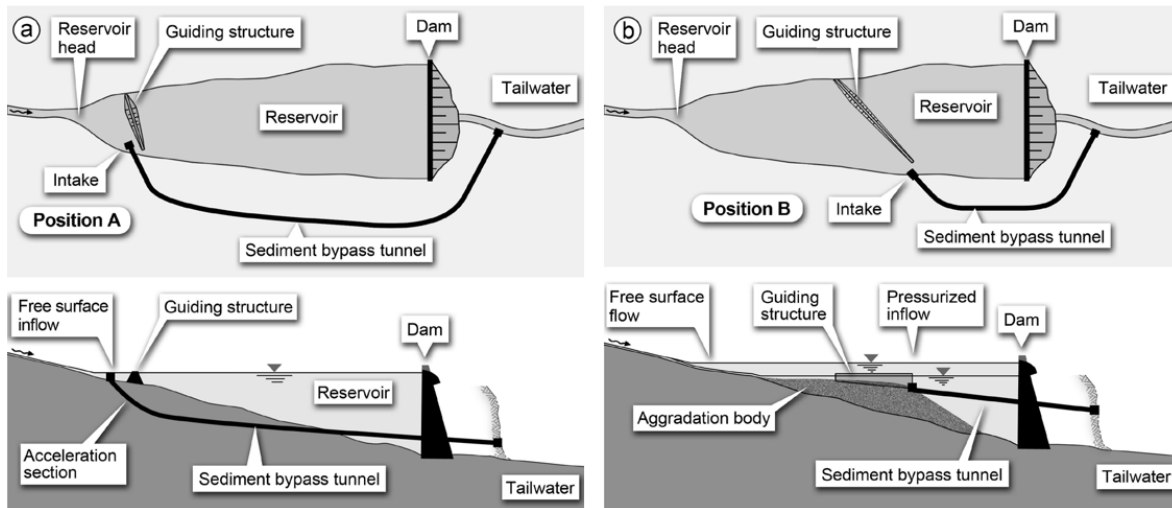


Figure 3: Schematic diagram of SBT having two positions: (a) near reservoir head (Position A) and (b) after aggradation body (Position B), from (Auel, 2014).

2.3.1 Existing SBTs

According to Demiral Yüzügüllü (2021), out of the thirty SBTs identified, two were under construction, four were in the planning stage, and twenty-four had been commissioned by 2021. Although the first two SBTs were commissioned over a century ago in Japan, the Karasuhara SBT in 1905 and the Nunobiki SBT in 1908, notable growth in their construction and commissioning has occurred in the 21st century, as depicted in **Figure 4**. This increase underscores the importance of these structures, as they can operate 24/7. Furthermore, they can be installed in new or existing reservoirs, making them practical for low- to moderate-capacity reservoirs (R. M. Boes et al., 2014; Sumi, 2006).

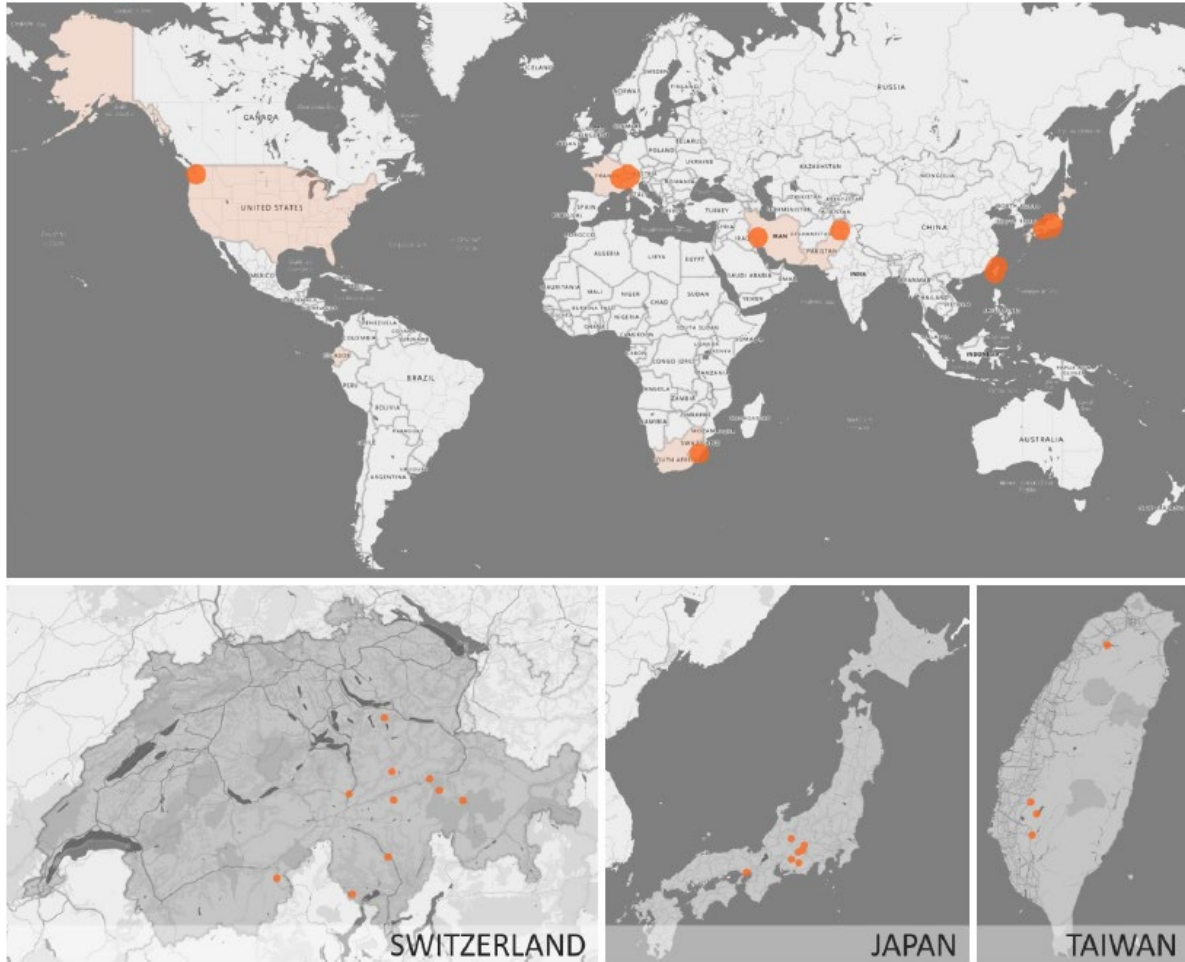


Figure 4: A mapped worldwide overview of SBT locations with country-specific cases for Switzerland, Japan, and Taiwan, from (Demiral Yüzügüllü, 2021).

2.3.2 Sediment Bypass Efficiency

Sediment bypass efficiency (SBE) is defined as the ratio of bypassed sediment volume to inflowing sediment volume and is influenced by the intake location of the SBT. SBE is a crucial parameter for determining the sediment-filling period of a reservoir, which in turn affects its lifespan. SBE depends on the hydrological characteristics and sediment transport rates within a specific catchment. It can be assessed by estimating or measuring the volumes of inflowing and bypassed sediment, or through numerical simulations of hydraulic

conditions and sediment transport (Albayrak et al., 2019; Morris, 2019; Sumi & Kantoush, 2011).

Auel et al., (2016) reported that the BE of the Asahi SBT in Japan was 77% during its initial operation in 1998, which extended the reservoir's lifespan by approximately 3.3 times its initial duration. The SBE of the Nunobiki SBT in Japan varied from 81% to over 94% between 1908 and 1989, an increase attributed to the effectiveness of Sabo check dams in reducing sediment yield by trapping sediments in the catchment area (Auel et al., 2016). The Miwa SBT exhibited an SBE of up to 63% between 2006 and 2011 (Kantoush et al., 2011).

Albayrak et al. (2019) evaluated the SBE of three SBTs in Switzerland—Pfaffensprung and Runcahez (type A) and Solis (type B)—based on measured and sediment transport data. They reported 98%, 83%, and 31% bypass efficiencies for Pfaffensprung, Runcahez, and Solis SBTs. Bathymetric data from the Solis Reservoir indicated that temporary sediment deposition affects SBE. Albayrak et al. (2019) concluded that the operational regime of the SBT and the reservoir directly influences the SBE of the Solis SBT. Increasing the operational duration and lowering the reservoir water level enhanced the amount of bypassed sediment. Therefore, it is recommended that reservoir operations be coordinated and optimized with continuous monitoring of hydraulic conditions and sediment transport to improve SBE.

Ho et al. (2019) conducted experimental and numerical studies to evaluate the desilting efficiency of the Nanhua SBT. They utilized a 1:81 Froude scale physical model test and performed numerical simulations using Flow 3D to investigate the sediment venting efficiency at varying water levels. Two scenarios were simulated, representing a 25-year return period discharge at high and low water levels. The results from the experimental study and numerical simulations were consistent, indicating that the SBE of the SBT was 24.1% at high and 68.2% at low water levels.

2.3.3 Eco-morphological Impacts

Sediment routing operations enhance river eco-morphology and habitat quality while reducing potential erosion and river incision downstream of the dam (R. Boes et al., 2019); see **Figure 5**. The SBT operation simulates natural flood conditions similar to pre-dam scenarios, positively impacting the river ecosystem. Facchini et al. (2015) investigated the ecological and morphological effects of the Solis SBT by monitoring riverbed elevation and particle size distributions at various downstream cross-sections in 2014. The data revealed significant changes in river morphology and grain size distribution due to flood events with SBT operations. Auel et al. (2017) monitored four SBTs in Japan and Switzerland—Asahi, Koshibu, Solis, and Pfaffensprung—to analyze their effects on downstream morphology and ecology by assessing grain size distributions and microhabitats and invertebrates based on richness and composition. The biotic data indicated increased microhabitat and invertebrate richness downstream of the dam with SBT operations.

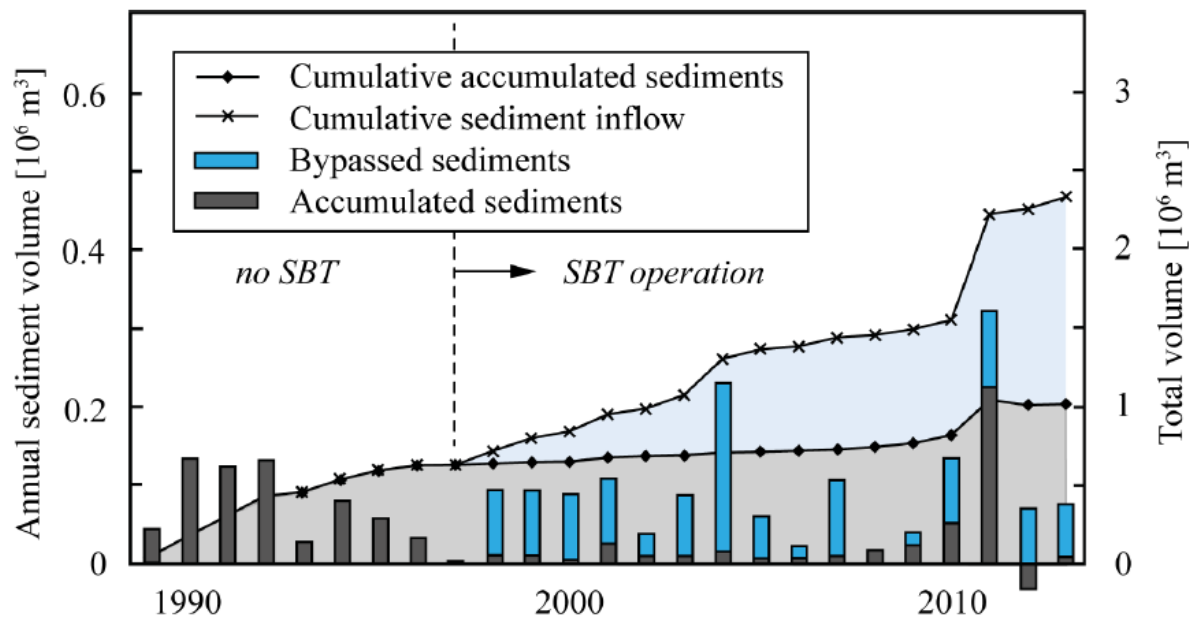


Figure 5: Accumulated and bypassed sediment volumes per year and development of the total aggradation volume before and after commissioning of the Asahi SBT in 1998, based on (Auel et al., 2018), including new data provided by Kansai Electric Power Company.

Systematic numerical simulations (Facchini et al., 2017) on the downstream morphological effects of sediment bypass tunnels (SBTs) indicate that sediment feeding by SBTs adjusts the downstream riverbed slope towards an equilibrium, using the upstream river stretch slope as a reference. The riverbed surface sediment composition also shifts towards that of the feeding material. However, the evolution of riverbed level and surface composition occurs on different timescales, with the latter progressing much faster. Consequently, even after a few SBT operations, the riverbed surface composition approaches equilibrium and is reworked with each operation. A lower bedload feed rate necessitates more operations to entirely alter the fractions of individual grain classes in the active riverbed layer. Conversely, the steepening of the riverbed slope (a one-dimensional morphological effect) is a slow process, requiring thousands of SBT operations to reach equilibrium. Sediments released during typical SBT operations behave like sediment pulses, translating, dispersing, or exhibiting mixed behavior depending on hydraulic conditions and sediment feed characteristics.

Overall, studies at Asahi (Fukuroi, 2012), Miwa (Sawagashira et al., 2017), and Solis (Facchini et al., 2017; Vetsch et al., 2024) dams demonstrated positive impacts of SBTs on morphology and habitats, with rapid eco-morphological adjustments following SBT operations. However, achieving quasi-pre-dam conditions regarding riverbed slopes requires multiple SBT operations.

2.3.4 Hydro-abrasion Challenge

Hydro-abrasion refers to the continuous material loss on the surface of a solid body due to mechanical stress exerted by sediments transported in the flow (Bitter, 1963a, 1963b). Various hydraulic structures, including weirs, spillways, diversion tunnels, and particularly SBTs, experience severe hydro-abrasion due to high flow velocities and sediment supply rates (**Figure 6**) (Auel, 2014; Hagmann et al., 2015; Lee et al., 2019). The damage caused by hydro-abrasion adversely affects the structural safety and operation of hydraulic structures, leading to high maintenance costs, which can amount to approximately 1% of the total

investment cost (Auel, 2014; Auel & Boes, 2011; Hagmann et al., 2015; Sumi, 2006). The magnitude and pattern of hydro-abrasion are influenced by flow characteristics, particle transport modes, and particle properties such as size, hardness, and invert material properties (Auel et al., 2017a, 2017b; Demiral et al., 2022; Sklar & Dietrich, 2004, 2012). Therefore, mitigating hydro-abrasion requires a comprehensive understanding of the governing processes, including flow characteristics, particle properties, and their interactions, which can be obtained through systematic laboratory and field studies (Auel, Albayrak, et al., 2017a, 2017b; Demiral et al., 2022; Demiral Yüzügüllü, 2021; Inoue et al., 2014; Johnson, 2014; Müller-Hagmann et al., 2020).



Asahi (Japan)



Koshibu (Japan)



Palagnedra (Switzerland)



Runcahez (Switzerland)

Figure 6: Representative Cases of Hydro-Abrasion Damage in Tunnel Systems.

Various bed lining materials, including granite paving, cast basalt plates, steel armoring, silica fume, roller-compacted and polymer concrete, and high-performance concrete reinforced with steel fibers, high modulus polymer fibers, and potassium aluminate, have been utilized in hydraulic structures to resist hydro-abrasion (Müller-Hagmann, 2018). Arnold et al. (2020) and Müller-Hagmann (2018) monitored hydraulic and sediment transport conditions using a laser scanner; they measured hydro-abrasion rates in the Solis, Pfaffensprung, and Runcahez SBTs. In the Solis SBT, suspended sediment and bedload transports are measured using turbidimeters and a Swiss Plate Geophone system at the tunnel outlet. At the same time, the Pfaffensprung and Runcahez SBTs are calculated using sediment transport formulas. Field observations revealed that irregularities and vulnerabilities in the inverted material and uneven bed lining implementation can enhance hydro-abrasion and should be avoided (Hagmann et al., 2015). Proper implementation and curing can increase inverted material strength, reducing hydro-abrasion. Bends in SBTs create Prandtl's first kind of secondary currents (Nezu & Nakagawa, 1993), concentrating sediment transport near the inner sidewalls of the tunnel (Müller-Hagmann et al., 2020). These currents cause higher abrasion rates in these areas due to increased sediment concentration. Müller-Hagmann et al. (2020) suggested avoiding these bends or reinforcing the regions near the inner sidewalls to reduce abrasion rates. Despite hydro-abrasion being a common issue in hydraulic structures, few guidelines or standards exist for the material selection, design, and operation of SBTs (Auel & Boes, 2011; Harada et al., 1998; Sumi, 2006). Additionally, uncertainties in incoming sediment transport rates, capacity, bed lining materials, and particle properties, such as diameter and hardness, make abrasion prediction challenging.

2.4. Recent Investigations: Evolving Trends

The sustainable use and operational safety of hydraulic structures affected by abrasion, bedrock incision, and landscape evolution necessitate an advanced understanding of hydro-

abrasion mechanisms. Over the years, these topics have been explored through analytical and numerical approaches (Aubert et al., 2016; Johnson, 2014; Kadia, 2024; Turowski, 2009; Turowski et al., 2007; Turowski & Hodge, 2017), experimental studies (Auel, Albayrak, et al., 2017a, 2017b; Demiral Yüzügüllü, 2021; Scheingross et al., 2014; Sklar & Dietrich, 2004, 2012) and direct field measurements (Albayrak et al., 2024; Arnold et al., 2020; Müller-Hagmann et al., 2020). The insights gained from these studies contribute to our understanding and are detailed in the following subsection.

2.4.1 Experimental work and numerical validation

The American Society for Testing and Materials (ASTM) developed a standard underwater test method for assessing the abrasion resistance of concrete, known as ASTM C1138, which is internationally recognized. The testing apparatus consists of a steel cylinder filled with water and eroding material (steel balls) agitated by a paddle. Sklar & Dietrich (2001) designed an abrasion mill based on the ASTM C1138 standard, as shown in **Figure 7**. Unlike the ASTM standard test, the abrasion mill can simulate sliding, rolling, and particle saltation. Consequently, this device is considered more suitable for simulating hydro-abrasion caused by grinding and impinging stresses and has been utilized in recent hydro-abrasion studies (Scheingross et al., 2014; Sklar & Dietrich, 2001). However, the previously mentioned tests were insufficient to fully understand the tunnels' conditions. Therefore, scaled physical model tests have also been developed to consider hydraulic characteristics and sediment transport measurements.

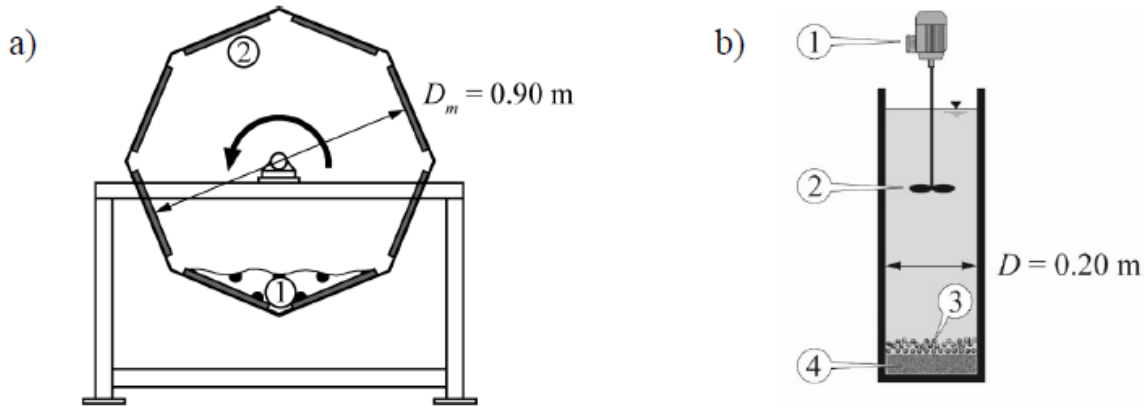


Figure 7: a) ASTM standard test with (1) abrasive charge and (2) samples, and b) abrasion mill with (1) motor, (2) paddle, (3) abrasive material, and (4) sample, from (Müller-Hagmann, 2018).

These tests are commonly applied to investigate bedrock erosion processes using fast-eroding substitute materials to accelerate the processes (Beer & Lamb, 2021; Chatanantavet & Parker, 2009; Inoue et al., 2014; Johnson, 2014; Lamb et al., 2015). Auel (2014) examined the correlation between flow field, particle motion, and abrasion in a scaled SBT model under various hydraulic and sediment supply conditions using the flume shown in **Figure 8**. Based on experimental results and literature data, Auel et al. (2017b) modified the abrasion model (Sklar & Dietrich, 2004) developed to account for supercritical flows in SBTs. However, in situ investigations are necessary to calibrate the model for field application.

Also, given the limited experimental investigations on supercritical narrow channel flow characteristics, Auel (2014) studied these flow characteristics under quasi-uniform and decelerating conditions across a broad range of Froude numbers (Fr) and aspect ratios, varying from 1.7 to 6.1 and 2.5 to 10.7, respectively. Subsequently, Demiral Yüzügüllü (2021) examined quasi-uniform and decelerating supercritical flows in narrower channels with aspect ratios ranging from 0.89 to 1.91 at Froude numbers between 1.84 and 3.33, comparable to SBTs.



Figure 8: Photograph of the model flume in the VAW laboratory, Switzerland, from (Auel, 2014).

However, most of the recent experimental investigations (Auel, 2014; Demiral Yüzügüllü, 2021) employed 2D velocity measurement techniques, which did not capture lateral velocity. These studies inferred secondary currents using longitudinal and vertical velocity measurements. Additionally, the decelerating flow conditions observed by (Auel, 2014; Demiral Yüzügüllü, 2021) can modify turbulent flow properties compared to uniform flows, as reported by (Graf, 1998; Song & Chiew, 2001) for subcritical flows. Free surface fluctuations associated with nonuniform supercritical flows can further influence these modifications, particularly at higher Froude numbers (Auel, 2014).

2.4.2 Field investigations

Hydro-abrasion impacts various types of hydraulic structures. However, prototype experiments are infrequent. Some in-situ investigations have been reported by (Albayrak et al., 2024; Jacobsen et al., 2015; Müller-Hagmann, 2018). They investigated the hydro-abrasion of concretes under supercritical flow conditions, considering bedload and suspended sediment load in situ under real operating conditions. These investigations analyzed the abrasion resistance of various concretes in situ and evaluated different laboratory tests to determine the feasibility of scaling up laboratory results for field applications. However, some discrepancies have been detected. These discrepancies between the results raise numerous questions and highlight the need for further investigation. Understanding the underlying reasons for these differences is crucial for improving the accuracy and reliability of hydro-abrasion assessments.

2.5 Current Practices in SBT Abrasion Prediction

The culmination of literature efforts has resulted in the development of two predominant model types: (I) stream power incision models (Lague, 2014; Seidl et al., 1992), which correlate abrasion rates with flow discharges, and (II) mechanistic models (Albayrak et al., 2024; Auel et al., 2017a, 2017b; Chatanantavet & Parker, 2009; Demiral et al., 2022; ISHIBASHI, 1983; Lamb et al., 2015; Sklar & Dietrich, 2004), which incorporate the impact of sediment particles.

Several mechanistic models for abrasion prediction exist, which consider the physical process of particle impact and are derived from experimental research on particle motion. These models can be categorized into two types: (I) bedrock incision models, which focus on sub- to low supercritical flow regimes typically found in river systems (Beer & Turowski, 2015; Chatanantavet & Parker, 2009; Lamb et al., 2008; Sklar & Dietrich, 2004), and (II) models for hydro-abrasion of concrete, which primarily account for supercritical flow conditions (Auel, 2014; Helbig et al., 2012; ISHIBASHI, 1983). Since bedrock and concrete

are brittle materials subjected to similar hydro-abrasion processes, these models apply to both hydro-abrasion at concrete structures and bedrock incisions in rivers. However, the first type of mechanistic model is regarded as the primary one, having been utilized for over two decades in numerous studies due to its practicality and applicability in various situations.

The saltation-abrasion model is a physically based framework designed to describe bedrock incisions. This model accounts for various factors, including bed shear stress, bedrock erodibility, particle size, particle impact energy, and sediment supply (Sklar & Dietrich, 2004, 2012). The fundamental formulation of this model is:

$$A_r = \left(\frac{Y_M}{K_v f_{st}^2} \right) \left(\frac{W_{im}^2}{L_p} \right) q_s \left(1 - \frac{q_s}{q_s^*} \right) \quad [m/s] \quad (1)$$

A_r represents the vertical abrasion rate, Y_M denotes Young's modulus, k_v is the dimensionless resistance coefficient, W_{im} is the mean vertical particle impact velocity, L_p represents hop length, and f_{st} signifies the splitting tensile strength. According to Sklar and Dietrich (2004), the variability in Y_M for rocks is minimal, thus treating it as a constant value of $Y_M = 50$ GPa. This simplification, however, may be contentious due to the considerable range of Y_M observed in softer rocks and concretes. The term $f_{st}/(2Y_M)$, "elastic strain energy density," quantifies the fracture energy necessary to detach a unit volume. The coefficient k_v pertains to energy transfer efficiency from impacting particles to the bedrock material. Sklar and Dietrich (2004, 2012) proposed a widely accepted value of $k_v = 10^6$ for rock, which is comparable to that for concrete. The second term represents the flux of kinetic impact energy per unit area and time, while the final term pertains to the cover effect, which accounts for the fraction of exposed bedrock.

The abrasion coefficient, k_v , is a critical factor in estimating abrasion and has been the subject of extensive research. Sklar and Dietrich (2004, 2012) referred to it as both a

"dimensionless resistance coefficient" and a "dimensionless proportionality constant." However, the assumption that k_v is a constant has been challenged by various studies (Auel, Albayrak, et al., 2017b; Beyeler & Sklar, 2010; Lamb et al., 2015; Scheingross et al., 2014; Turowski, 2012). Recent field studies have suggested that the abrasion coefficient, k_v , may exhibit a quasi-constant behavior under certain conditions (Albayrak et al., 2024; Müller-Hagmann et al., 2020). For instance, field calibration of abrasion prediction models for hydraulic structures, such as those conducted at Swiss SBTs, has shown that average and material-specific calibration coefficients can significantly reduce prediction errors. These findings imply that while k_v may not be strictly constant, it can behave quasi-constantly when considering specific conditions and materials. This variation is due to factors such as the properties of the impinging sediment (e.g., angularity and hardness) and the inverted material (Beer & Turowski, 2015).

2.6 Knowledge Gaps and the Need for Future Research

Given the diverse range of hydraulic and sediment transport conditions under which hydro-abrasion occurs, no single test setup can fully simulate all influencing factors. While various tests exist, they primarily assess relative abrasion resistance under laboratory conditions. Parameters such as particle velocity, impact angle, and material-particle interactions analyzed in laboratory settings may significantly differ from those in the field. Consequently, there is no definitive correlation between laboratory and field data, rendering the upscaling from laboratory to field scale uncertain and necessitating further research. This deep understanding will significantly enhance our approach to predicting abrasion damage and improving maintenance strategies.

Despite using high-strength concrete in tunnel floors, many SBTs incur considerable damage. Even tunnels with granite flooring—approximately six times more durable than high-strength concrete, as evidenced in some Swiss tunnels—have experienced foundation loss exceeding two meters during flood events. Additionally, current abrasion prediction models

often overlook critical design parameters, such as tunnel geometry and cross-sectional profiles, raising concerns about whether the inherent design contributes to the problem. This issue is exemplified by the Koshiu SBT—one of the most modern designs worldwide—which suffered severe hydro-abrasion damage that suspended operations for three years, underscoring the urgent need for further research that integrates tunnel design considerations into predictive models. This challenge is particularly complex due to several factors, including hydraulic conditions, sediment characteristics, tunnel geometry, and boundary material properties. Existing predictive models for abrasion damage remain limited in accuracy due to two primary issues:

1. **Abrasion Coefficient Variability:** The abrasion coefficient, a crucial parameter in mechanistic models, is typically considered constant across various conditions. However, recent field studies suggest it may demonstrate quasi-constant behavior. This uncertainty prompts a fundamental question: Does this coefficient remain constant or fluctuate under different hydraulic and sediment transport conditions? Understanding this variability is essential for improving existing abrasion prediction models.
2. **Lack of Spatial Resolution:** All models rely on average-based estimates, which fail to capture localized damage patterns. This leads to gaps in understanding the spatial variability of abrasion processes.

2.7 State-of-the-Art and Current Study Scope

To enhance predictive capabilities, this study leverages high-resolution laser scanning data from the Koshiu SBT, which spans 4 kilometers with a 2 cm × 2 cm resolution. This advanced data collection method allows for detailed analysis of abrasion damage patterns, providing a comprehensive understanding of the factors influencing hydro-abrasion.

The primary research objectives of this study are as follows:

- **Assessing Abrasion Damage Patterns:** This involves thoroughly examining the abrasion damage observed in the field. By correlating these patterns with findings from previous literature, the study aims to identify consistent trends and anomalies that can inform future predictive models.
- **Evaluating Abrasion Coefficient Variability:** The study seeks to understand how the abrasion coefficient varies across different damage patterns. This variability is crucial for improving the accuracy of mechanistic models, as it challenges the assumption that the coefficient remains constant under varying hydraulic and sediment transport conditions.
- **Developing High-Dimensional Machine Learning Models:** Utilizing the detailed field data, the study aims to create sophisticated machine learning models capable of predicting abrasion damage in one-dimensional (1D), two-dimensional (2D), and three-dimensional (3D) frameworks. These models will enhance the precision and practicality of engineering solutions, offering more reliable predictions for tunnel maintenance and design.

By integrating field data analysis with advanced machine learning techniques, this study endeavors to bridge existing knowledge gaps and significantly enhance the predictive capabilities of abrasion models.

2.8 References

- Albayrak, I., Arnold, R., Demiral-Yüzügüllü, D., Maddahi, M., & Boes, R. M. (2024). Field monitoring and modelling of sediment transport, hydraulics and hydroabrasion at Sediment Bypass Tunnels. *Journal of Hydro-Environment Research*.
<https://doi.org/10.1016/j.jher.2024.05.002>
- Albayrak, I., Müller-Hagmann, M., & Boes, R. (2019). Efficiency evaluation of Swiss Sediment Bypass Tunnels. *Proceedings of the 3rd International Workshop on Sediment Bypass Tunnels*, 239–245. <https://doi.org/10.3929/ethz-b-000337945>
- Anari, R., Hotchkiss, R. H., & J. Langendoen, E. (2020). Elements for the successful computer simulation of sediment management strategies for reservoirs. *Water*, 12(3), 714. <https://www.mdpi.com/2073-4441/12/3/714>
- Annandale, G. W., Morris, G. L., & Karki, P. (2016). *Extending the life of reservoirs: Sustainable sediment management for dams and run-of-river hydropower*. Washington, DC: World Bank. <https://openknowledge.worldbank.org/items/a91a766d-fc7a-5c4a-8cf3-a13c05025702>
- Arnold, R., Albayrak, I., & Boes, R. (2020). *Field monitoring of sediment transport, hydraulics, and hydro-abrasion at Swiss sediment bypass tunnels* (SI/501609-01, SFOE) [Technical].
- Aubert, G., Langlois, V. J., & Allemand, P. (2016). Bedrock incision by bedload: Insights from direct numerical simulations. *Earth Surface Dynamics*, 4(2), 327–342.
- Auel, C. (2014). *Flow characteristics, particle motion and invert abrasion in sediment bypass tunnels* (p. 1 Band) [ETH Zurich; Application/pdf]. <https://doi.org/10.3929/ETHZ-A-010243883>
- Auel, C. (2018). Sediment Bypassing – A Sustainable and Eco-Friendly Strategy Against Reservoir Sedimentation*. In *Twenty-Sixth International Congress on Large Dams: Vingt-Sixième Congrès International des Grands Barrages*. CRC Press.
- Auel, C., Albayrak, I., Sumi, T., & Boes, R. M. (2017a). Sediment transport in high-speed flows over a fixed bed: 1. Particle dynamics: Sediment transport in high-speed flows: 1. Particle dynamics. *Earth Surface Processes and Landforms*, 42(9), 1365–1383. <https://doi.org/10.1002/esp.4128>
- Auel, C., Albayrak, I., Sumi, T., & Boes, R. M. (2017b). Sediment transport in high-speed flows over a fixed bed: 2. Particle impacts and abrasion prediction: Sediment transport in high-speed flows: 2. Particle impacts. *Earth Surface Processes and Landforms*, 42(9), 1384–1396. <https://doi.org/10.1002/esp.4132>
- Auel, C., & Boes, R. M. (2011). Sediment bypass tunnel design – review and outlook. In *Dams and Reservoirs under Changing Challenges*. CRC Press.
- Auel, C., Boes, R. M., & Sumi, T. (2018). Abrasion prediction at Asahi sediment bypass tunnel based on Ishibashi's formula. *Journal of Applied Water Engineering and Research*, 6(2), 125–138. <https://doi.org/10.1080/23249676.2016.1265470>

- Auel, C., Kantoush, S., & Sumi, T. (2016, May 18). Positive effects of reservoir sedimentation management on reservoir life—Examples from Japan. *Positive Effects of Reservoir Sedimentation Management on Reservoir Life - Examples from Japan*.
- Auel, C., Kobayashi, S., Takemon, Y., & Sumi, T. (2017). Effects of sediment bypass tunnels on grain size distribution and benthic habitats in regulated rivers. *International Journal of River Basin Management*, 15(4), 433–444. <https://doi.org/10.1080/15715124.2017.1360320>
- Auel, C., Thene, J., Müller-Hagmann, M., Albayrak, I., & Boes, R. (2017). *Abrasion prediction at Mud Mountain sediment bypass tunnel* [Application/pdf]. <https://doi.org/10.3929/ETHZ-B-000185304>
- Beer, A. R., & Lamb, M. P. (2021). Abrasion regimes in fluvial bedrock incision. *Geology*, 49(6), 682–386. <https://pubs.geoscienceworld.org/gsa/geology/article/594891/Abrasion-regimes-in-fluvial-bedrock-incision>
- Beer, A. R., & Turowski, J. M. (2015). Bedload transport controls bedrock erosion under sediment-starved conditions. *Earth Surface Dynamics*, 3(3), 291–309.
- Beyeler, J. D., & Sklar, L. S. (2010). Bedrock resistance to fluvial erosion: The importance of rock tensile strength, crystal grain size and porosity in scaling from the laboratory to the field. *AGU Fall Meeting Abstracts, 2010*, EP41D-0740.
- Bitter, J. G. A. (1963a). A study of erosion phenomena part I. *Wear*, 6(1), 5–21. [https://doi.org/10.1016/0043-1648\(63\)90003-6](https://doi.org/10.1016/0043-1648(63)90003-6)
- Bitter, J. G. A. (1963b). A study of erosion phenomena: Part II. *Wear*, 6(3), 169–190. [https://doi.org/10.1016/0043-1648\(63\)90073-5](https://doi.org/10.1016/0043-1648(63)90073-5)
- Boes, R., Auel, C., Müller-Hagmann, M., & Albayrak, I. (2014). *Sediment bypass tunnels to mitigate reservoir sedimentation and restore sediment continuity* (pp. 221–228). <https://doi.org/10.1201/b17397-27>
- Boes, R. M., Auel, C., Hagmann, M., & Albayrak, I. (2014). *Sediment bypass tunnels to mitigate reservoir sedimentation and restore sediment continuity*. *Reservoir Sedimentation (Schleiss, AJ, De Cesare, G., Franca, MJ, Pfister, M., eds.)*. Taylor & Francis Group, London, UK.
- Boes, R., Müller-Hagmann, M., & Albayrak, I. (2019). Design, operation and morphological effects of bypass tunnels as a sediment routing technique. *Proceedings of the 3rd International Workshop on Sediment Bypass Tunnels*, 40–50. <https://doi.org/10.3929/ethz-b-000337946>
- Chatanantavet, P., & Parker, G. (2009). Physically based modeling of bedrock incision by abrasion, plucking, and macroabrasion. *Journal of Geophysical Research: Earth Surface*, 114(F4).
- Demiral, D., Albayrak, I., Turowski, J. M., & Boes, R. M. (2022). Particle saltation trajectories in supercritical open channel flows: Roughness effect. *Earth Surface Processes and Landforms*.
- Demiral Yüzügüllü, D. (2021). *Hydro-abrasion processes and modelling at hydraulic structures and steep bedrock rivers* [PhD Thesis]. ETH Zurich.
- Emara, A., Kantoush, S. A., Saber, M., Sumi, T., Nourani, V., & Mabrouk, E. (2025a). Advanced 3D abrasion mapping in sediment bypass tunnels using XGBoost: A high-dimensional approach

- to predictive modeling. *Expert Systems with Applications*, 282, 127686. <https://doi.org/10.1016/j.eswa.2025.127686>
- Emara, A., Kantoush, S. A., Saber, M., Sumi, T., Nourani, V., & Mabrouk, E. (2025b). Machine learning approach for 2D abrasion mapping in Sediment Bypass Tunnels: A case study of Koshibu SBT, Japan. *Engineering Applications of Computational Fluid Mechanics*, 19(1), 2444419. <https://doi.org/10.1080/19942060.2024.2444419>
- Facchini, M., Siviglia, A., & Boes, R. M. (2015). Downstream morphological impact of a sediment bypass tunnel—preliminary results and forthcoming actions. *Proc. First International Workshop on Sediment Bypass Tunnels, VAW-Mitteilungen*, 232, 137–146.
- Facchini, M., Siviglia, A., & Boes, R. M. (2017). Downstream morphological effects of SBT releases: 1D numerical study and preliminary LiDAR data analysis. *Proceedings of the 2nd International Workshop on Sediment Bypass Tunnels*, 1–12. <https://repository.kulib.kyoto-u.ac.jp/dspace/handle/2433/245506>
- Fan, J., & Morris, G. L. (1998). *Reservoir Sedimentation Handbook: Design and Management of Dams, Reservoirs, and Watersheds for Sustainable Use*. McGraw-Hill.
- Fukuroi, H. (2012). Damage from Typhoon Talas to Civil engineering Structures for Hydropower and the effect of the Sediment Bypass System at Asahi dam. *Proc. Int. Symposium on Dams for a Changing World—Need for Knowledge Transfer across the Generations and the World*.
- Graf, W. H. (1998). *Fluvial hydraulics: Flow and transport processes in channels of simple geometry*. John Wiley & Sons. [https://books.google.com/books?hl=en&lr=&id=bRIXEQAAQBAJ&oi=fnd&pg=PA683&dq=Kironoto+and+Graf+\(1995\)+for+subcritical+flows&ots=i4C83K6YG6&sig=tEyBmloWOEmIGvTp2QrDa2W8fsA](https://books.google.com/books?hl=en&lr=&id=bRIXEQAAQBAJ&oi=fnd&pg=PA683&dq=Kironoto+and+Graf+(1995)+for+subcritical+flows&ots=i4C83K6YG6&sig=tEyBmloWOEmIGvTp2QrDa2W8fsA)
- Hagmann, M., Albayrak, I., & Boes, R. M. (2015). Field research: Invert material resistance and sediment transport measurements. *Proc. First International Workshop on Sediment Bypass Tunnels, VAW-Mitteilungen*, 232, 123–135.
- Harada, M., Kokubo, T., & Deno, T. (1998). Hydraulic Properties of Sediment Transport in The Tunnel of Sediment-Bypass System of a Reservoir. *Doboku Gakkai Ronbunshu*, 1998(600), 69–84.
- Helbig, U., Horlacher, H.-B., Stamm, J., Bellmann, C., Butler, M., & Mechtcherine, V. (2012). Nachbildung der Hydroabrasionsbeanspruchung im Laborversuch: Teil 2—Korrelation mit Verschleißwerten und Prognoseansätze. *Bautechnik*, 89(5), 320–330.
- Ho, T.-C., Hwang, G.-J., Hwang, K.-S., Hsieh, K.-C., & Chen, L.-W. (2019). *Experimental and numerical study on desilting efficiency of the bypassing tunnel for Nan-Hua reservoir*.
- Inoue, T., Izumi, N., Shimizu, Y., & Parker, G. (2014). Interaction among alluvial cover, bed roughness, and incision rate in purely bedrock and alluvial-bedrock channel: Interaction - alluvial cover, roughness. *Journal of Geophysical Research: Earth Surface*, 119(10), 2123–2146. <https://doi.org/10.1002/2014JF003133>
- ISHIBASHI, T. (1983). A hydraulic study on protection for erosion of sediment flush equipments of dams. *Proceedings of the Japan Society of Civil Engineers*, 1983(334), 103–112.

- Jacobsen, S., Scherer, G. W., & Schulson, E. M. (2015). Concrete–ice abrasion mechanics. *Cement and Concrete Research*, 73, 79–95. <https://doi.org/10.1016/j.cemconres.2015.01.001>
- Johnson, J. P. L. (2014). A surface roughness model for predicting alluvial cover and bed load transport rate in bedrock channels. *Journal of Geophysical Research: Earth Surface*, 119(10), 2147–2173. <https://doi.org/10.1002/2013JF003000>
- Kadia, S. (2024). *Secondary Currents, Turbulence Characteristics, and Bed Shear Stress Variations in Supercritical Narrow Channel Flows*. <https://doi.org/10.13140/RG.2.2.15214.01606>
- Kadia, S., Larsson, S., Billstein, M., Lia, L., & Pummer, E. (2024). Experimental and numerical investigations of the water surface profile and wave extrema of supercritical flows in a narrow channel bend. *Scientific Reports*, 14, 12247. <https://doi.org/10.1038/s41598-024-61297-8>
- Kantoush, S., Sumi, T., & Murasaki, M. (2011). Evaluation of sediment bypass efficiency by flow field and sediment concentration monitoring techniques. *Journal of Japan Society of Civil Engineers, Ser. B1 (Hydraulic Engineering)*, 67(4), I_169-I_174.
- Kondolf, G. M., Gao, Y., Annandale, G. W., Morris, G. L., Jiang, E., Zhang, J., Cao, Y., Carling, P., Fu, K., & Guo, Q. (2014). Sustainable sediment management in reservoirs and regulated rivers: Experiences from five continents. *Earth's Future*, 2(5), 256–280.
- Koshiba, T. (2020). *Improvement of Signal Analysis for Surrogate Bedload Monitoring at Sediment Bypass Tunnels* [Thesis, Kyoto University]. <https://repository.kulib.kyoto-u.ac.jp/dspace/bitstream/2433/253255/1/ykogk04680.pdf>
- Koshiba, T., Auel, C., Tsutsumi, D., Kantoush, S. A., & Sumi, T. (2018). Application of an impact plate – Bedload transport measuring system for high-speed flows. *International Journal of Sediment Research*, 33(1), 35–46. <https://doi.org/10.1016/j.ijsrc.2017.12.003>
- Koshiba, T., Kantoush, S. A., & Sumi, T. (2017). Field experiment of bedload transport rate measurement at sediment bypass tunnel. *Proc. 37th IAHR World Congress*, 1115–1124.
- Koshiba, T., & Sumi, T. (2020). Bedload transport and abrasion monitoring at the Koshibu Dam sediment bypass tunnel and proposing countermeasures against the abrasion problem. *Icold1st*, 13-49–19.
- Lague, D. (2014). The stream power river incision model: Evidence, theory and beyond. *Earth Surface Processes and Landforms*, 39(1), 38–61. <https://doi.org/10.1002/esp.3462>
- Lamb, M. P., Dietrich, W. E., & Sklar, L. S. (2008). A model for fluvial bedrock incision by impacting suspended and bed load sediment. *Journal of Geophysical Research: Earth Surface*, 113(F3), 2007JF000915. <https://doi.org/10.1029/2007JF000915>
- Lamb, M. P., Finnegan, N. J., Scheingross, J. S., & Sklar, L. S. (2015). New insights into the mechanics of fluvial bedrock erosion through flume experiments and theory. *Geomorphology*, 244, 33–55.
- Lee, C.-H., Zhan, S.-S., Chang, S.-H., Lien, S.-Y., & Chang, J.-H. (2019). *Abrasion resistance design of sediment sluicing tunnel in Taiwan: A case study*.

- MMS. (2013). *Consistently Accurate Measurement*.
http://www.mitsubishielectric.co.jp/mms/pdf/mms_e.pdf
- MMS Website. (2024). *Mitsubishi Electric, Latest Version of GPS, MMS*.
<http://www.mitsubishielectric.co.jp/mms/tokucho.html>
- Morris, G. L. (2019). *SEDIMENT BYPASS TUNNELS: IMPACT OF HYDROLOGY ON FEASIBILITY*.
- Morris, G. L. (2020). Classification of management alternatives to combat reservoir sedimentation. *Water*, 12(3), 861.
- Müller-Hagmann, M. (2018). *Hydroabrasion by high-speed sediment-laden flows in sediment bypass tunnels* [PhD Thesis]. ETH Zurich.
- Müller-Hagmann, M., Albayrak, I., Auel, C., & Boes, R. M. (2020). Field Investigation on Hydroabrasion in High-Speed Sediment-Laden Flows at Sediment Bypass Tunnels. *Water*, 12(2), Article 2. <https://doi.org/10.3390/w12020469>
- Nakajima, H., Otsubo, Y., & Omoto, Y. (2015). Abrasion and corrective measures of a sediment bypass system at Asahi Dam. *Proc. Int. Workshop on Sediment Bypass Tunnels*, 21–32.
- Nezu, I., & Nakagawa, H. (1993). Turbulence in open-channel flows, *iahr-monogr. Ser., A*, 1–281.
- Sakurai, T., Tsujimoto, T., Sumi, T., Kunimura, I., Takeuchi, H., & Ishida, K. (2018). Plan and Operation Results of the Koshiyama Dam Sediment Bypass Tunnel. *Twenty-Sixth International Congress on Large Dams/Vingt-Sixième Congrès International Des Grands Barrages*, Q100_298-Q100_316. <https://www.taylorfrancis.com/chapters/edit/10.1201/9780429465086-20/plan-operation-results-koshiyama-dam-sediment-bypass-tunnel-toshiyuki-sakurai-tetsuro-tsujimoto-tetsuya-sumi-ichiro-kunimura-hiroyuki-takeuchi-katsushi-ishida>
- Sawagashira, Y., Suzuki, A., & Fukumoto, A. (2017). Sedimentation control effect and environmental impact of sediment bypass in Miwa Dam Redevelopment Project. *Proceedings of the 2nd International Workshop on Sediment Bypass Tunnels*, 1–12. <https://repository.kulib.kyoto-u.ac.jp/dspace/handle/2433/245513>
- Scheingross, J. S., Brun, F., Lo, D. Y., Omerdin, K., & Lamb, M. P. (2014). Experimental evidence for fluvial bedrock incision by suspended and bedload sediment. *Geology*, 42(6), 523–526.
- Schleiss, A. J., Franca, M. J., Juez, C., & De Cesare, G. (2016). Reservoir sedimentation. *Journal of Hydraulic Research*, 54(6), 595–614. <https://doi.org/10.1080/00221686.2016.1225320>
- Seidl, M. A., Dietrich, W. E., Schmidt, K. H., & De Ploey, J. (1992). The problem of channel erosion into bedrock. *Functional Geomorphology*, 23, 101–124. [https://books.google.com/books?hl=en&lr=&id=kTSBAAAQBAJ&oi=fnd&pg=PT362&dq=Seidl,+M.A.+%26+Dietrich,+W.E.+\(1992\)+The+problem+of+channel+erosion+into+bedrock.+Catena+Supplement,+23,+101%E2%80%93124.&ots=KkNy-1M1lZ&sig=_WVCAv3durnocysG7Kg3uEd2-IU](https://books.google.com/books?hl=en&lr=&id=kTSBAAAQBAJ&oi=fnd&pg=PT362&dq=Seidl,+M.A.+%26+Dietrich,+W.E.+(1992)+The+problem+of+channel+erosion+into+bedrock.+Catena+Supplement,+23,+101%E2%80%93124.&ots=KkNy-1M1lZ&sig=_WVCAv3durnocysG7Kg3uEd2-IU)
- Sklar, L. S., & Dietrich, W. E. (2001). Sediment and rock strength controls on river incision into bedrock. *Geology*, 29(12), 1087–1090. [https://doi.org/10.1130/0091-7613\(2001\)029<1087:SARSCO>2.0.CO;2](https://doi.org/10.1130/0091-7613(2001)029<1087:SARSCO>2.0.CO;2)

- Sklar, L. S., & Dietrich, W. E. (2004). A mechanistic model for river incision into bedrock by saltating bed load. *Water Resources Research*, 40(6). <https://doi.org/10.1029/2003WR002496>
- Sklar, L. S., & Dietrich, W. E. (2012). Correction to “A mechanistic model for river incision into bedrock by saltating bed load.” *Water Resources Research*, 48(6). <https://doi.org/10.1029/2012WR012267>
- Song, T., & Chiew, Y. M. (2001). Turbulence Measurement in Nonuniform Open-Channel Flow Using Acoustic Doppler Velocimeter (ADV). *Journal of Engineering Mechanics*, 127(3), 219–232. [https://doi.org/10.1061/\(ASCE\)0733-9399\(2001\)127:3\(219\)](https://doi.org/10.1061/(ASCE)0733-9399(2001)127:3(219))
- Sumi, T. (2006). Reservoir sediment management measures and necessary instrumentation technologies to support them. *6th Japan-Taiwan Joint Seminar on Natural Hazard Mitigation, Kyoto*.
- Sumi, T., & Kantoush, S. A. (2011). Comprehensive sediment management strategies in Japan: Sediment bypass tunnels. *Proceedings of the 34th World Congress of the International Association for Hydro-Environment Research and Engineering, 33rd Hydrology and Water Resources Symposium and 10th Conference on Hydraulics in Water Engineering Valentine*.
- T.D.I.M Office. (2021). Tenryu River Dam Integrated Management Office. <https://www.cbr.mlit.go.jp/tendamu/>
- Turowski, J. M. (2009). Stochastic modeling of the cover effect and bedrock erosion. *Water Resources Research*, 45(3), 2008WR007262. <https://doi.org/10.1029/2008WR007262>
- Turowski, J. M. (2012). Semi-alluvial channels and sediment-flux-driven bedrock erosion. *Gravel-Bed Rivers: Processes, Tools, Environments*, 399–418.
- Turowski, J. M., & Hodge, R. (2017). A probabilistic framework for the cover effect in bedrock erosion. *Earth Surface Dynamics*, 5(2), 311–330. <https://doi.org/10.5194/esurf-5-311-2017>
- Turowski, J. M., Lague, D., & Hovius, N. (2007). Cover effect in bedrock abrasion: A new derivation and its implications for the modeling of bedrock channel morphology. *Journal of Geophysical Research: Earth Surface*, 112(F4).
- Vetsch, D., Facchini, M., Boes, R., & Siviglia, A. (2024). Modeling the morphological response of gravel-bed rivers subject to repeated sediment bypass tunnel operations. *Frontiers of Earth Science*, 1357759. <https://doi.org/10.3389/feart.2024.1357759>
- Walling, D. E. (2009). *The impact of global change on erosion and sediment transport by rivers: Current progress and future challenges*. <https://books.google.com/books?hl=en&lr=&id=zwhpknVKEsQC&oi=fnd&pg=PA1&dq=Global+sediment+dynamics+and+reservoir+sedimentation+are+intensifying+under+the+influence+of+climate+change,+leading+to+increased+sediment+transport+rates&ots=L0K-EJXnnh&sig=ssCgjr-wvSwo1o6RpuAjYfdrUMM>

CHAPTER 3

Topographic and Hydraulic Analysis of Koshiibu SBT

3.1. Introduction to the Case Study

The Koshiibu Dam lies on the left branch of the Tenryu River in Nagano Prefecture, Japan (see **Figure 9**). Completed in 1969, it serves as a flood control, irrigation, and hydropower facility for a 288 km² catchment. To preserve reservoir capacity and maintain downstream sediment continuity, an SBT was incorporated into the dam's design. This Koshiibu SBT was planned to prevent the dam from silting up while allowing sediment (gravel, sand, silt) to pass around the reservoir. The bypass facility was finalized in 2016 and has since been closely monitored by academics and engineers (a special committee was formed during planning). Its operation target is substantial: about 310,000 m³ of bed sediment per year is intended to be rerouted downstream, supplementing the average 570,000 m³/yr inflow of water (Sakurai et al., 2018).



Figure 9: Location of Koshibu Dam and Overview of the Selected SBT Case Study.

Structurally, the Koshibu SBT is approximately 3.98 km long and constructed as a concrete diversion tunnel. The tunnel has a horseshoe-shaped cross-section roughly 6.5 m wide and 7.2 m high. It is designed to convey extremely high-speed, sediment-laden flows. The peak design discharge is $370 \text{ m}^3/\text{s}$. The tunnel profile begins with a very steep "acceleration" reach: the first $\sim 50 \text{ m}$ has a longitudinal slope of about 20% to rapidly build flow momentum. Downstream of this high-gradient zone, the slope changes to approximately 2% for the remainder of the tunnel length. Midway along the tunnel ($\sim 700 \text{ m}$ upstream of the outlet), the alignment curves toward the right bank on an arc of $\sim 1000 \text{ m}$ radius; the tunnel remains straight elsewhere. The inlet end of the SBT features specialized components: two crest spillways (flood-control gates) regulate the flow into the tunnel, and the intake structure is lined with abrasion-resistant materials. In particular, the low-velocity flow over the gate is directed across a rubber-coated steel plate, and a steel lining protects the downstream high-speed section. The outlet discharges into an energy dissipation basin at the far end to absorb residual flow energy, as illustrated in **Figure 10**. The Koshibu SBT represents a state-of-the-art sediment management installation: a long, steep tunnel engineered for heavy

loads, with an upstream acceleration zone, protective linings, gated intake, and an instrumented outlet basin. These design details make it ideal for studying sediment transport and abrasion phenomena under extreme flow conditions.



Figure 10: Operational view of the Koshibu SBT outlet.

3.2. Data Acquisition and Processing Techniques

3.2.1 Laser Scanning Technology and Field Deployment

Data on the Koshibu SBT invert topography were acquired using high-precision 3D laser scanning instruments. In practice, the dam operators drove a mobile laser scanning (MMS) system through the tunnel. A Mitsubishi Mobile Laser Scanner (MMS) interfaced with GPS/INS positioning for precise georeferencing (MMS, 2013; MMS Website, 2024). The scanner was calibrated using the Flaechenkorrektur Parameter (FKP) method to correct positional errors and ensure alignment with control points (MMS Website, 2024; T.D.I.M Office, 2021). Over multiple field surveys, the entire invert surface (basically all accessible

floor areas) was surveyed. The result was an extremely dense point cloud of the tunnel floor. The scanning achieved roughly 2 cm spacing between points in both horizontal directions. In practical terms, the derived Digital Elevation Model (DEM) has a pixel resolution of 2×2 cm. Such satisfactory resolution is adequate to capture even small damage features, as shown in **Figure 11**.

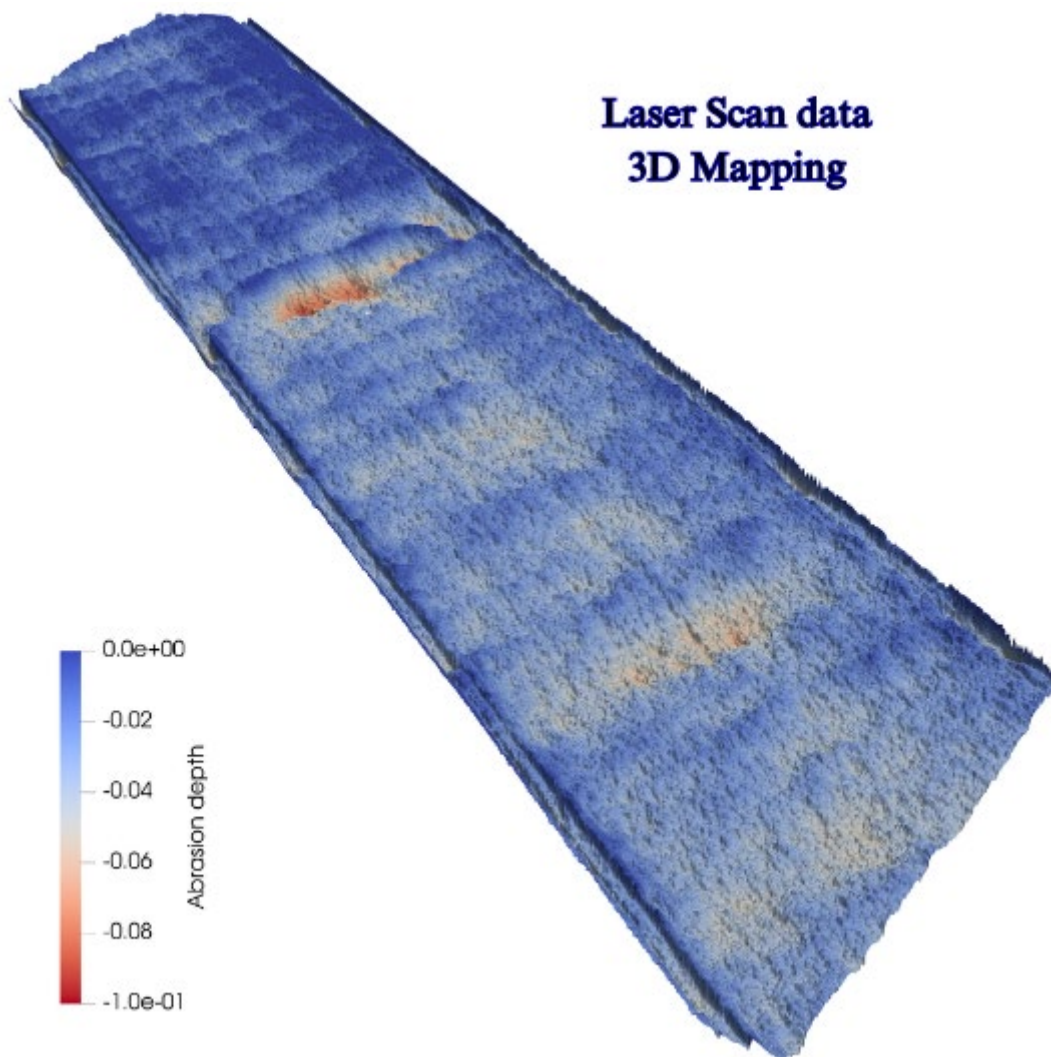


Figure 11: 3D Point Cloud Mapping of the Tunnel Surface.

3.2.2 Generation and Analysis of the Topographies

Topography I and II represent the updated tunnel floor following the analyzed flood events. Topography I was conducted after eight operational events, while Topography II occurred after four additional events. It is generated directly from the processed laser scanning DEM mentioned above. The Topography encodes the actual 3D elevation of every point on the surface, showing all the worn depressions and scratch lines carved by sediment transport. Topography I reveals abrasion depths exceeding 20 cm below the original floor. However, Topography II exhibits a greater depth severity, exceeding 1 meter in certain tunnel regions. The following histograms illustrate the distribution of abrasion damage throughout the tunnel length; see **Figures 12 and 13**.

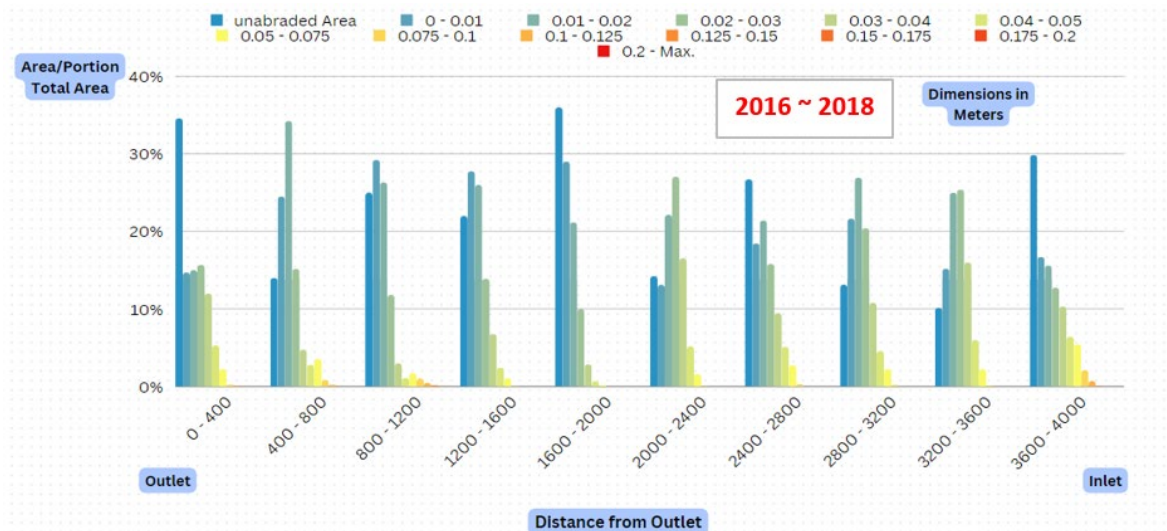


Figure 12: Longitudinal Distribution of Tunnel Abrasion Damage (2016–2018).

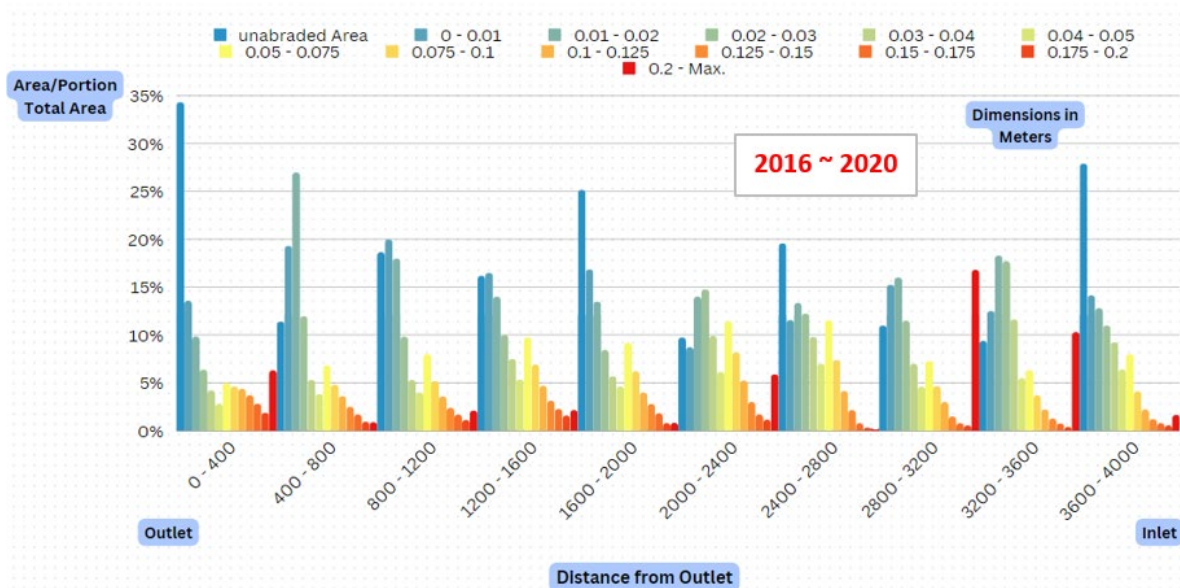


Figure 13: Longitudinal Distribution of Tunnel Abrasion Damage (2016–2020).

3.3. Hydraulic Characterization of Flood Events

Between the tunnel's commissioning in 2016 and the end of 2018, eight flood events were routed through the Koshiu SBT (labeled Op.1 through Op.8). These events vary widely in intensity and duration. **Table 1** summarizes their key parameters. For example, Op.1 (October 2016) had a peak intake discharge of $\sim 60 \text{ m}^3/\text{s}$, lasting around 20 hours, whereas Op.8 (September 2018) reached nearly $200 \text{ m}^3/\text{s}$ for ~ 70 hours. The increasing peak discharges in later events reflect an unusually active typhoon season in 2018. The tunnel flow is essentially supercritical. It is noted that the hydrodynamics of this tunnel can be “analogized to a tsunami” due to the very high flow velocities, which is why direct instrumentation inside the tunnel is impractical.

Table 1: Operational Overview of the Koshibu SBT (2016–2018), (Koshiba & Sumi, 2020).

Operation	Date	Duration, T	Discharge, Q_{max}
No.	[-]	[hours]	[m ³ /s]
Op1	09/2016	16	80
Op2	09/2016	5.8	60
Op3	07/2017	3.1	120
Op4	10/2017	9.7	180
Op5	10/2017	48.8	90
Op6	07/2018	10.7	150
Op7	09/2018	44.2	175
Op8	10/2018	69.5	200

Because direct measurements of velocity or depth inside the tunnel are not available, we reconstruct the hydraulic conditions using standard back-calculation methods. We start from each event's recorded peak discharge Q (from the intake gauge). We assume that after the acceleration section, the flow becomes nearly uniform. In the main portion (2% slope), we apply the Darcy–Weisbach equation to compute the corresponding flow depth (h) and velocity (v) that would convey Q through the tunnel. Such methodology is commonly adopted to derive hydraulic features within the tunnel, as documented by (Auel et al., 2018; Demiral Yüzügüllü, 2021; Emara et al., 2025b, 2025a). Based on the centrifugal force at each cross-section, we also calculate the superelevation (the difference in water surface height between the inner and outer walls) induced by curvature.

Thus, for each of the eight events, we derive four hydraulic parameters at every location: (1) flow velocity v , (2) flow depth h , (3) event duration (flood duration), and (4) lateral superelevation. These parameters fully characterize the flow field inside the tunnel during

each event to the extent our steady-flow assumption holds. (Note that the initial 50 m acceleration zone is assumed to establish steady conditions rapidly. The key point is that we now have spatial maps of velocity and depth along the tunnel for each flood, which we can link to the observed abrasion.

3.4. Spatial distribution and severity of abrasion (Topo_I vs Topo_II)

The Koshiu SBT abrasion data show a marked intensification of abrasion in Topo_II (2016–2020) compared to Topo_I (2016–2018), as shown in **Table 2**. In the *scatter* region (approx. 0–2500 m), Topo_I had a relatively high fraction of unabraded floor and mostly shallow incisions (depth ≤ 0.02 m). For example, the average unabraded area was $\approx 22\%$, with 0–0.01 m and 0.01–0.02 m classes contributing $\sim 19\%$ and $\sim 22\%$, respectively. In Topo_II, the unabraded floor in the same region fell to $\approx 17\%$, and the deepest class (0.05+ m) rose dramatically (from 3% to 28%). In intermediate segments (2500–3200 m, *edged* region), Topo_I still had a high unabraded area ($\sim 23.5\%$) and shallow-dominated abrasion, whereas Topo_II shows many segments with the 0.05+ class covering ~ 25 – 30% of the floor. Downstream of the bend (3200–4000 m, *skewed* region), Topo_I had mixed shallow wear (unabraded $\sim 24\%$, 0.01–0.02 m $\sim 25\%$), but Topo_II exhibits inner-wall dominance: at 3200–3600 m the deepest class jumps from $\sim 4.7\%$ to $\sim 21.2\%$, and at 3600–4000 m the 0.05+ class is $\sim 28.8\%$ (Table 1). Overall, Topo_II is characterized by much larger areas of deep abrasion in almost every segment.

Table 2: Average area percentages by depth class in three tunnel regions for Topo_I (2016–2018) and Topo_II (2016–2020). (Scatter: 0–2400 m; Edged: 2400–3200 m; Skewed: 3200–4000 m).

Region (m)	Class	Topo_I (%)	Topo_II (%)	Δ (Topo_II – Topo_I)
Scatter (0– 2400)	Unabraded	21.7	17.1	–4.6
	0–0.01	19.0	13.2	–5.8
	0.01–0.02	22.0	14.7	–7.3
	0.02–0.03	18.6	12.6	–6.0
	0.03–0.04	11.0	8.9	–2.1
	0.04–0.05	4.7	5.7	+1.0
	0.05+	3.0	27.8	+24.8
Edged (2400– 3200)	Unabraded	23.5	17.4	–6.1
	0–0.01	28.5	18.2	–10.3
	0.01–0.02	26.2	16.0	–10.2
	0.02–0.03	12.9	9.9	–3.0
	0.03–0.04	4.9	6.4	+1.5

	0.04–0.05	1.8	4.7	+2.9
	0.05+	2.3	27.3	+25.0
Skewed (3200– 4000)	Unabraded	24.3	22.9	–1.4
	0–0.01	19.6	16.4	–3.2
	0.01–0.02	24.6	18.4	–6.2
	0.02–0.03	15.4	9.2	–6.2
	0.03–0.04	8.4	4.8	–3.6
	0.04–0.05	4.1	3.3	–0.7
	0.05+	3.7	25.0	+21.3

These data reveal that overall abrasion severity increased from Topo_I to Topo_II. In Topo_I, the highest peak abrasion fractions often occurred in shallow classes or as unabraded zones, whereas in Topo_II, many segments become dominated by the 0.05+ m class. For example, in segments 400–800 m through 2800–3200 m, the most significant fraction shifts from <27% in shallow classes to ~25–35% in the >0.05 m class. In contrast, the last segment (3600–4000 m) remains the highest in the unabraded area, indicating a reduction in abrasion right at the outlet. The shifts in peak abrasion zones are dramatic: Topo_I had six of ten segments peaked by unabraded or 0.01–0.02 m classes, but in Topo_II, seven of ten peaked in the 0.05+ m class. These shifts highlight how prolonged operation leads to the formation of new, deep channels, while diminishing the extent of lightly abraded areas.

3.5. Regional abrasion patterns (scatter, edged, skewed)

The spatial layout of abrasion in Topo_I can be categorized into three zones, consistent with recognized SBT damage patterns, see **Figures 14** and **15**. The **scatter** zone (0–2500 m) shows multiple isolated incision channels amid undamaged areas (resembling “island” preservation). In Topo_I, this zone had moderate abrasion (**Table 2**), and its two main channels near the centerline produced two local peaks of 0.02–0.03 m abrasion. Topo_II intensifies this: unabraded islands shrink (17% vs 22%), while the deepest channels widen (0.05+ class rises to 28%). This suggests deepening the same channels without a uniform pattern (still “scattered”). The **edge** zone (2500–3350 m) has a dominant left-side channel and tapers toward the center. In Topo_I, this appeared as higher abrasion near one wall (reflected by the higher 0.01–0.02 m averages); Topo_II exhibits the most extreme wear here, with deep-class coverage of 30% (**Table 2**). The lateral pattern remains—heavy on one side and light on the other—but overall wear is stronger. Finally, the **skewed** zone (3350–4000 m) in the right-hand bend shows asymmetric abrasion on the inner wall. In Topo_I, the inner side was worn, but a substantial, unabraded floor remained. In Topo_II, the skew increases: at 3200–3600 m, the 0.05+ class jumps from 4.7% to 21.2% of the area, and at 3600–4000 m, it is 28.8%, indicating that the right wall now bears the brunt of erosion. The last section (3600–4000 m) still has a large undamaged portion (34.3%), suggesting some relief near the outlet. Overall, each region’s pattern persists from Topo_I to II, but with more extreme depth in Topo_II.

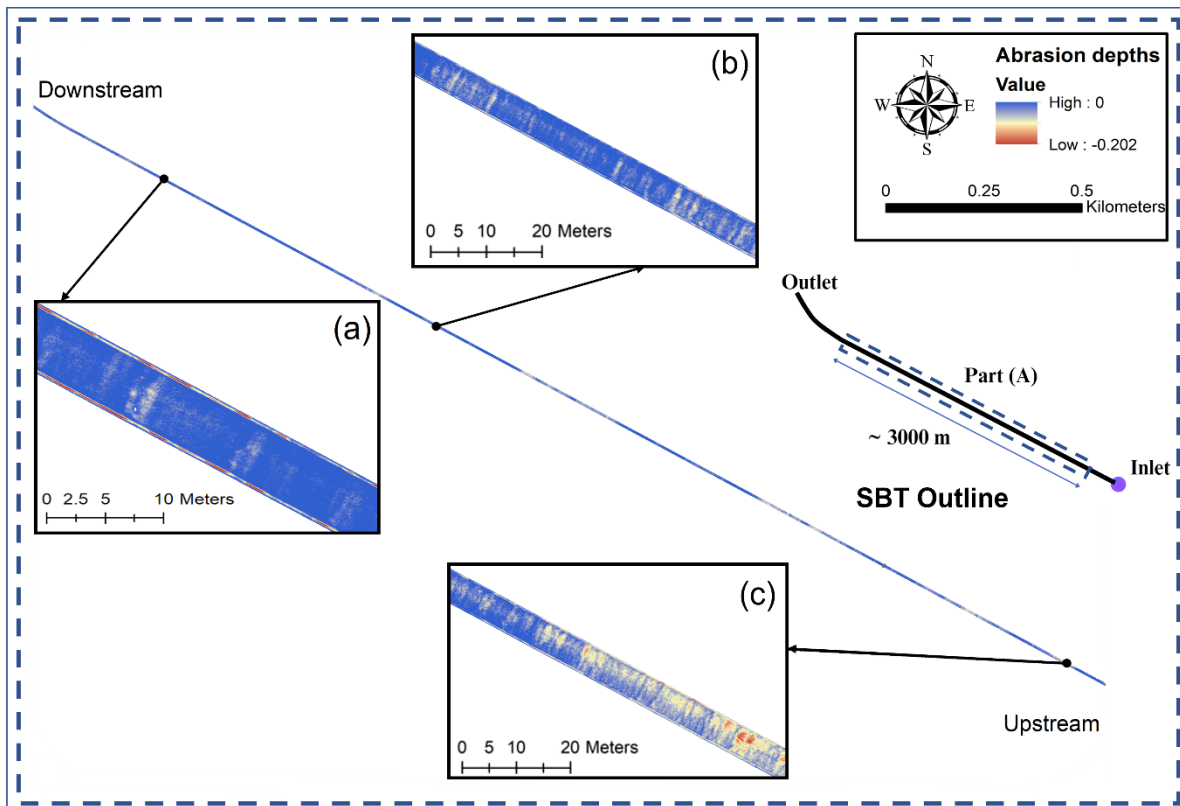


Figure 14: Abrasion Topography I of SBT Straight Part (A) Captured by Laser Scanning: (a) Edged, (b) Wave-like, and (c) Scattered Patterns.

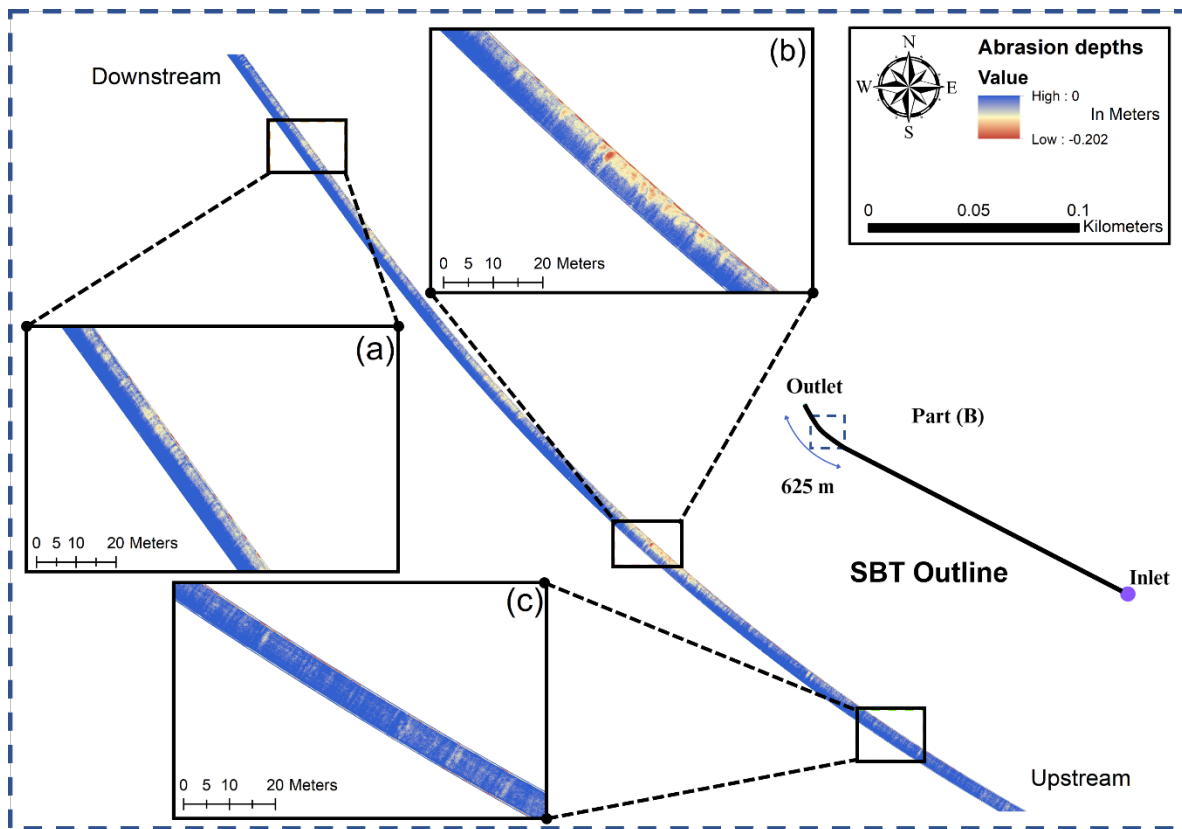


Figure 15: Abrasion Topography I via Laser Scanning of SBT Part (B): (a) After the Curve, (b) Center Zone, (c) Start of Curvature.

- **Scatter region (0–2500 m):** In Topo_I, the unabraded area was relatively high (~22%), and abrasion was spread across shallow classes. In Topo_II, unabraded drops to 17%, and the deepest class swells to ~28%. This indicates that multiple shallow channels in Topo_I have deepened (consistent with an undeveloped “scattered” profile).
- **Edged region (2500–3350 m):** Topo_I featured an edgy profile (high wear near one side) with 23.5% undamaged area. Topo_II shows a dramatic increase in deep damage: ~27% of the area is now >0.05 m deep. The lateral disparity (left vs center) likely remains, but overall damage is more severe.
- **Skewed region (3350–4000 m):** Topo_I’s peak damage was moderate (0.01–0.02 m class ~24.6%). In Topo_II, the skewed pattern intensifies: the inner (right) wall’s

deepest abrasion is now the dominant class (~25% of the area on average). However, the outlet segment rebounds in the undamaged area (34%), indicating partial sediment redistribution just before exiting.

3.6. Evolution of peak abrasion zones

Comparing Topo_I and Topo_II reveals clear temporal evolution in the zones of maximum erosion. In Topo_I, many segments peaked in the shallow to mid-abrasion classes. For instance, the segment 800–1200 m peaked at 0.01–0.02 m (26.9%), and the segment 3200–3600 m peaked at 0.01–0.02 m (34.2%). By contrast, Topo_II shifts most peaks into the deepest class: segments 800–1200, 1200–1600, 1600–2000, 2000–2400, 2400–2800, and 2800–3200 all have their highest percentage in the 0.05+ m class (ranging 24.3–36.7%). In other words, the “peak abrasion zone” in each segment moves from a shallow channel or surface patch (Topo_I) to a deep gouge (Topo_II). Only the upstream (0–400 m) and downstream (3600–4000 m) ends still have the largest unabraded areas in Topo_II; intermediate sections are dominated by deep scour. This shift is evident quantitatively (**Table 2**) and indicates an overall migration of maximum wear towards deeper depths as the number of flow events increases.

3.7. Upstream influence and flow–sediment interactions

The observed skewed pattern in the downstream bend and its evolution support the (curvature-induced) influence on abrasion, even under supercritical flow. Experiments and prior studies confirm that at SBT bends, secondary flow currents drive sediment toward the inner wall, causing persistent inner-wall abrasion downstream. In particular, (Kadia et al., 2024) showed that developing secondary currents push high-momentum fluid outward and sediments inward along the bend, producing deeper inner-wall abrasion that continues into subsequent straight reaches.

Our data mirror these findings; see **Figure 15**. The increased severity on the inner (right) side in Topo_II, with more than 25% of the floor abraded deeper than 0.05 m around 3200–

3600 m, strongly indicates the effect of curvature-induced sediment focusing (**Table 2**). Although supercritical flow often limits upstream influence, the persistence of skewness downstream suggests that sediment inertia is present. Near the outlet, the partial return of the unabraded area (34% in 3600–4000 m) implies some lateral spreading of sediments as the flow exits the curve, consistent with the expected gradual redistribution. The Koshibu abrasion patterns (especially in Topo_II) prove that secondary currents from the upstream bend drive the observed skewed wear.

3.8. Dynamics and Abrasion Localization

In this section, the talweg—defined as the line connecting the deepest points along the tunnel's length—was analyzed to understand its shifting behavior and its relationship with the severity of abrasion. Topographic results (**Figure 16**) show that initially, the talweg stayed centered, with moderate depth deviations toward the right side in plan view. After 850 m, however, the talweg migrated entirely to the left over a span of 1,650 m, with occasional moderate depth shifts back to the center just upstream of the curvature zone. Within this zone, which positions the talweg on the inner (right) side of the bend as seen in other tunnels in the literature, extreme lateral excursions were recorded, alternating between far-right and far-left alignments. A second talweg profile (**Figure 17**) reveals an incipient right-side channel at the tunnel entrance that becomes fully centered before reaching a maximum depth of about 700 m, indicating a zone of severe abrasion. Two more peaks occur at roughly 450 m and again at 700 m downstream, all coinciding with the same foundation type. This co-location suggests a strong foundation influence on abrasion patterns, a new finding that warrants attention in future tunnel design. Between the first and second maxima, the central channel splits into two closely spaced, moderate-depth channels. A similar split appears after the second maximum, although the left channel deepens more severely and extends beyond the third maximum. Notably, just upstream of the curvature and mirroring the behavior in the first talweg, paired channels reemerge despite supercritical flow conditions, which theoretically prevent upstream influence from

downstream sections. We hypothesize that the interaction between flow and sediment particles creates a quasi-supercritical state, where downstream geomorphic features partially influence upstream abrasion rates. This dual coupling of hydraulic forces and sediment dynamics introduces a new insight into abrasion processes, highlighting the need for targeted experimental and numerical studies to validate the mechanism and quantify its impact on sediment bypass tunnel performance.

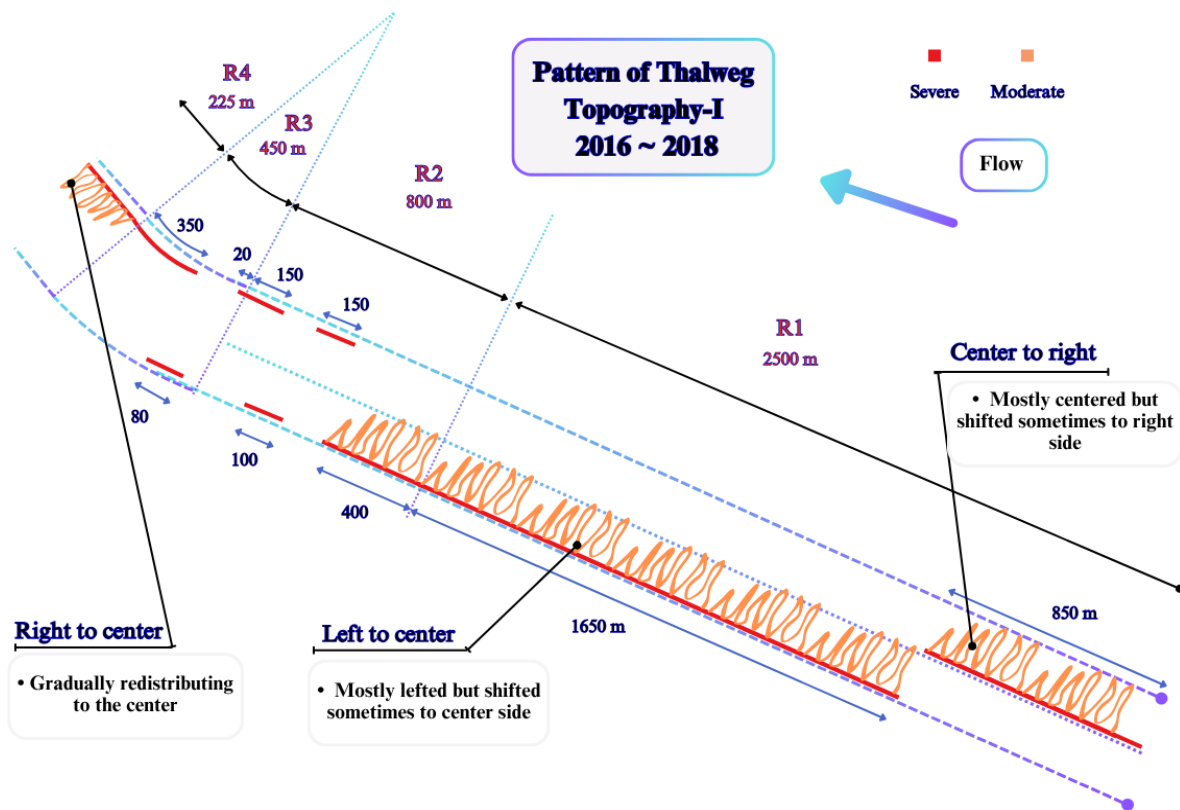


Figure 16: Plan view showing talweg alignment shifts for Topography I.

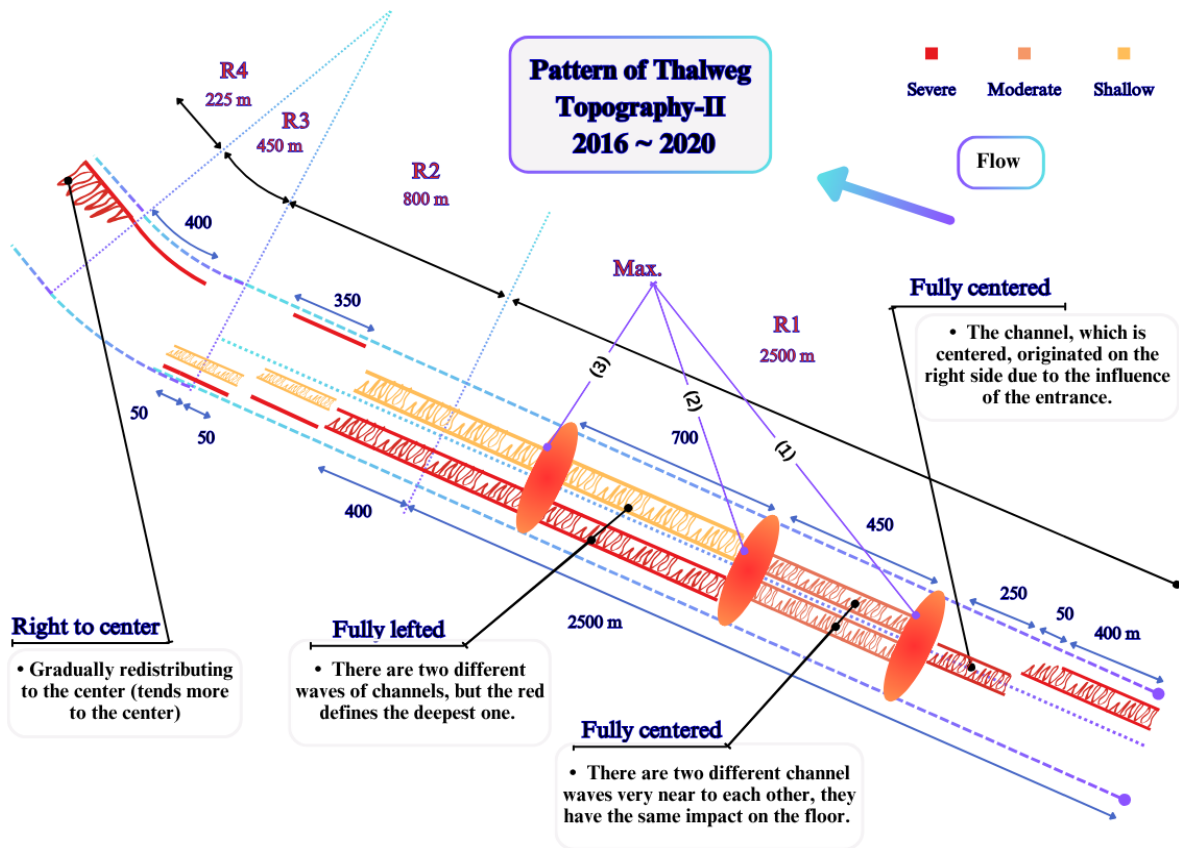


Figure 17: Longitudinal profile of the talweg highlighting depth maxima of Topography II.

3.9. Conclusion

This chapter demonstrates that the progression of abrasion damage within SBTs is not random but is significantly governed by pre-existing damage patterns. The topographic analysis indicates that previously damaged zones experience greater deepening over time compared to newly formed areas, suggesting a path-dependent nature of abrasion evolution.

A key finding is the pronounced influence of the tunnel foundation: the most severe abrasion consistently aligns with zones built on specific types of foundation. This highlights the critical role of geological and structural conditions, reinforcing the necessity of detailed

geotechnical investigations and their incorporation into tunnel design and risk assessment frameworks.

Additionally, the talweg analysis uncovers a notable deviation from classical hydraulic theory. Although the tunnel flow remains predominantly supercritical—where downstream changes should theoretically have no upstream effect—observations reveal that downstream geometric features, particularly curvature zones, exert partial influence on upstream abrasion patterns. This implies a complex coupling between flow dynamics and sediment transport, where quasi-supercritical flow regimes and localized sediment accumulations modulate abrasion beyond purely downstream-controlled processes.

Collectively, these insights underscore the need for comprehensive design strategies that integrate detailed topographic monitoring, foundation characterization, and advanced numerical modeling to predict and mitigate abrasion damage. Future research should focus on quantifying these coupled interactions through high-resolution simulations and field-scale validation to inform the design of more resilient SBTs.

3.10. References

- Auel, C., Boes, R. M., & Sumi, T. (2018). Abrasion prediction at Asahi sediment bypass tunnel based on Ishibashi's formula. *Journal of Applied Water Engineering and Research*, 6(2), 125–138. <https://doi.org/10.1080/23249676.2016.1265470>
- Demiral Yüzügüllü, D. (2021). *Hydro-abrasion processes and modelling at hydraulic structures and steep bedrock rivers* [PhD Thesis]. ETH Zurich.
- Emara, A., Kantoush, S. A., Saber, M., Sumi, T., Nourani, V., & Mabrouk, E. (2025a). Advanced 3D abrasion mapping in sediment bypass tunnels using XGBoost: A high-dimensional approach to predictive modeling. *Expert Systems with Applications*, 282, 127686. <https://doi.org/10.1016/j.eswa.2025.127686>
- Emara, A., Kantoush, S. A., Saber, M., Sumi, T., Nourani, V., & Mabrouk, E. (2025b). Machine learning approach for 2D abrasion mapping in Sediment Bypass Tunnels: A case study of Koshiibu SBT, Japan. *Engineering Applications of Computational Fluid Mechanics*, 19(1), 2444419. <https://doi.org/10.1080/19942060.2024.2444419>
- Kadia, S., Larsson, S., Billstein, M., Lia, L., & Pummer, E. (2024). Experimental and numerical investigations of the water surface profile and wave extrema of supercritical flows in a narrow channel bend. *Scientific Reports*, 14, 12247. <https://doi.org/10.1038/s41598-024-61297-8>
- Koshiiba, T., & Sumi, T. (2020). Bedload transport and abrasion monitoring at the Koshiibu Dam sediment bypass tunnel and proposing countermeasures against the abrasion problem. *Icold1st*, 13-49–19.
- MMS. (2013). *Consistently Accurate Measurement*. http://www.mitsubishielectric.co.jp/mms/pdf/mms_e.pdf
- MMS Website. (2024). *Mitsubishi Electric, Latest Version of GPS, MMS*. <http://www.mitsubishielectric.co.jp/mms/tokucho.html>
- Sakurai, T., Tsujimoto, T., Sumi, T., Kunimura, I., Takeuchi, H., & Ishida, K. (2018). Plan and Operation Results of the Koshiibu Dam Sediment Bypass Tunnel. *Twenty-Sixth International Congress on Large Dams/Vingt-Sixième Congrès International Des Grands Barrages*, Q100_298-Q100_316. <https://www.taylorfrancis.com/chapters/edit/10.1201/9780429465086-20/plan-operation-results-koshiibu-dam-sediment-bypass-tunnel-toshiyuki-sakurai-tetsuro-tsujimoto-tetsuya-sumi-ichiro-kunimura-hiroyuki-takeuchi-katsushi-ishida>
- T.D.I.M Office. (2021). Tenryu River Dam Integrated Management Office. <https://www.cbr.mlit.go.jp/tendamu/>

CHAPTER 4

Calibration of the Existing Mechanistic Model (Resolving the Abrasion Coefficient Issue)

4.1. Introduction

The SBT structures typically convey high-speed, supercritical flows directly from rivers to downstream reaches, bypassing the impoundment. However, the intense flow velocities and sediment concentrations cause severe hydroabrasion of the tunnel invert. As a result, SBTs are often constructed with exceptionally durable lining materials. For example, the Koshiu (Nagano, Japan) SBT is paved almost entirely with 50 N/mm² high-strength concrete to withstand wear (Koshiu, 2020). Accurate prediction of such abrasion is therefore critical for SBT design and maintenance. Mechanistic models (e.g., saltation-abrasion models) are commonly used to predict invert abrasion from flow and sediment conditions (Albayrak et al., 2024; Auel et al., 2018; Müller-Hagmann et al., 2020). These models include an empirical abrasion coefficient, K_v , representing the material's wear resistance. Historically, K_v has been calibrated under simplified laboratory conditions and applied uniformly. However, emerging field data indicate that this approach may overlook the essential effects of the complex flow regime, as discussed next.

4.1.1. Overview of Abrasion Prediction Challenges in SBTs

Predicting abrasion in SBTs is challenging because the flow and sediment conditions are highly energetic and heterogeneous. In practice, SBT flows are often supercritical (high Froude number), causing sediment grains to saltate vigorously and impact the lining at steep angles. Unlike small-scale flume experiments (which tend to exhibit quasi-two-dimensional flow), prototype SBT flows develop strong three-dimensional structures. Field studies have documented intense secondary currents in SBTs – for instance, Prandtl’s first-kind vortices in bends and second-kind vortices in straight sections – closely linked to the observed abrasion patterns. Müller-Hagmann et al. (2020) showed that such 3D flow features create distinct incision channels and undulating abrasion along the tunnel invert. Consequently, abrasion in an SBT is highly nonuniform, with specific segments experiencing much more serious damage than others.

Material and sediment properties introduce additional variability. Abrasion rates depend strongly on the lining’s mechanical strength and the hardness of the impacting grains. The Swiss studies found hard reinforced concretes and rock (e.g., granite, basalt, steel) resisted wear far better than softer materials (Albayrak et al., 2024; Müller-Hagmann et al., 2020). When comparing high-strength concrete vs. granite linings, the field-derived abrasion coefficient K_v was roughly an order of magnitude larger for granite than for concrete. Natural inhomogeneities – such as joints, casting layers, and repairs – also create weak spots. Together, these factors mean that the actual wear pattern can be patchy and flow-dependent even with a uniform invert material and uniform sediment load. This complexity makes it difficult to extrapolate from simplified models to real SBT conditions without detailed calibration.

4.1.2. Gaps in Traditional Abrasion Prediction Models

Most existing mechanistic abrasion models assume a constant K_v for a given material and apply it uniformly along the tunnel (Auel, Albayrak, et al., 2017b, 2017a; Lamb et al., 2008, 2015; Sklar & Dietrich, 2004, 2012). In other words, they predict abrasion based on the

average flow and sediment conditions, implicitly treating the flow as two-dimensional and the material response as homogeneous. While such models can approximately match the spatially averaged abrasion rates, they do not adequately account for the significant local variations observed in practice. For example, Müller-Hagmann et al. (2020) used field abrasion measurements to calibrate models for concrete and granite linings in 10-meter-long test fields. The models reproduced the mean abrasion depth, but the maximum local depth in the data was approximately twice the average. This indicates that a single K_v will either under-predict peak abrasion or over-predict in other sections. Moreover, different model formulations yield very different K_v values. In fact, the prototype-derived K_v values exhibit considerable uncertainty (on the order of ± 50 to ± 90 %) (Müller-Hagmann et al., 2020), reflecting errors in estimating hydraulic conditions and material properties. In other words, traditional models, particularly the saltating mechanics models, overlook the role of flow heterogeneity and localized hydraulics; the assumption of a constant K_v leads to systematic conflicts between predictions and observations.

4.1.3. Objectives of the Calibration Analysis

The present study aims to resolve these issues by recalibrating the mechanistic model using detailed data from the Koshiu SBT. The Koshiu case is ideal because its conditions are well-characterized: the tunnel invert is uniformly lined with 50 N/mm² concrete, and five impact plates at the outlet continuously monitor the cross-sectional bedload distribution (Koshiu & Sumi, 2020). Thus, variations in abrasion damage can be attributed primarily to flow effects rather than material or sediment differences. We will compute K_v locally for different tunnel segments based on the measured abrasion depths. By comparing these local K_v values with the corresponding hydraulic regimes (e.g., nearly 2D core flow vs 3D flow with strong secondary currents), we will test whether the abrasion coefficient depends on flow structure. The objective is to extract a spatially varying K_v from the model to correlate with the observed abrasion pattern accurately. In doing so, we seek to reconcile the discrepancy between previous constant- K_v predictions and field observations, thereby

improving the mechanistic model's predictive power. It should be noted that topography is the primary focus here, as it is the only topography to which this modeling can be applied.

4.2. Data Sources

4.2.1. Data Collection and Monitoring Framework

A systematic field survey was conducted over multiple bypass events. Flow discharge was logged continuously at the tunnel intake and outlet, ensuring the supercritical flow regime was well characterized. Simultaneously, sediment-laden flow was sampled using impact plates (described below). The tunnel invert was surveyed using high-resolution laser scanning. This integrated monitoring framework follows best practices and SBT studies, providing time- and space-resolved data to drive and validate the abrasion model.

4.2.1.1. Laser Scanning and 3D Mapping

Detailed topographic surveys of the tunnel invert were obtained using mobile laser scanning, as mentioned before; see Chapter 3. Mobile laser scanners or LIDAR units traverse the tunnel (often on a small vehicle or by hand) to produce dense point clouds of the concrete invert surface. These data are post-processed to generate high-resolution 3D cloud points. By differencing scans from before and after bypass operations, the volume and depth of abrasion at every location can be computed. The 3D abrasion maps not only quantify total material loss but also reveal spatial patterns (e.g., spots and channels). In similar studies (e.g., Demiral Yüzügüllü, 2021; Müller-Hagmann, 2018), such “advanced 3D abrasion mapping” has been the key to diagnosing abrasion mechanisms and feeding back into predictive models.

4.2.1.2. Hydraulic Discharge Measurements

The sediment bypass system is engineered to release sediment during flood events. The bypass gate starts flood discharge when the river flow surpasses 60 cubic meters per second (m^3/s) (Sakurai et al., 2018). The bypass operates at full capacity at the flood's peak to release as much sediment-laden water as possible. Each discharge event from the SBT

operation is recorded and documented individually. These recorded discharges are crucial for incorporation into the abrasion model. The average discharges and their respective durations are detailed in **Table 3**.

4.2.1.3. Sediment Transport Observations

The sediment transport within the tunnel was measured to reflect the sediment transport conditions accurately. This was achieved by deploying Geophones Impact Plates (GIP) at the tunnel outlet region, as shown in **Figure 18**, which had been calibrated both in laboratory settings (Koshiba et al., 2018) and on-site (Koshiba et al., 2017; Koshiba & Sumi, 2020). The collected data were further validated through hydrological simulations, supported by extensive field investigations conducted upstream and downstream of the tunnel before and after flood events (Sakurai et al., 2018; *T.D.I.M Office*, 2021).

Table 3: The operation of Koshiba SBT from 2016 to 2018.

Operation	Date	Duration, T	Discharge, $Q_{average}$
No.	[-]	[hours]	[m ³ /s]
Op1	09/2016	16	37
Op2	09/2016	5.8	30
Op3	07/2017	3.1	65
Op4	10/2017	9.7	119.5
Op5	10/2017	48.8	36.2
Op6	07/2018	10.7	98
Op7	09/2018	44.2	85
Op8	10/2018	69.5	80.8



Figure 18: Koshiu Dam SBT outlet with five IPs installed. White arrows indicate the impact plates, from (Koshiu & Sumi, 2020).

4.2.1.4. Tunnel surface Material Properties

The mechanical and physical properties of the invert concrete were measured in the laboratory. Samples of the as-built lining were tested for compressive and tensile strength, Young's modulus, and hardness. These material parameters enter directly into the abrasion model. Thus, accurate values of these parameters are needed to compute the amount of energy required to detach a unit volume of concrete (T.D.I.M Office, 2021).

4.2.1.5. Observed Patterns of Abrasion

Analysis of the topography I revealed three characteristic abrasion patterns on the tunnel invert: (1) **scatter-type**, with isolated pits and patches; (2) **edged-type**, with continuous damage lines along the lateral edges; and (3) **skewed (one-sided)**, with abrasion

concentrated on one bank (usually the inner bend). These patterns are consistent with both field observations in other SBTs and laboratory findings. Demiral Yüzügüllü, (2021) showed that channel geometry and material homogeneity strongly influence abrasion form: in narrow flumes (low width/depth ratio) with uniform bed, erosion tends to form central or dual side channels, whereas a heterogeneous lining breaks up into “potholes” or scattered pits. In the Koshiba tunnel, the scatter pattern suggests a 2D flow region, which is happening in most of the events. The edged pattern resembles the dual side-wall channels seen at higher aspect ratios, and the skewed pattern reflects the classic bend-induced damage (more abrasion on the concave side) noted in the Asahi and Mud Mountain tunnels (Auel et al., 2017, 2018).

4.3. Methodology for Model Calibration

The core of the mechanistic model is the saltation-abrasion relation, which links particle impacts to concrete erosion. The Saltation Abrasion Model (SAM), developed by (Sklar & Dietrich, 2004, 2012), expresses the local abrasion rate A_r (volume loss per area per time) as illustrated in Equation (1), Chapter 2. We calibrated the k_v by iteratively adjusting its value until the modeled abrasion depths aligned with observed values obtained from 3D scan data. Additionally, we considered refinements introduced by (Demiral Yüzügüllü, 2021), which incorporate particle hardness and the probability of saltation to enhance predictive accuracy.

4.4. Results and Analysis

4.4.1. Simulated Hydraulic Response

The hydraulic dynamics along the Koshibu SBT were simulated based on backwater curve computations for eight distinct flood discharges (Q_1 – Q_8). These simulations incorporated field-measured flow rates and sediment impact quantification from calibrated abrasion plates. The resulting water surface profiles (**Figure 19**) reveal spatial variations in the aspect ratio B/h (channel width to flow depth), a critical parameter influencing the flow

dimensionality and associated sediment transport mechanisms. The B/h parameter serves as a reliable indicator for classifying flow regimes, with 2D flow typically sustained when $B/h > 5$ and 3D flow regimes occurring below $B/h < 4$, in agreement with hydraulic theory and secondary current observations (Nezu & Nakagawa, 1993).

As depicted in **Figure 19**, the aspect ratio B/h decreases longitudinally along the tunnel axis, from inlet to outlet. High values of $B/h > 5$, particularly in the upstream sections, denote 2D flow regimes. These regions are characterized by uniform velocity distribution and minimal vertical or transverse velocity gradients, which correlate strongly with the scatter-type abrasion observed on the tunnel invert. The uniformity of shear stress distribution in these segments inhibits concentrated abrasion, instead promoting widespread, shallow effects, consistent with prior studies on uniform channel abrasion patterns (Auel, 2014; Demiral Yüzügüllü, 2021). As the aspect ratio declines and approaches the critical threshold of $B/h = 4$ to 5, highlighted by the red dashed lines, the flow begins to transition into a 3D regime, particularly evident in curved or narrowed tunnel segments downstream. Secondary currents and helical flow structures emerge in these zones due to lateral flow confinement and channel curvature. These flow patterns induce a spatial concentration of bed shear stress, particularly near the outer banks and invert shoulders. As a result, a distinct edge-type or skewed-type abrasion pattern emerges, attributed to directional particle motion and intensified impact forces along specific streamlines. The influence of 3D flow amplifies as discharge increases (Q_6 – Q_8), resulting in asymmetric abrasion along the tunnel walls and invert boundaries. These patterns correspond with findings in similar hydraulic systems, where tunnel geometry and flow-induced turbulence exacerbate localized damage (Auel et al., 2017).

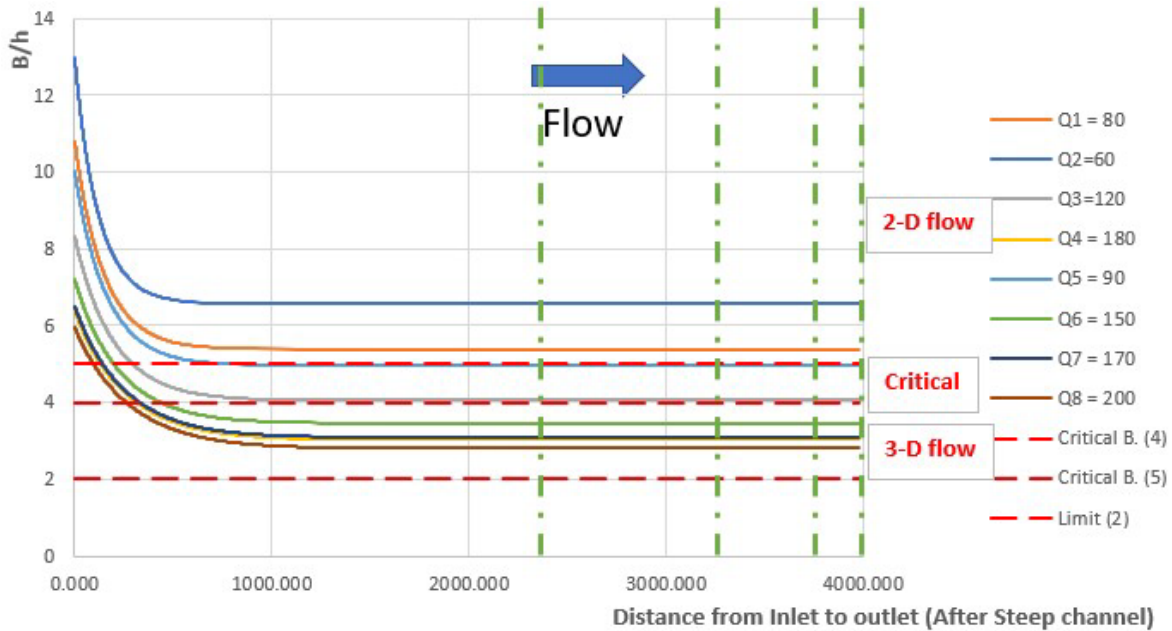


Figure 19: Hydraulic characterization of flow regimes and critical B/h limits across eight flood events in the Koshibu SBT.

4.4.2. Sediment Transport Trends

The sediment flux through the tunnel was quantified from the impact-plate data. Each impact sensor record was converted to a volumetric bedload transport rate by calibrating against known sediment loads during controlled experiments (Koshiba et al., 2018). The mechanism is accounted for by grain-size distribution (coarse vs. fine) in interpreting the data; for example, larger clasts produce stronger signals but have fewer impacts (Koshiba et al., 2017). We used these transport rates as input to the abrasion model. Note that impact plates provide an integrated measure of bedload impacts (see **Figure 20**, Koshiba, 2020; T.D.I.M Office, 2021), whereas alternative methods exist (e.g., acoustic sensors, sediment traps, or tracers). These alternatives were not employed here but would yield qualitatively similar information about bedload flux if available.

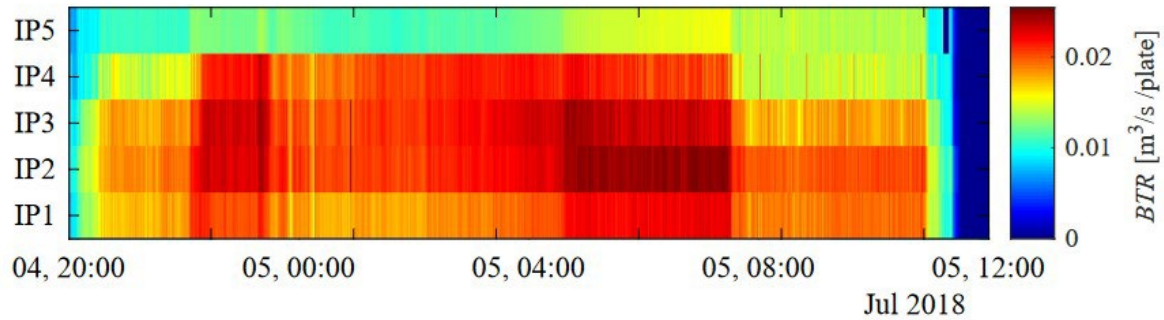


Figure 20: Bedload transport rate (BTR) during a specific event as measured by impact plate data from (Koshiba, 2020).

4.4.3. Spatial Patterns of Abrasion Damage

4.4.3.1. Scatter-Type Abrasion

Figure 21 (up) presents a 3D laser scan of the tunnel invert within the upstream segment, showing distinct scatter-type abrasion, characterized by numerous point-wise pits and shallow depressions. The corresponding histogram (down) confirms a dominant presence of minimally abraded areas (blue), with isolated zones experiencing deeper abrasion (orange/red). This pattern indicates discrete, stochastic impact events, rather than continuous or aligned sediment wear. From a hydraulic perspective, this region corresponds to the upstream-most section of the tunnel, identified in **Figure 19** by the first vertical dotted line, where the flow regime predominantly exhibits 2D characteristics, with B/h ratios exceeding 5. Such flow conditions are associated with high near-bed velocities and uniformly distributed turbulence across the section, as noted in experimental works by Nezu & Nakagawa, (1993) and further discussed in Demiral Yüzügüllü, (2021). These flows lack secondary circulation, preventing sediment from concentrating along specific lateral zones and promoting random ricochet dynamics of sediment particles. Interestingly, while three of the eight flood events (Q_6 – Q_8) show localized 3D flow intrusions in this region, these discharges occurred later in the sequence, implying limited cumulative impact. The early events (Q_1 – Q_3), which dominate the abrasion history, were primarily governed by 2D

conditions, exerting a more substantial influence on the observed scatter pattern. This temporal hierarchy supports the interpretation that the earliest discharges control the fundamental abrasion signature, particularly in sections with limited cumulative sediment redistribution. Physically, this type of abrasion arises when heterogeneous particle sizes (e.g., coarse gravels and cobbles) impact the surface without consistent alignment, generating scattered potholes and minor pits. The largest particles deliver high-energy point impacts, while finer particles may scour less aggressively across broader zones. This mechanism is consistent with observations by (Demiral Yüzügüllü, 2021), who noted that non-uniform material interactions under supercritical turbulent conditions yield this “patchy” wear mode. Moreover, the tunnel lining's local surface heterogeneity may amplify this effect. The lack of organized secondary flow results in a checkerboard distribution of shear stress and sediment contact, leading to the irregular, scattered pit morphology in this region.

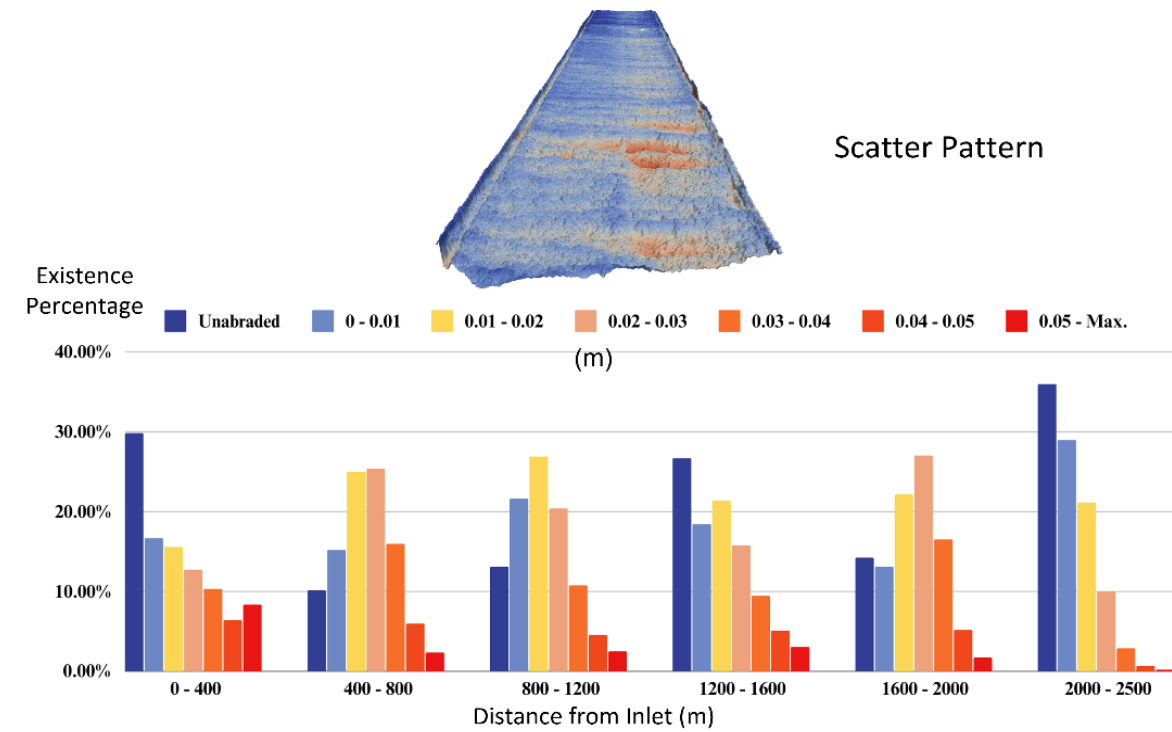


Figure 21: A 3D laser scan of the tunnel showing distinct scatter-type abrasion with depth percentage histogram.

4.4.3.2. Edged-Type Abrasion

Extending beyond the scatter zone, this segment exhibits a transition in flow dynamics, where 3D effects become more prevalent due to local reductions in B/h . These conditions likely initiate localized secondary currents, promoting asymmetric sediment trajectories that contribute to edged abrasion along the tunnel. **Figure 22** (left): 3D laser-scan of a tunnel section with edged-type abrasion (wear concentrated along left and right edges), (right): corresponding depth-frequency distribution in two downstream segments. The edged pattern displays pronounced erosion strips flanking the center of the invert. This indicates that high-momentum flow and sediment concentration were funneled along the sidewalls. In the laboratory flume experiments of (Demiral Yüzügüllü, 2021), flows at moderate aspect ratios ($B/h = 4 \sim 2$) produced exactly this configuration: abrasion was confined to dual channels near the sidewalls. This aligns with our case here, as most discharges lie in $B/h > 2$;

strong near-wall secondary vortices can lift low-momentum fluid out of the corners and concentrate shear along the edges. The figure's mostly uniform (blue) 3D surface shows minimal damage in the middle. The accompanying depth-frequency histograms (for 2500–2800 m) show elevated percentages of shallow-to-moderate wear (0.01–0.03 m) along the edges, particularly at maximum depth. These observations align with theoretical and experimental findings: under intermediate B/h , Prandtl's second-kind vortices deposit high-momentum grains against the walls, thereby scouring linear channels (Nezu & Nakagawa, 1993). Moreover, the transition into a 3D flow regime correlates with slight geometric changes, lining joints, that serve as nuclei for vortex amplification. In practice, the edged pattern underscores the importance of smoothing interior corners and reinforcing sidewall–floor joints to mitigate concentrated erosion.

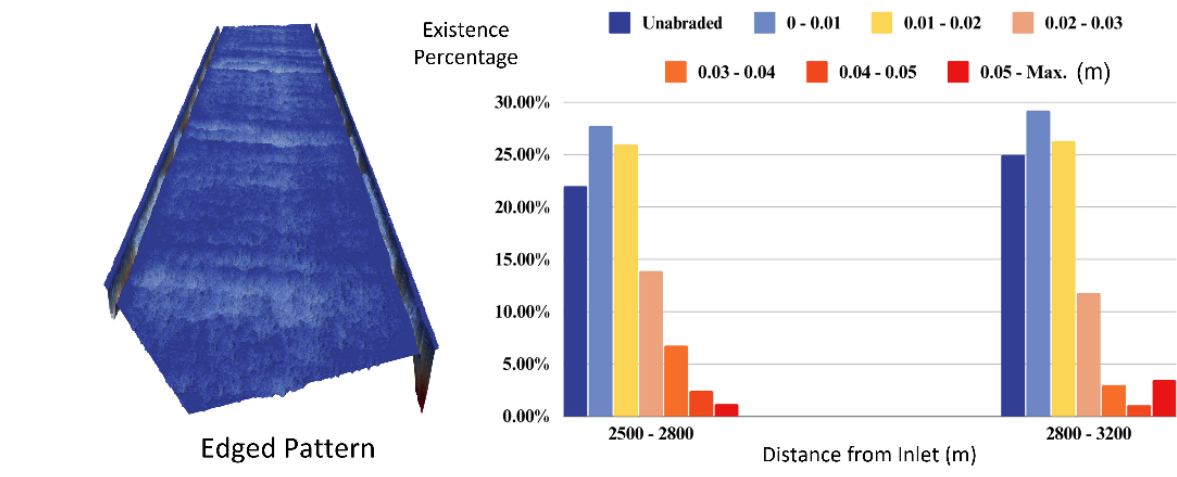


Figure 22: A 3D laser scan of the tunnel showing distinct edged-type abrasion with depth percentage histogram.

4.4.3.3. Skewed-Type Abrasion

The skewed pattern refers to one-sided wear, essentially the case where one bank (typically the inner bend) is preferentially abraded, as shown in **Figure 23**. This is readily explained by

bend hydraulics. In curved flow, bend-induced (Prandtl's first-kind) secondary currents arise from the centrifugal pressure gradient (Kadia et al., 2024). These currents drive heavier particles into the inner curve, while the flow's inertia pushes water outward. The result is a higher frequency of impact on the inner bank. Consistent with this, Nakajima et al., (2015) reported that in the Asahi SBT, the abrasion depth on the left (inner) wall in the curved section was significantly larger than on the outer wall. They also noted that just upstream of the bend, the right bank had experienced more wear (due to a slightly deflected inlet flow), but once through the bend, the left side dominated. Similarly, a recent study of several SBTs found that inner-wall scour in bends consistently exceeded outer-wall erosion, and that this asymmetry often persisted downstream into straight reaches (Müller-Hagmann, 2018; Müller-Hagmann et al., 2020). Our case illustrates this effect: virtually all large-clast impacts are concentrated on the concave side, creating a one-sided abrasion profile (the "skew" in abrasion) not only in the curvature zone but also extending to the straight part after the curvature. In short, the skewed pattern is a signature of the curvature and illustrates why design guidelines for SBTs recommend avoiding sharp in-plane bends whenever possible.

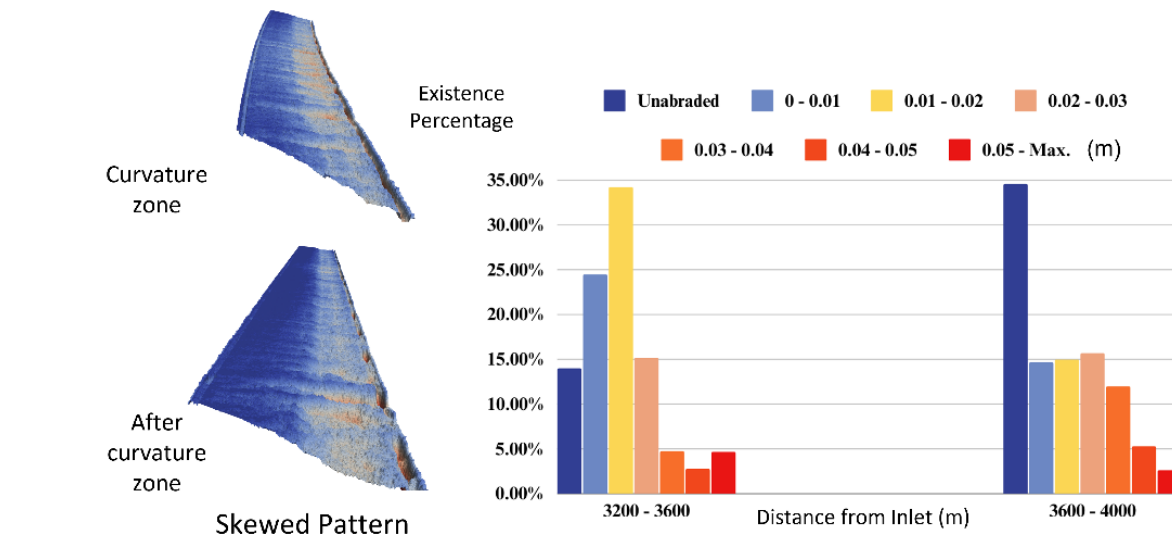


Figure 23: A 3D laser scan of the tunnel showing skewed-type abrasion with depth percentage histogram.

4.5. Linking Kv Variability to Tunnel Damage Patterns

Given the substantial variability in reported abrasion coefficient (K_v) values across the literature (which will be systematically compared later in this study), this work hypothesizes that K_v is not constant along the tunnel length but instead varies spatially in correlation with the observed patterns of abrasion damage. This hypothesis suggests a potential causal relationship between localized tunnel damage characteristics and the spatial distribution of K_v values, which may offer a refined understanding of abrasion mechanisms and support the development of more accurate predictive models for tunnel design and maintenance.

4.6. Key Findings

Based on the provided data and objectives, we calculated the average abraded volume as an indicator for the abrasion coefficient for each region (R1, R2, R3, R4) and determined their statistical ranges. Below is a summary table presenting these calculations (**Table 4**):

Table 4: Key statistics for every region by tunnel length.

Region	Mean Abraded Volume (m ³)	Min	Max
R1	1.889	0.17	4.97
R2	2.625	0.29	5.31
R3	2.509	0.55	5.45
R4	2.936	0.39	8.11

The average values were computed by summing all recorded abrasion volumes within each region and dividing by the total number of measurements. The minimum and maximum values represent the range of abrasion volumes observed in each respective region. These calculations reveal that R4 exhibits the highest average abrasion, and also shows the widest range due to extreme values such as 8.11 m³ near the end of the tunnel.

To effectively visualize these findings, a scatterplot has been generated. **Figure 24** illustrates individual abrasion data points distributed along the tunnel length, using distinct color styles to represent each region: a scattered pattern for R1, an edged pattern for R2, a curvature-specific pattern for R3, and after curvature for R4. The left column of the figure shows the abraded volume, while the right column presents the corresponding abrasion coefficient (Kv). Additionally, the mean Kv value calculated for each region is identified and plotted to highlight regional variations and potential spatial trends in abrasion behavior.

Based on the calibration process and the data presented in **Figure 24**, four mean values of the K_v were obtained for the defined regions. Specifically, K_v for the scatter region (R1) was found to be 4×10^4 ; for the edged region (R2), 3.74×10^4 ; for the curvature region (R3), 3.81×10^4 ; and for the post-curvature region (R4), 3.61×10^4 . As shown, these mean K_v values across regions are relatively close, which effectively rejects the initial hypothesis that K_v would vary significantly between regions.

To reinforce this finding, the analysis was extended by introducing variability as a more robust indicator, as shown in **Table 5**. A single overall K_v value for the entire tunnel (labelled “All”) was derived and compared with each regional mean. The maximum positive deviation observed was +3.25%, while the maximum negative deviation was -8.66%, further confirming the limited variation of K_v across regions.

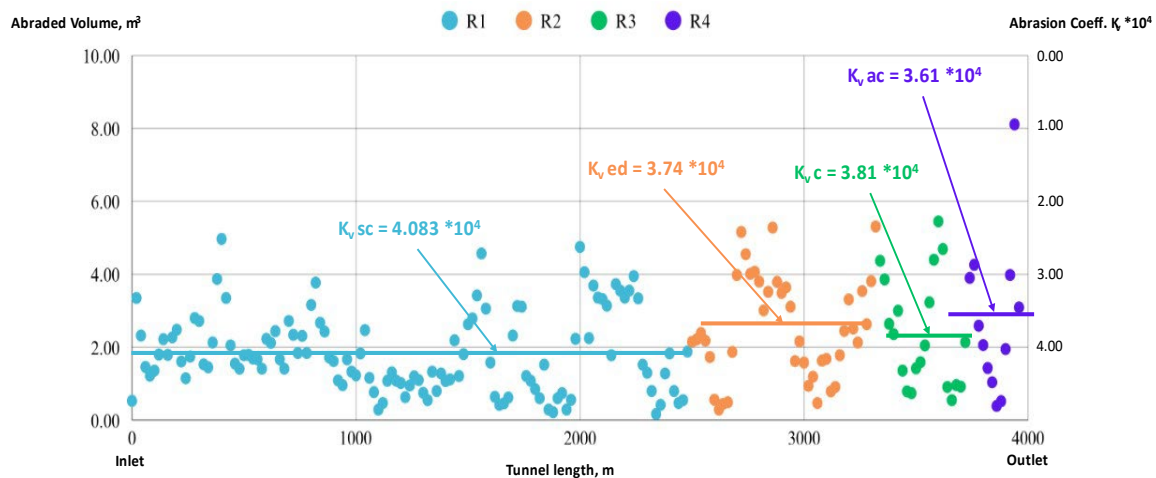


Figure 24: Spatial Variation of the Abraded Volume Across Tunnel Regions.

Table 5: Regional Mean Kv Values and Variability Analysis Along the Tunnel.

Region	Damage Shape	Mean (Kv $\pm$ Std Div.) $\times 10^4$	Coeff. of Variability (CV)	Δ from All (%)
R1	Scatter	(4.08 $\pm$ 0.54)	13.2 %	+ 3.25 %
R2	Edged	(3.74 $\pm$ 0.70)	18.7 %	– 5.51 %
R3	Skewed (Curvature)	(3.81 $\pm$ 0.76)	20 %	– 3.54 %
R4	Skewed (After curvature)	(3.61 $\pm$ 1.07)	29.6 %	– 8.66 %
All	—	(3.95 $\pm$ 0.66)	16.7 %	—

However, an important insight emerged when examining the coefficient of variability within each region (see **Table 5**). The calculated coefficients of variability were: 13.2% for R1, 18.7% for R2, 20% for R3, and approximately 30% for R4. This indicates that although the mean Kv remains relatively stable between regions, the internal variability within each region differs substantially. Notably, higher variability tends to occur in regions with more concentrated damage, revealing a novel finding about the localized nature of abrasion processes within the tunnel.

4.7. Comparison of Calibrated Kv with Literature

Early investigations into the abrasion coefficient Kv established a “universal” first-order value of approximately 1×10^6 , as proposed by Sklar & Dietrich (2004). Their meta-analysis, summarized in **Table 6**, reported a variability of up to 46%, reflecting inherent

heterogeneity in terrestrial rock properties and experimental methods. Lamb et al. (2008) corroborated this order-of-magnitude estimate through the field-scale measurements in bedrock rivers, also concluding that K_v “of order 10^6 ” provides a reasonable baseline for large-scale landscape and conduit models (see **Table 6**).

Subsequent work highlighted the influence of rock hardness and material specificity on K_v . Auel et al. (2018) found that granite exhibits $K_v \approx 2.4 \times 10^6$ —roughly ten times higher than concrete ($K_v \approx 2.1 \times 10^5$)—while Müller-Hagmann et al. (2020) recommended material-specific coefficients of 1.3×10^6 for concrete and 1.4×10^7 for granite, with reported variabilities between 87 % and 91 % (**Table 6**). In contrast, Demiral (2021) and Albayrak et al. (2024) each provided a constant ($K_v \approx 5 \times 10^4$) across diverse materials, however, with broad uncertainty bounds (± 50 % and ± 46 %, respectively), signaling a trend toward lower, more uniform coefficients for engineered channels.

The present study’s calibrated mean K_v of $(3.95 \pm 0.66) \times 10^4$ closely matches these recent field-scale values but demonstrates substantially reduced variability ($\sim 17\%$). Whereas earlier “universal” and material-specific estimates exhibited dispersion of up to 90%, our regionally stratified calibration procedure constrains K_v within $\pm 20\%$ for comparable tunnel conditions. This tighter uncertainty band enhances the reliability of predictive abrasion models, suggesting that, with appropriate calibration, K_v may be treated as a robust parameter across heterogeneous tunnel zones.

Table 6: Comparison of Kv Values and Variability in Literature and Present Study.

Source	kv value	Notes / Variability
Sklar & Dietrich (2004)	$\approx 1.0 \sim 9.0 \times 10^6$	Proposed as a first-order “universal” value for terrestrial rocks; Kv $\approx 1 \times 10^6$ roughly constant to first order. The variability has reached 46%.
Lamb et al. (2008)	1.0×10^6	Considered the first field values for the bedrock river. They conclude kv “of order 10^6 ”.
Auel et al. (2018)	Concrete: 2.1×10^5 ; Granite: 2.4×10^6	Found kv scaling with material hardness: granite (stronger rock) has $\sim 10\times$ higher kv than concrete.
Müller-Hagmann et al. (2020)	Concrete: 1.3×10^6 ; Granite: 1.4×10^7	Values are recommended based on calibration results for different materials and tunnels. It is suggested to use a material-specific kv, as variability reached 87% to 91%.
Demiral (2021)	$(5.0 \pm 2.4) \times 10^4$	Recommended a <i>quasi-constant</i> kv $\approx 5 \times 10^4$ for all tested materials. This lower value (than earlier studies) accounts for material effects. Uncertainty $\pm 50\%$.
Albayrak et al. (2024)	$(4.8 \pm 2.2) \times 10^4$	Found a nearly constant kv $\approx 5 \times 10^4$ across all materials. This single value is suitable for lab- and field-scale modeling of sediment-laden flows. The $\pm 2.2 \times 10^4$ spread reflects material and measurement variability.
Present Study (2025)	$(3.95 \pm 0.66) \times 10^4$	These values are very close to those in the most recent literature, with minimal variability $\approx 17\%$.

4.8. Conclusion

The calibration process successfully addressed the long-standing uncertainty in estimating the abrasion coefficient (K_v) within mechanistic abrasion models. By integrating high-resolution field data—including laser scanning, impact-plate sediment transport measurements, and detailed hydraulic observations—with a physically based saltation–abrasion framework, we derived a calibrated mean K_v of approximately 3.95×10^4 . This value closely aligns with recent field-scale estimates reported by Albayrak et al. (2024) and Demiral (2021), while exhibiting notably reduced variability (~17% compared to ~50% reported in earlier studies).

Importantly, the analysis revealed two key findings regarding spatial variability:

- I. K_v variability increases with damage severity: The coefficient of variation rises from 13% in less damaged, scatter-dominated regions to about 30% in highly abraded, after-curvature zones. This indicates that abrasion processes become more stochastic and spatially uneven in areas experiencing concentrated or turbulent flow conditions.
- II. Average K_v remains relatively stable across regions: Despite the contrasting abrasion patterns (scattered, edged, and curvature-driven), the mean K_v for each region varies within only $\pm 10\%$ of the overall average (3.95×10^4). This result rejects the initial hypothesis that the average K_v would change significantly with local damage patterns.

Collectively, these findings demonstrate that while K_v becomes more variable in zones of severe damage—particularly near bends or curvature where secondary currents and flow concentration amplify abrasion—the mean K_v itself is sufficiently stable. This suggests that region-specific adjustment of design K_v values may not be necessary. However, accounting for increased variability remains important for engineering design, especially in critical or high-risk tunnel zones.

4.9. References

- Albayrak, I., Arnold, R., Demiral-Yüzügüllü, D., Maddahi, M., & Boes, R. M. (2024). Field monitoring and modelling of sediment transport, hydraulics and hydroabrasion at Sediment Bypass Tunnels. *Journal of Hydro-Environment Research*. <https://doi.org/10.1016/j.jher.2024.05.002>
- Albayrak, I., Müller-Hagmann, M., & Boes, R. (2019). Efficiency evaluation of Swiss Sediment Bypass Tunnels. *Proceedings of the 3rd International Workshop on Sediment Bypass Tunnels*, 239–245. <https://doi.org/10.3929/ethz-b-000337945>
- Anari, R., Hotchkiss, R. H., & J. Langendoen, E. (2020). Elements for the successful computer simulation of sediment management strategies for reservoirs. *Water*, 12(3), 714. <https://www.mdpi.com/2073-4441/12/3/714>
- Annandale, G. W., Morris, G. L., & Karki, P. (2016). *Extending the life of reservoirs: Sustainable sediment management for dams and run-of-river hydropower*. Washington, DC: World Bank. <https://openknowledge.worldbank.org/items/a91a766d-fc7a-5c4a-8cf3-a13c05025702>
- Arnold, R., Albayrak, I., & Boes, R. (2020). *Field monitoring of sediment transport, hydraulics, and hydro-abrasion at Swiss sediment bypass tunnels* (SI/501609-01, SFOE) [Technical].
- Aubert, G., Langlois, V. J., & Allemand, P. (2016). Bedrock incision by bedload: Insights from direct numerical simulations. *Earth Surface Dynamics*, 4(2), 327–342.
- Auel, C. (2014). *Flow characteristics, particle motion and invert abrasion in sediment bypass tunnels* (p. 1 Band) [ETH Zurich; Application/pdf]. <https://doi.org/10.3929/ETHZ-A-010243883>
- Auel, C. (2018). Sediment Bypassing – A Sustainable and Eco-Friendly Strategy Against Reservoir Sedimentation*. In *Twenty-Sixth International Congress on Large Dams: Vingt-Sixième Congrès International des Grands Barrages*. CRC Press.
- Auel, C., Albayrak, I., Sumi, T., & Boes, R. M. (2017a). Sediment transport in high-speed flows over a fixed bed: 1. Particle dynamics: Sediment transport in high-speed flows: 1. Particle dynamics. *Earth Surface Processes and Landforms*, 42(9), 1365–1383. <https://doi.org/10.1002/esp.4128>
- Auel, C., Albayrak, I., Sumi, T., & Boes, R. M. (2017b). Sediment transport in high-speed flows over a fixed bed: 2. Particle impacts and abrasion prediction: Sediment transport in high-speed flows: 2. Particle impacts. *Earth Surface Processes and Landforms*, 42(9), 1384–1396. <https://doi.org/10.1002/esp.4132>
- Auel, C., & Boes, R. M. (2011). Sediment bypass tunnel design – review and outlook. In *Dams and Reservoirs under Changing Challenges*. CRC Press.
- Auel, C., Boes, R. M., & Sumi, T. (2018). Abrasion prediction at Asahi sediment bypass tunnel based on Ishibashi's formula. *Journal of Applied Water Engineering and Research*, 6(2), 125–138. <https://doi.org/10.1080/23249676.2016.1265470>

- Auel, C., Kantoush, S., & Sumi, T. (2016, May 18). Positive effects of reservoir sedimentation management on reservoir life—Examples from Japan. *Positive Effects of Reservoir Sedimentation Management on Reservoir Life - Examples from Japan*.
- Auel, C., Kobayashi, S., Takemon, Y., & Sumi, T. (2017). Effects of sediment bypass tunnels on grain size distribution and benthic habitats in regulated rivers. *International Journal of River Basin Management*, 15(4), 433–444. <https://doi.org/10.1080/15715124.2017.1360320>
- Auel, C., Thene, J., Müller-Hagmann, M., Albayrak, I., & Boes, R. (2017). *Abrasion prediction at Mud Mountain sediment bypass tunnel* [Application/pdf]. <https://doi.org/10.3929/ETHZ-B-000185304>
- Beer, A. R., & Lamb, M. P. (2021). Abrasion regimes in fluvial bedrock incision. *Geology*, 49(6), 682–386. <https://pubs.geoscienceworld.org/gsa/geology/article/594891/Abrasion-regimes-in-fluvial-bedrock-incision>
- Beer, A. R., & Turowski, J. M. (2015). Bedload transport controls bedrock erosion under sediment-starved conditions. *Earth Surface Dynamics*, 3(3), 291–309.
- Beyeler, J. D., & Sklar, L. S. (2010). Bedrock resistance to fluvial erosion: The importance of rock tensile strength, crystal grain size and porosity in scaling from the laboratory to the field. *AGU Fall Meeting Abstracts, 2010*, EP41D-0740.
- Bitter, J. G. A. (1963a). A study of erosion phenomena part I. *Wear*, 6(1), 5–21. [https://doi.org/10.1016/0043-1648\(63\)90003-6](https://doi.org/10.1016/0043-1648(63)90003-6)
- Bitter, J. G. A. (1963b). A study of erosion phenomena: Part II. *Wear*, 6(3), 169–190. [https://doi.org/10.1016/0043-1648\(63\)90073-5](https://doi.org/10.1016/0043-1648(63)90073-5)
- Boes, R., Auel, C., Müller-Hagmann, M., & Albayrak, I. (2014). *Sediment bypass tunnels to mitigate reservoir sedimentation and restore sediment continuity* (pp. 221–228). <https://doi.org/10.1201/b17397-27>
- Boes, R. M., Auel, C., Hagmann, M., & Albayrak, I. (2014). *Sediment bypass tunnels to mitigate reservoir sedimentation and restore sediment continuity*. *Reservoir Sedimentation (Schleiss, AJ, De Cesare, G., Franca, MJ, Pfister, M., eds.)*. Taylor & Francis Group, London, UK.
- Boes, R., Müller-Hagmann, M., & Albayrak, I. (2019). Design, operation and morphological effects of bypass tunnels as a sediment routing technique. *Proceedings of the 3rd International Workshop on Sediment Bypass Tunnels*, 40–50. <https://doi.org/10.3929/ethz-b-000337946>
- Chatanantavet, P., & Parker, G. (2009). Physically based modeling of bedrock incision by abrasion, plucking, and macroabrasion. *Journal of Geophysical Research: Earth Surface*, 114(F4).
- Demiral, D., Albayrak, I., Turowski, J. M., & Boes, R. M. (2022). Particle saltation trajectories in supercritical open channel flows: Roughness effect. *Earth Surface Processes and Landforms*.
- Demiral Yüzügüllü, D. (2021). *Hydro-abrasion processes and modelling at hydraulic structures and steep bedrock rivers* [PhD Thesis]. ETH Zurich.
- Emara, A., Kantoush, S. A., Saber, M., Sumi, T., Nourani, V., & Mabrouk, E. (2025a). Advanced 3D abrasion mapping in sediment bypass tunnels using XGBoost: A high-dimensional approach

- to predictive modeling. *Expert Systems with Applications*, 282, 127686. <https://doi.org/10.1016/j.eswa.2025.127686>
- Emara, A., Kantoush, S. A., Saber, M., Sumi, T., Nourani, V., & Mabrouk, E. (2025b). Machine learning approach for 2D abrasion mapping in Sediment Bypass Tunnels: A case study of Koshibu SBT, Japan. *Engineering Applications of Computational Fluid Mechanics*, 19(1), 2444419. <https://doi.org/10.1080/19942060.2024.2444419>
- Facchini, M., Siviglia, A., & Boes, R. M. (2015). Downstream morphological impact of a sediment bypass tunnel—preliminary results and forthcoming actions. *Proc. First International Workshop on Sediment Bypass Tunnels, VAW-Mitteilungen*, 232, 137–146.
- Facchini, M., Siviglia, A., & Boes, R. M. (2017). Downstream morphological effects of SBT releases: 1D numerical study and preliminary LiDAR data analysis. *Proceedings of the 2nd International Workshop on Sediment Bypass Tunnels*, 1–12. <https://repository.kulib.kyoto-u.ac.jp/dspace/handle/2433/245506>
- Fan, J., & Morris, G. L. (1998). *Reservoir Sedimentation Handbook: Design and Management of Dams, Reservoirs, and Watersheds for Sustainable Use*. McGraw-Hill.
- Fukuroi, H. (2012). Damage from Typhoon Talas to Civil engineering Structures for Hydropower and the effect of the Sediment Bypass System at Asahi dam. *Proc. Int. Symposium on Dams for a Changing World—Need for Knowledge Transfer across the Generations and the World*.
- Graf, W. H. (1998). *Fluvial hydraulics: Flow and transport processes in channels of simple geometry*. John Wiley & Sons. [https://books.google.com/books?hl=en&lr=&id=bRIXEQAAQBAJ&oi=fnd&pg=PA683&dq=Kironoto+and+Graf+\(1995\)+for+subcritical+flows&ots=i4C83K6YG6&sig=tEyBmloWOEmIGvTp2QrDa2W8fsA](https://books.google.com/books?hl=en&lr=&id=bRIXEQAAQBAJ&oi=fnd&pg=PA683&dq=Kironoto+and+Graf+(1995)+for+subcritical+flows&ots=i4C83K6YG6&sig=tEyBmloWOEmIGvTp2QrDa2W8fsA)
- Hagmann, M., Albayrak, I., & Boes, R. M. (2015). Field research: Invert material resistance and sediment transport measurements. *Proc. First International Workshop on Sediment Bypass Tunnels, VAW-Mitteilungen*, 232, 123–135.
- Harada, M., Kokubo, T., & Deno, T. (1998). Hydraulic Properties of Sediment Transport in The Tunnel of Sediment-Bypass System of a Reservoir. *Doboku Gakkai Ronbunshu*, 1998(600), 69–84.
- Helbig, U., Horlacher, H.-B., Stamm, J., Bellmann, C., Butler, M., & Mechtcherine, V. (2012). Nachbildung der Hydroabrasionsbeanspruchung im Laborversuch: Teil 2—Korrelation mit Verschleißwerten und Prognoseansätze. *Bautechnik*, 89(5), 320–330.
- Ho, T.-C., Hwang, G.-J., Hwang, K.-S., Hsieh, K.-C., & Chen, L.-W. (2019). *Experimental and numerical study on desilting efficiency of the bypassing tunnel for Nan-Hua reservoir*.
- Inoue, T., Izumi, N., Shimizu, Y., & Parker, G. (2014). Interaction among alluvial cover, bed roughness, and incision rate in purely bedrock and alluvial-bedrock channel: Interaction - alluvial cover, roughness. *Journal of Geophysical Research: Earth Surface*, 119(10), 2123–2146. <https://doi.org/10.1002/2014JF003133>
- ISHIBASHI, T. (1983). A hydraulic study on protection for erosion of sediment flush equipments of dams. *Proceedings of the Japan Society of Civil Engineers*, 1983(334), 103–112.

- Jacobsen, S., Scherer, G. W., & Schulson, E. M. (2015). Concrete–ice abrasion mechanics. *Cement and Concrete Research*, 73, 79–95. <https://doi.org/10.1016/j.cemconres.2015.01.001>
- Johnson, J. P. L. (2014). A surface roughness model for predicting alluvial cover and bed load transport rate in bedrock channels. *Journal of Geophysical Research: Earth Surface*, 119(10), 2147–2173. <https://doi.org/10.1002/2013JF003000>
- Kadia, S. (2024). *Secondary Currents, Turbulence Characteristics, and Bed Shear Stress Variations in Supercritical Narrow Channel Flows*. <https://doi.org/10.13140/RG.2.2.15214.01606>
- Kadia, S., Larsson, S., Billstein, M., Lia, L., & Pummer, E. (2024). Experimental and numerical investigations of the water surface profile and wave extrema of supercritical flows in a narrow channel bend. *Scientific Reports*, 14, 12247. <https://doi.org/10.1038/s41598-024-61297-8>
- Kantoush, S., Sumi, T., & Murasaki, M. (2011). Evaluation of sediment bypass efficiency by flow field and sediment concentration monitoring techniques. *Journal of Japan Society of Civil Engineers, Ser. B1 (Hydraulic Engineering)*, 67(4), I_169-I_174.
- Kondolf, G. M., Gao, Y., Annandale, G. W., Morris, G. L., Jiang, E., Zhang, J., Cao, Y., Carling, P., Fu, K., & Guo, Q. (2014). Sustainable sediment management in reservoirs and regulated rivers: Experiences from five continents. *Earth's Future*, 2(5), 256–280.
- Koshiba, T. (2020). *Improvement of Signal Analysis for Surrogate Bedload Monitoring at Sediment Bypass Tunnels* [Thesis, Kyoto University]. <https://repository.kulib.kyoto-u.ac.jp/dspace/bitstream/2433/253255/1/ykogk04680.pdf>
- Koshiba, T., Auel, C., Tsutsumi, D., Kantoush, S. A., & Sumi, T. (2018). Application of an impact plate – Bedload transport measuring system for high-speed flows. *International Journal of Sediment Research*, 33(1), 35–46. <https://doi.org/10.1016/j.ijsrc.2017.12.003>
- Koshiba, T., Kantoush, S. A., & Sumi, T. (2017). Field experiment of bedload transport rate measurement at sediment bypass tunnel. *Proc. 37th IAHR World Congress*, 1115–1124.
- Koshiba, T., & Sumi, T. (2020). Bedload transport and abrasion monitoring at the Koshibu Dam sediment bypass tunnel and proposing countermeasures against the abrasion problem. *Icold1st*, 13-49–19.
- Lague, D. (2014). The stream power river incision model: Evidence, theory and beyond. *Earth Surface Processes and Landforms*, 39(1), 38–61. <https://doi.org/10.1002/esp.3462>
- Lamb, M. P., Dietrich, W. E., & Sklar, L. S. (2008). A model for fluvial bedrock incision by impacting suspended and bed load sediment. *Journal of Geophysical Research: Earth Surface*, 113(F3), 2007JF000915. <https://doi.org/10.1029/2007JF000915>
- Lamb, M. P., Finnegan, N. J., Scheingross, J. S., & Sklar, L. S. (2015). New insights into the mechanics of fluvial bedrock erosion through flume experiments and theory. *Geomorphology*, 244, 33–55.
- Lee, C.-H., Zhan, S.-S., Chang, S.-H., Lien, S.-Y., & Chang, J.-H. (2019). *Abrasion resistance design of sediment sluicing tunnel in Taiwan: A case study*.

- MMS. (2013). *Consistently Accurate Measurement*.
http://www.mitsubishielectric.co.jp/mms/pdf/mms_e.pdf
- MMS Website. (2024). *Mitsubishi Electric, Latest Version of GPS, MMS*.
<http://www.mitsubishielectric.co.jp/mms/tokucho.html>
- Morris, G. L. (2019). *SEDIMENT BYPASS TUNNELS: IMPACT OF HYDROLOGY ON FEASIBILITY*.
- Morris, G. L. (2020). Classification of management alternatives to combat reservoir sedimentation. *Water*, 12(3), 861.
- Müller-Hagmann, M. (2018). *Hydroabrasion by high-speed sediment-laden flows in sediment bypass tunnels* [PhD Thesis]. ETH Zurich.
- Müller-Hagmann, M., Albayrak, I., Auel, C., & Boes, R. M. (2020). Field Investigation on Hydroabrasion in High-Speed Sediment-Laden Flows at Sediment Bypass Tunnels. *Water*, 12(2), Article 2. <https://doi.org/10.3390/w12020469>
- Nakajima, H., Otsubo, Y., & Omoto, Y. (2015). Abrasion and corrective measures of a sediment bypass system at Asahi Dam. *Proc. Int. Workshop on Sediment Bypass Tunnels*, 21–32.
- Nezu, I., & Nakagawa, H. (1993). Turbulence in open-channel flows, *iahr-monogr. Ser., A*, 1–281.
- Sakurai, T., Tsujimoto, T., Sumi, T., Kunimura, I., Takeuchi, H., & Ishida, K. (2018). Plan and Operation Results of the Koshiyama Dam Sediment Bypass Tunnel. *Twenty-Sixth International Congress on Large Dams/Vingt-Sixième Congrès International Des Grands Barrages*, Q100_298-Q100_316. <https://www.taylorfrancis.com/chapters/edit/10.1201/9780429465086-20/plan-operation-results-koshiyama-dam-sediment-bypass-tunnel-toshiyuki-sakurai-tetsuro-tsujimoto-tetsuya-sumi-ichiro-kunimura-hiroyuki-takeuchi-katsushi-ishida>
- Sawagashira, Y., Suzuki, A., & Fukumoto, A. (2017). Sedimentation control effect and environmental impact of sediment bypass in Miwa Dam Redevelopment Project. *Proceedings of the 2nd International Workshop on Sediment Bypass Tunnels*, 1–12. <https://repository.kulib.kyoto-u.ac.jp/dspace/handle/2433/245513>
- Scheingross, J. S., Brun, F., Lo, D. Y., Omerdin, K., & Lamb, M. P. (2014). Experimental evidence for fluvial bedrock incision by suspended and bedload sediment. *Geology*, 42(6), 523–526.
- Schleiss, A. J., Franca, M. J., Juez, C., & De Cesare, G. (2016). Reservoir sedimentation. *Journal of Hydraulic Research*, 54(6), 595–614. <https://doi.org/10.1080/00221686.2016.1225320>
- Seidl, M. A., Dietrich, W. E., Schmidt, K. H., & De Ploey, J. (1992). The problem of channel erosion into bedrock. *Functional Geomorphology*, 23, 101–124. [https://books.google.com/books?hl=en&lr=&id=kTSBAAAQBAJ&oi=fnd&pg=PT362&dq=Seidl,+M.A.+%26+Dietrich,+W.E.+\(1992\)+The+problem+of+channel+erosion+into+bedrock.+Catena+Supplement,+23,+101%E2%80%93124.&ots=KkNy-1M1IZ&sig=_WVCAv3durnocysG7Kg3uEd2-IU](https://books.google.com/books?hl=en&lr=&id=kTSBAAAQBAJ&oi=fnd&pg=PT362&dq=Seidl,+M.A.+%26+Dietrich,+W.E.+(1992)+The+problem+of+channel+erosion+into+bedrock.+Catena+Supplement,+23,+101%E2%80%93124.&ots=KkNy-1M1IZ&sig=_WVCAv3durnocysG7Kg3uEd2-IU)
- Sklar, L. S., & Dietrich, W. E. (2001). Sediment and rock strength controls on river incision into bedrock. *Geology*, 29(12), 1087–1090. [https://doi.org/10.1130/0091-7613\(2001\)029<1087:SARSCO>2.0.CO;2](https://doi.org/10.1130/0091-7613(2001)029<1087:SARSCO>2.0.CO;2)

- Sklar, L. S., & Dietrich, W. E. (2004). A mechanistic model for river incision into bedrock by saltating bed load. *Water Resources Research*, 40(6). <https://doi.org/10.1029/2003WR002496>
- Sklar, L. S., & Dietrich, W. E. (2012). Correction to “A mechanistic model for river incision into bedrock by saltating bed load.” *Water Resources Research*, 48(6). <https://doi.org/10.1029/2012WR012267>
- Song, T., & Chiew, Y. M. (2001). Turbulence Measurement in Nonuniform Open-Channel Flow Using Acoustic Doppler Velocimeter (ADV). *Journal of Engineering Mechanics*, 127(3), 219–232. [https://doi.org/10.1061/\(ASCE\)0733-9399\(2001\)127:3\(219\)](https://doi.org/10.1061/(ASCE)0733-9399(2001)127:3(219))
- Sumi, T. (2006). Reservoir sediment management measures and necessary instrumentation technologies to support them. *6th Japan-Taiwan Joint Seminar on Natural Hazard Mitigation, Kyoto*.
- Sumi, T., & Kantoush, S. A. (2011). Comprehensive sediment management strategies in Japan: Sediment bypass tunnels. *Proceedings of the 34th World Congress of the International Association for Hydro-Environment Research and Engineering, 33rd Hydrology and Water Resources Symposium and 10th Conference on Hydraulics in Water Engineering Valentine*.
- T.D.I.M Office. (2021). Tenryu River Dam Integrated Management Office. <https://www.cbr.mlit.go.jp/tendamu/>
- Turowski, J. M. (2009). Stochastic modeling of the cover effect and bedrock erosion. *Water Resources Research*, 45(3), 2008WR007262. <https://doi.org/10.1029/2008WR007262>
- Turowski, J. M. (2012). Semi-alluvial channels and sediment-flux-driven bedrock erosion. *Gravel-Bed Rivers: Processes, Tools, Environments*, 399–418.
- Turowski, J. M., & Hodge, R. (2017). A probabilistic framework for the cover effect in bedrock erosion. *Earth Surface Dynamics*, 5(2), 311–330. <https://doi.org/10.5194/esurf-5-311-2017>
- Turowski, J. M., Lague, D., & Hovius, N. (2007). Cover effect in bedrock abrasion: A new derivation and its implications for the modeling of bedrock channel morphology. *Journal of Geophysical Research: Earth Surface*, 112(F4).
- Vetsch, D., Facchini, M., Boes, R., & Siviglia, A. (2024). Modeling the morphological response of gravel-bed rivers subject to repeated sediment bypass tunnel operations. *Frontiers of Earth Science*, 1357759. <https://doi.org/10.3389/feart.2024.1357759>
- Walling, D. E. (2009). *The impact of global change on erosion and sediment transport by rivers: Current progress and future challenges*. <https://books.google.com/books?hl=en&lr=&id=zwhpknVKEsQC&oi=fnd&pg=PA1&dq=Global+sediment+dynamics+and+reservoir+sedimentation+are+intensifying+under+the+influence+of+climate+change,+leading+to+increased+sediment+transport+rates&ots=L0K-EJXnnh&sig=ssCgjr-wvSwo1o6RpuAjYfdrUMM>

CHAPTER 5

Advanced Abrasion Susceptibility Mapping [ASM Model] (Machine Learning in Action)

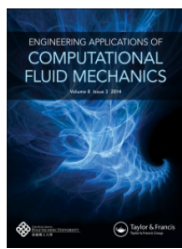
5.1. Summary

As mentioned earlier, conventional empirical or physics-based models have been unable to resolve localized wear patterns along the tunnel lining. The present work addresses this critical gap and introduces the first field-validated, two-dimensional Abrasion Susceptibility Model (ASM) based on the eXtreme Gradient Boosting (XGBoost) algorithm. High-resolution laser scanning of Japan's four km-long Koshiu SBT provided over 1 million labeled points, distinguishing between abraded and non-abraded surfaces. Leveraging geometric (e.g., curvature, longitudinal distance) and hydraulic (e.g., flow velocity, event time) predictors, the model achieved an overall classification accuracy of 0.864, with sensitivities and specificities exceeding 0.85 in straight and curved sections. This study overcomes the coarse resolution of earlier approaches by pinpointing spatially discrete abrasion hotspots, offering practitioners a data-driven tool for targeted inspection, maintenance planning, and lifetime management of SBTs.

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Machine learning approach for 2D abrasion mapping in Sediment Bypass Tunnels: a case study of Koshiu SBT, Japan

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5.2. Paper Content

Machine Learning Approach for 2D Abrasion Mapping in Sediment Bypass Tunnels: A Case Study of Koshibu SBT, Japan

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Abstract

Sediment Bypass Tunnels (SBTs) effectively mitigate reservoir sedimentation by diverting flood-laden flows, but they face significant challenges due to hydroabrasive erosion, which compromises their sustainability. Predicting this abrasion is complex due to the intricate interactions between flow hydraulics and sediment transport, along with limited high-quality data. In this study, we explore, for the first time, the potential of using the XGBoost machine learning algorithm to predict the spatial abrasion of SBTs. The Koshiu SBT in Japan, extending approximately 4 km, was selected as the case study. Three experimental scenarios were evaluated: the entire tunnel, the straight section, and the curved section. A spatial abrasion topography was measured using laser scanning tools with a spatial resolution of 2 cm. The controlling factors for abrasion were developed based on geometric and hydraulic features. The abrasion inventory map, consisting of over 1 million data points indicating damaged and non-damaged sites, was divided equally for training and testing the XGBoost algorithm. Results indicate that the XGBoost model effectively predicts 2D spatial abrasions in SBTs, achieving an overall accuracy of 0.864, exceeding 0.9 in some sections. The developed abrasion map accurately captures various complex patterns throughout the tunnel but has some limitations in areas with small wave-like patterns. Overall, this study demonstrates the potential of machine learning algorithms for predicting tunnel abrasion in SBTs.

Keywords: spatial abrasion of SBTs, abrasion inventory map, XGBoost machine learning, abrasion pattern predicting

Paper highlights:

- This study introduces a validated 2D model for tunnel abrasion based on field data, contributing to improved sediment management in SBTs.
- ASM Model efficiently predicts abrasion mapping in SBT, achieving 86.4 % overall accuracy.
- High sensitivity and specificity in distinguishing abraded and non-abraded areas.
- Captures four complex abrasion patterns in straight and curved sections but is limited to relatively small wave-like patterns.
- Geometric and hydraulic parameters, particularly the elongated distance and flow velocity, exhibit significant impacts in the ASM model.

1. Introduction

The process of hydroabrasion describes the progressive erosion of solid material surfaces resulting from the repeated impact of sedimentary particles in a fluid medium undergoing dynamic motion. These impacts generate silt or sand-sized fragments at the mineral grain scale (Beer & Turowski, 2015; Beer & Lamb, 2021). Hydroabrasion mostly happens in steep bedrock rivers and mountainous torrents, playing a critical role in landscape evolution (Sklar & Dietrich, 2004; Turowski, 2012; Turowski & Hodge, 2017a). Similar mechanisms occur in hydraulic structures exposed to sediment-laden flows, including SBTs, low-level outlets, and sluicing and flushing channels. These processes contribute to structural stability challenges and high maintenance costs, especially with climate change's adverse effects, which intensify these issues by increasing the severity of flood events (Ha et al., 2017; Zhang et al., 2023).

Advancing our understanding of hydroabrasion phenomena and developing abrasion prediction models are crucial for improved river dynamics and landscape evolution predictions. Further, optimizing sustainable hydraulic structures faces these complexities. In recent years, this phenomenon has been investigated through various methodologies, encompassing both analytical and numerical approaches as demonstrated by some researchers (Aubert et al., 2016; Johnson, 2014; Lee et al., 2006; Turowski, 2009; Turowski et al., 2007; Turowski & Hodge, 2017b), or some experimental studies (e.g., see Auel et al., 2017a, 2017b; Demiral et al., 2020, 2022; ISHIBASHI, 1983; Scheingross et al., 2014; Sklar & Dietrich, 2001), and direct field measurements that have provided valuable insights (Albayrak et al., 2024; Arnold et al., 2020; Müller-Hagmann et al., 2020a; Nakajima et al., 2015).

In scientific literature, researchers have developed several models that fall into two main categories: stream power incision models (Lague, 2014; Seidl et al., 1992) and mechanistic models (Albayrak et al., 2024; Auel et al., 2017b; Chatanantavet & Parker, 2009; Demiral et al., 2022; ISHIBASHI, 1983; Lamb et al., 2008; Sklar & Dietrich, 2004). Stream power models describe the abrasion rate as a function of discharge, primarily considering hydraulic parameters. Whereas mechanistic models consider additional factors such as particle impact and sediment supply.

These two existing types of models still exhibit drawbacks. For instance, mechanistic models affirm that abrasion depths increase with higher bedload mass, implying a direct correlation between

sediment loads and damaged volumes. Yet, these models face constraints when dealing with greater damage thicknesses, as the validity of key parameters becomes unreliable beyond certain thresholds (Auel et al., 2017b; Chatanantavet & Parker, 2009; Demiral et al., 2022; ISHIBASHI, 1983). Furthermore, both stream power and mechanistic models typically provide averaged results, yielding bulk abrasion volumes or rates that lack the localized specificity needed for detecting damage at critical points within the tunnel.

Despite the generalized nature of these models, they still exhibit deviations in their results due to inherent uncertainties in some of their parameters. For instance, in the (Auel et al., 2016) study, there was an overestimation of the tunnel abrasion volume by 138% compared to the actual measurements. However, upon excluding certain parameters, this overestimation was reduced to 30%, a value still considered a notable deviation. Similarly, (Müller-Hagmann et al., 2020b) pointed out uncertainties that resulted in an error of 87% to 91% in abrasion rate estimation for one of the model's key parameters which significantly influenced the final calculated results. In the latest update for this key parameter by (Albayrak et al., 2024), they managed to reduce the deviation to 45%, which is still considered a notable value. These results underscore the ongoing challenges in achieving precise and reliable predictions from these models. Adding to these challenges, real-time measurements inside the tunnel during flood events are extremely difficult to obtain, often bordering on impossible due to safety and accessibility concerns. These obstacles make it challenging to gather high-quality data for model validation. So, under these complexities and limitations, further research is needed. Developing approaches that account for localized damage are crucial steps for advancing tunnel management and mitigating abrasion damage.

Therefore, there is a pressing need for a more comprehensive model capable of predicting abrasion in both one-dimensional (1D) and two-dimensional (2D) criteria, addressing the limitations inherent in traditional models. To construct models of this nature, a comprehensive dataset is essential, which includes accurately mapped topographies of the tunnel floor that have been subjected to damage, in conjunction with the dynamic flow rates of flood-borne discharges and the corresponding volumes of sediment transport. This endeavor poses a significant challenge, especially during flood events. Moreover, the model must account for the variability of the flow surface within the tunnel, which adds a layer of complexity to the process. Additionally, the

geometric properties and the material composition of the tunnel floor must be factored into the model. Yet, ML algorithms may potentially provide a solution to unravel these complex challenges. We believe that this approach can uncover the complex relationships between the abrasion damage on the tunnel floors and the controlling factors causing this damage, providing insights not just on a general level but also in terms of localized “1D and 2D” dimensions.

ML techniques, which excel in handling non-linear and multifaceted phenomena, have been implemented in diverse areas of flood risk management. The extensive application of ML algorithms in prior studies is well-established. Gradient boosting methods like CatBoost and XGBoost have been instrumental in creating flash flood susceptibility maps, as presented by (Abedi et al., 2022; Alamoudi et al., 2023; Saber et al., 2022, 2023), validating their predictive accuracy. (Wang et al., 2024) introduced an innovative approach by integrating deep learning methods with flash flood simulation to propose a model capable of predicting the spatiotemporal dynamics of flash floods. In a similar vein, (Ansari et al., 2023) employed a deep learning approach to forecast damage states in tunnels affected by seismic activities, highlighting the potential of ML techniques in structural damage assessment. Despite the widespread application of these techniques across various fields, their utilization in predicting abrasion damage within SBTs remains unexplored. Therefore, to the best of our knowledge, we examine XGBoost for the first time to predict a 2D abrasion susceptibility map (ASM) in SBT floors.

In this study, we investigate the potential of utilizing the XGBoost ML algorithm to predict spatial abrasion in SBTs. The Koshibu SBT in Japan, approximately 4 km in length, was chosen as the case study. A high-resolution spatial abrasion topography was measured using laser scanning tools with a spatial resolution of 2 cm × 2cm. We evaluated three experimental scenarios: the entire tunnel, the straight section, and the curved section. Our methodology integrated hydraulic conditions from eight distinct flood events, aligning with the paradigm of stream flow modeling, alongside geometric parameters as controlling factors. Moreover, we explore the influence of input parameters and consecutive flood events on model precision. This study underscores the potential of integrating the ML approach to improve the prediction and management of abrasion in SBTs. By implementing the hydraulic characteristics of upcoming flood events, the ASM model can evaluate the vulnerability of

the tunnel to abrasion damage, contributing to more effective maintenance and operational strategies.

2. Koshiu SBT Case Study

The Koshiu SBT in Japan stands as an exemplary illustration of SBT implementation. In Nagano prefecture, Japan, Koshiu SBT is a pivotal local sediment management strategy component. Constructed to address the sedimentation challenges in the Koshiu River basin, the tunnel spans about 3.982 kilometers, effectively diverting sediment-laden water and preventing sediment deposition in the reservoir, see **Fig (1)**, is also considered a modern design worldwide with a 370 m³/s maximum design discharge capacity.

Most of the structure consists of a rectilinear tunnel; however, the terminal segment, approximately 700 meters proximal to the outlet, deviates into a curve oriented along the orographic right with a radius of curvature equal to 1000 meters. The cross-sectional dimensions are 6.5 m in width and 7.2 m in height. The tunnel has a longitudinal slope profile that consists of an acceleration section at the entrance with a high slope of 20 %, followed by a relatively low slope of 2 % for the remaining tunnel. The acceleration section, extending for the first 50 m of the tunnel, provides sufficient energy for conveying sediment-laden floodwater. Moreover, the inlet section's design incorporates an expanded cross-sectional area to enhance the capture efficiency of sediment-laden flood water. The outlet section of the tunnel has various instruments, such as geophone plates, to measure some of the flood-laden characteristics (Koshiu & Sumi, 2020).

3. Data and Methodology

The overall methodology employed in this investigation is shown in **Fig (2)**. The procedural workflow encompasses a series of stages, beginning with data preprocessing, which involves the rasterization of topography and the extraction of terrain features. This is followed by selecting geometric and hydraulic parameters, compiling and preparing training datasets for the XGBoost algorithm, and modeling phase. Then, the whole datasets were normalized to be consistent for ML applications. The methodology further includes an accuracy assessment and validation process, resulting in the generation of the model. The final evaluative phase entails a comparative analysis between the observed topographical data and the simulated outcomes. The details are presented below.

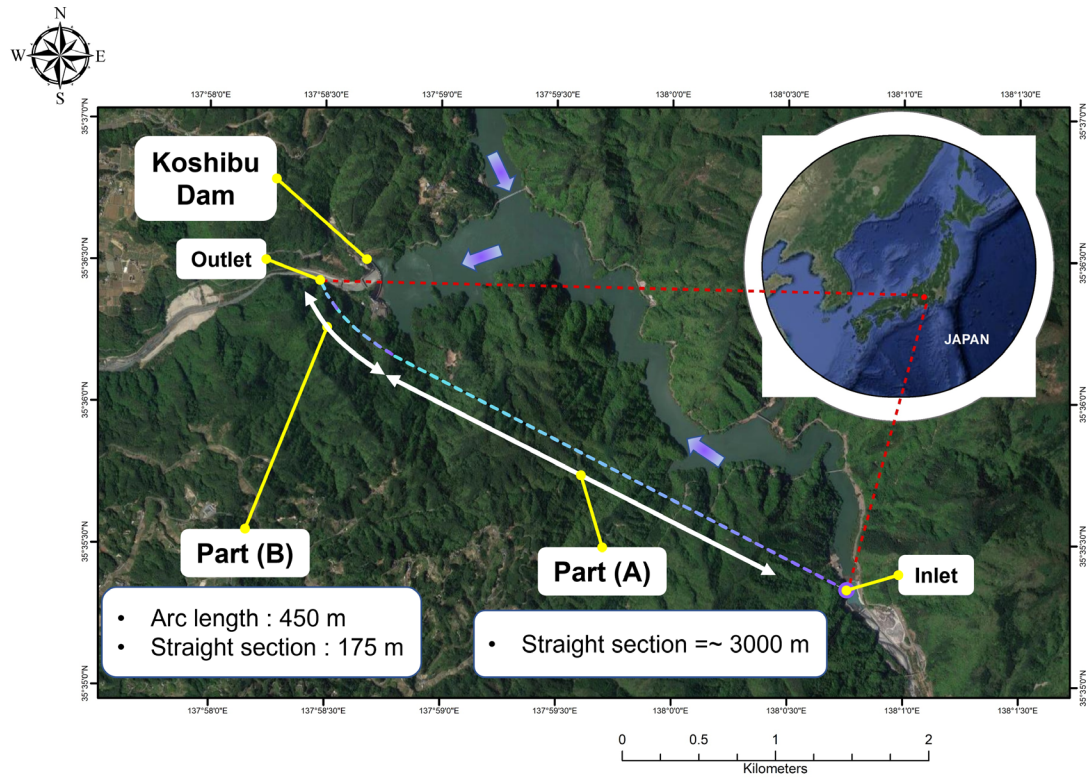


Fig (1) Koshibu SBT case study having the parts under consideration.

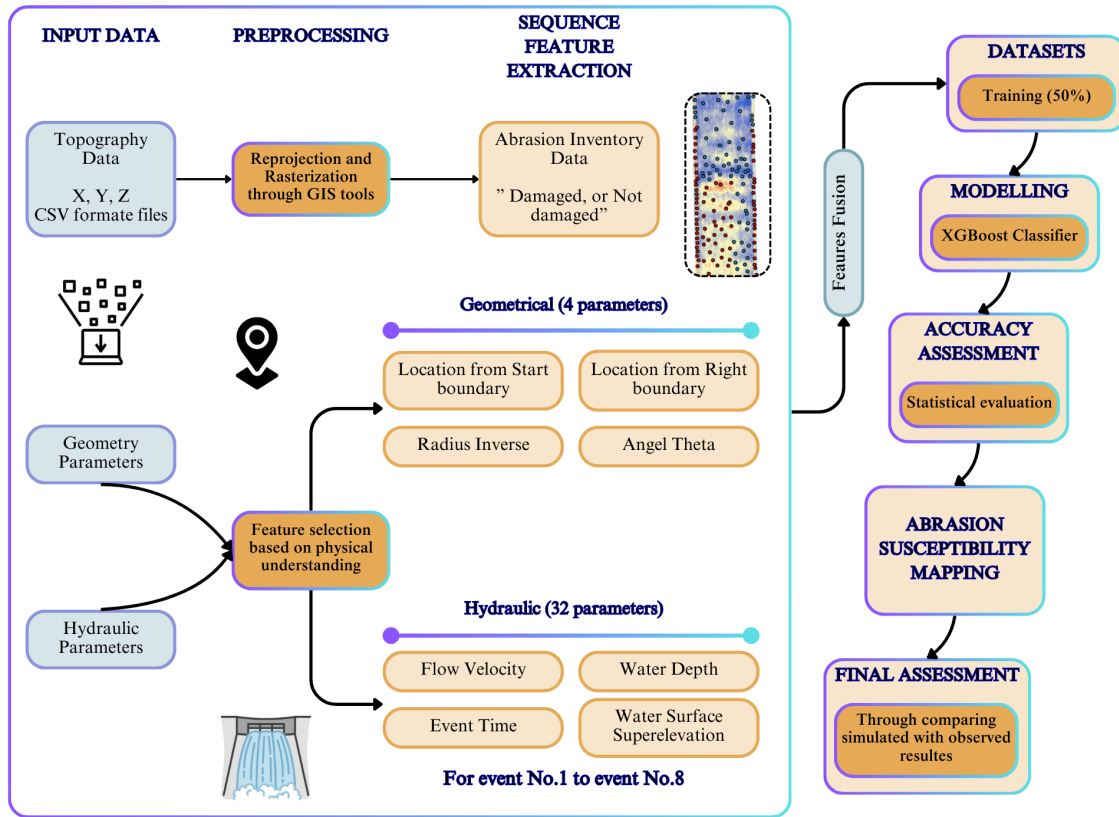


Fig (2) Overall methodology implemented in this investigation.

3.1 Tunnel Characteristics and Datasets

A precise mapping of the damaged floor is essential for developing and validating the ASM model. The laser scanning was set up at all locations within the tunnel floor to capture high-resolution 3D point clouds. The damaged floor topography data (abrasion map) are from two years of operation since 2016. The data is then processed using ArcGIS's specialized software to create a detailed digital elevation model (DEM) of the tunnel floor.

3.1.1 Tunnel Divisions

Following visual inspection of the data, severe and complex abrasion was observed throughout the tunnel floor, particularly in the inlet and outlet zones. The inlet region has specific geometries, whereas the outlet zone involves complex measurement installations. Consequently, we have excluded these zones from the present analysis. An additional reason for this exclusion is to mitigate boundary effects.

The study includes a tripartite analysis for the SBT system including a whole tunnel (integrating parts A and B), a straight section (Part A), and a curved section (Part B) as depicted in **Fig (1)**.

In the first division part (A), the straight portion spans approximately 3000 meters and exhibits diverse abrasion patterns. The second division, part (B), starts with a curved section with an arc length of 450 m. Following the curved portion, part (B) transitions into a linear section 175 m in length, **Fig (1)**. Details of which will be elaborated upon.

3.1.2 Laser scan data

The laser scan data for this analysis was collected using a Mitsubishi Mobile Laser Scanner (MMS) from the Koshiu Dam office (T.D.I.M Office, 2021). The MMS system overlays 3D laser point clouds compiled with Geographic Information System (GIS) data. This method ensures consistent accuracy even in challenging structures such as bypass tunnels, where long distances and other factors may affect the measurement. The device employs laser pulses to generate highly accurate 3D point clouds. The MMS is equipped with a dual-axis compensator that automatically corrects for tilt and ensures consistent vertical accuracy, which is critical for maintaining precision in environments with uneven surfaces. The GPS correction (i.e., flächen korrektur parameter [FKP] method) is applied for surface correction parameters, (Mitsubishi, 2013; MMS Website, 2024). The GPS correction accounts for satellite signal distortions and provides surface corrections even in environments with limited satellite visibility, such as inside tunnels. The scanner captures 3D data with a high spatial resolution, producing 2 cm x 2 cm intervals, producing a high-resolution DEM of the topography. The accuracy in the Z direction (depths) underwent additional calibration and was found to be ± 2 cm (T.D.I.M Office, 2021). The DEM shows the damage depth ranging from 0 (origin floor surface) to over 20 cm in specific regions, being the basis for developing and verifying the ASM model.

3.1.3 Abrasion inventory data

The algorithm uses DEM pixels as a fundamental element to establish the relationship between the abrasion damage and the other characteristics. So, the pixels are categorized as damaged or undamaged based on the abrasion inventory data. To develop these data, around 1,161,352 data points were distributed along the length of the study area of the tunnel, with 1,001,352 for part (A) and 160,000 for part (B). Based on the laser scan data accuracy, the data points are labeled 1 for

abraded points (depths > 0.02 m) and 0 for non-abraded points (depths < 0.02 m); see **Fig (3)**. Following this criterion, the instrument depth measurement errors can be eliminated.

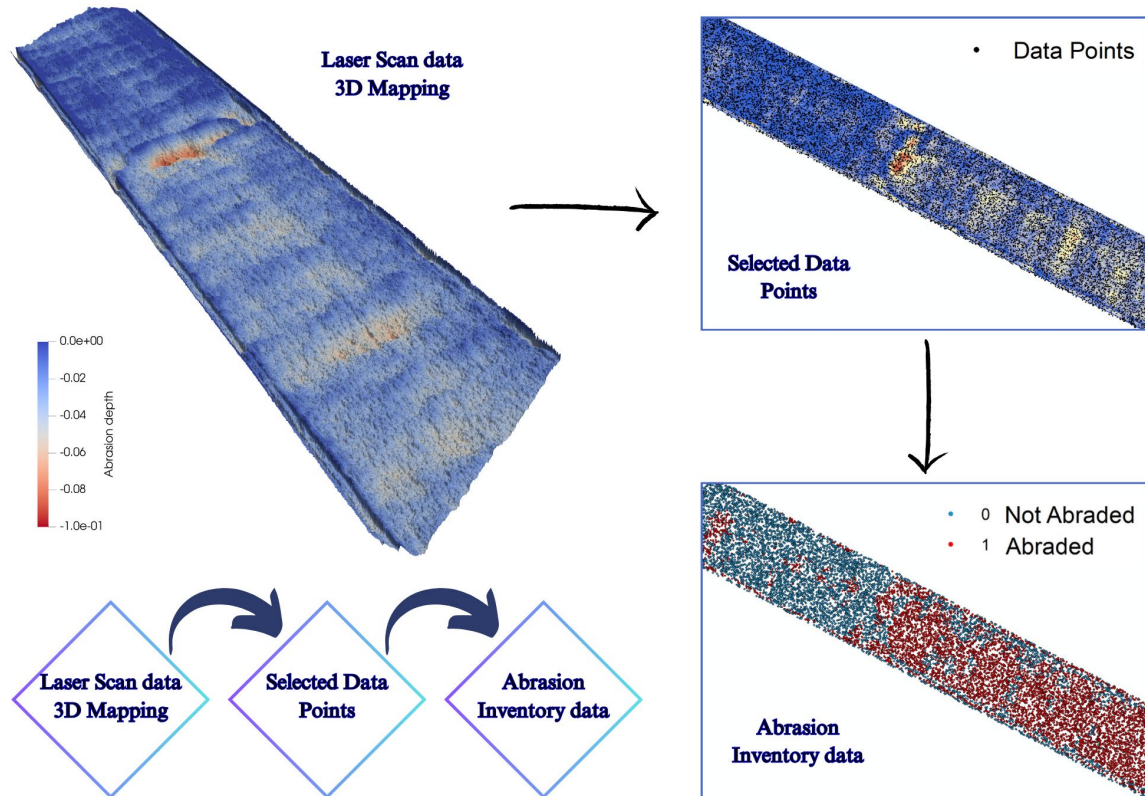


Fig (3) Extraction of abrasion inventory data.

3.1.4 Geometry and Hydraulic features

The abrasion phenomenon involves intricate physical processes, yet it can be modeled by parameters that are applicable and liable to machine computation. By implementing these parameters into the algorithm, we can establish a relationship between the main drivers and the topography, indicating whether the floor is damaged. These parameters include hydraulic characteristics, sediment properties, floor material properties including also the geological condition, and the geometric configuration of the tunnel. In this study, the investigation was

confined where floor damage did not penetrate beyond the concrete slab to reach the geological foundation of the tunnel. So, the impact of floor material (a single material in this case) and geological conditions were excluded from consideration. Additionally, sediment properties were also omitted due to their unknown variable nature within the tunnel, which is treated as a black box in this context. The focus of this study was thus primarily on the hydraulic and geometric characteristics of the system. Key factors influencing this phenomenon include the system's geometry and hydraulic characteristics, as detailed in **Table (1)**. The hydraulic characteristics and geometrical features are carefully adjusted to mirror the tunnel's conditions.

Table (1) Geometric and Hydraulic Parameters Investigated in the Study

Parameter	Type	Unit	Sort	Input
Distance from Start boundary, D_s	Geometry	[m]	Laser scan	One value per pixel
Distance from Right boundary, D_R	Geometry	[m]	Laser scan	One value per pixel
Radius Inverse, $1/R$	Geometry	[1/m]	Laser scan	One value per pixel
Angle Theta, θ	Geometry	[degree]	Laser scan	One value per pixel
Flow Velocity, v	Hydraulic	[m/s]	Calculated	Eight values per pixel
Water Depth, y	Hydraulic	[m]	Calculated	Eight values per pixel
Event Time, T	Hydraulic	[hr]	Measured	Eight values per pixel
Water Superelevation, Δh	Hydraulic	[m]	Calculated	Eight values per pixel

Since geometry has a significant effect on this kind of structure, and by taking advantage of very accurate, refined laser scan data, four geometry parameters are considered for each data point. Two parameters specify the location of the data point from the start and the right boundaries. Given the tunnel's fixed cross-section dimensions, these two parameters provide sufficient information about the studied data point's exact location. Parameters 3 and 4 are the inverse of radius and angle theta, respectively. They play a critical role in the curvature part. However, the radius is considered infinity in straight parts and thus, the inverse radius becomes zero. This allows the algorithm to distinguish between straight and curved parts. As for theta, it is the angle measured from the tangent of the data point anticlockwise to the main direction of the straight section part (A). This

means that the theta of data points at the beginning of the curvature is almost zero, and it reaches its maximum at the end. The angle theta remains constant for the straight part following the curvature, as it forms a fixed angle with part (A). The longitudinal slope is constant for the examined parts of the tunnel. Therefore, this factor is not considered in this analysis.

Regarding the hydraulic parameters within the tunnel, the dynamics of this system, which can be analogized to a tsunami due to the high velocities inside the tunnel, present significant challenges to deal with. It is extremely hard to implement any measurement devices inside the tunnel to quantify the real-time hydraulic characteristics. Nonetheless, we can extract some hydraulic features along the tunnel length, based on the recorded maximum discharges entering the Koshiu tunnel **Table (2)**.

The considered hydraulic features are as follows: for each discharge, we have four parameters related to each data point: flow velocity, water depth, event time, and superelevation of water surface (the difference in water levels between the left and right sides of the tunnel), see **Table (1)**. The event time parameter is measured during different events. However, the other three parameters can be calculated through backwater curve calculations using the Darcy-Weisbach formula. Such methodology is commonly adopted to derive hydraulic features inside the tunnel, as documented by (Auel et al., 2016, 2017a; Demiral Yüzüğüllü, 2021; Müller-Hagmann et al., 2020a). The calculations were conducted as follows:

The main function of the acceleration section is to give the flow the required momentum to flow downstream without section clogging. Therefore, for simplicity, we assume that the acceleration section fully fulfills its function, meaning that the flow reaches its steady state and maximum velocity after the acceleration section. Based on this assumption, we can apply the Manning equation for the acceleration section, with a steel lining, to obtain the initial flow condition.

The bed roughness height in Koshiu SBT is $k_s = 0.001$ m, derived from back-water calculations for design discharge and corresponding flow depths. This value is corroborated by experimental hydraulic simulations performed by the dam authority and is consistent with typical roughened concrete surfaces (Fenton, 2010; T.D.I.M Office, 2021). Simultaneously, Manning's coefficient for

the acceleration section $n = 0.015$, was obtained based on the characteristics of the employed steel lining material.

So, based on the previous values, the resultant maximum flow velocity varies from 17.4 m/s to 26.6 m/s at $Q_2 = 60 \text{ m}^3/\text{s}$ and $Q_8 = 200 \text{ m}^3/\text{s}$, respectively, immediately downstream of the acceleration section. As the flow velocity and the aspect ratio of B/h (tunnel width to flow height) are inversely related, these flow velocities correspond to an aspect ratio of $B/h = 13 \sim 6$, which implies a shallow open channel regime (2D-flow) (Nakagawa, 2017; Nezu & Nakagawa, 1993). However, according to the backwater curve calculations, the flow transitions to a deep open channel regime (3D-flow) along the tunnel length for all the considered discharges, except for $Q_2 = 60 \text{ m}^3/\text{s}$, which remains in the shallow regime. As a result, the velocity and water depth can be calculated at every data point on the tunnel floor. The superelevation parameter is affected by the centrifugal forces during the curvature part, and it can be calculated based on this formula (Reinauer & Hager, 1997):

$$\Delta h = h_L - h_R = \frac{v^2 B}{Rg} \quad (1)$$

Where v is the velocity, B is the tunnel width, R is the data point radius from the curvature center point, and g is the gravitational acceleration. However, in straight parts, the superelevation becomes zero as the radius reaches infinity. In summary, we have eight discharges, each with four parameters, resulting in 32 hydraulic features related to each data point.

3.1.5 Insights into Tunnel Topography

This section presents the observed damage pattern within the examined tunnel and the correlation with literature findings is conducted to understand the topographical characteristics deeply. **Figs (4,5)** illustrate localized slots of damage within parts (A) and (B), respectively.

The observed damage within the tunnel can be systematically categorized into four principal patterns: (1) edged, (2) wave-like, (3) undefined (scatter), and (4) skewed. The first trio of patterns has undergone experimental analysis, whereas the fourth is documented across various SBTs.

Table (2) The Considered operations of Koshibu SBT from 2016 to 2018 (Koshiba & Sumi, 2020)

Operation	Date	Duration, T	Discharge, $Q_{\max}$
No.	[-]	[hours]	[m ³ /s]
Op1	09/2016	16	80
Op2	09/2016	5.8	60
Op3	07/2017	3.1	120
Op4	10/2017	9.7	180
Op5	10/2017	48.8	90
Op6	07/2018	10.7	150
Op7	09/2018	44.2	175
Op8	10/2018	69.5	200

The edged pattern exhibits concentrated damage along both lateral margins of the tunnel's cross-section, as shown in **Fig (4-a)**. This pattern is particularly obvious in the downstream reaches of the straight Part (A), where 3D flow occurs during various events. This pattern aligns with findings from experimental studies, (Auel, 2014; Demiral Yüzügüllü, 2021), which investigated the effects of 3D flow regimes and concluded that intensified secondary currents and localized bed shear stress near the cross-section edges are the primary causes of this phenomenon.

Secondly, the wave-like pattern (**Fig (4-b)**) manifests longitudinally throughout the tunnel. This pattern is prevalent due to the predominant saltation transport of sediment particles under typical hydraulic conditions, as discussed and experimentally documented by Auel (Auel, 2014). The scatter pattern, characterized by its lack of discernible shape, is shown in **Fig (4-c)**. Notably, this pattern is evident in the upstream segments of Part (A), where shallow (2D) flow prevails during most discharge events. This pattern was also experimentally proved by (Demiral Yüzügüllü, 2021), who stated that it typically arises in shallow flow regimes and that surface roughness has a significant effect.

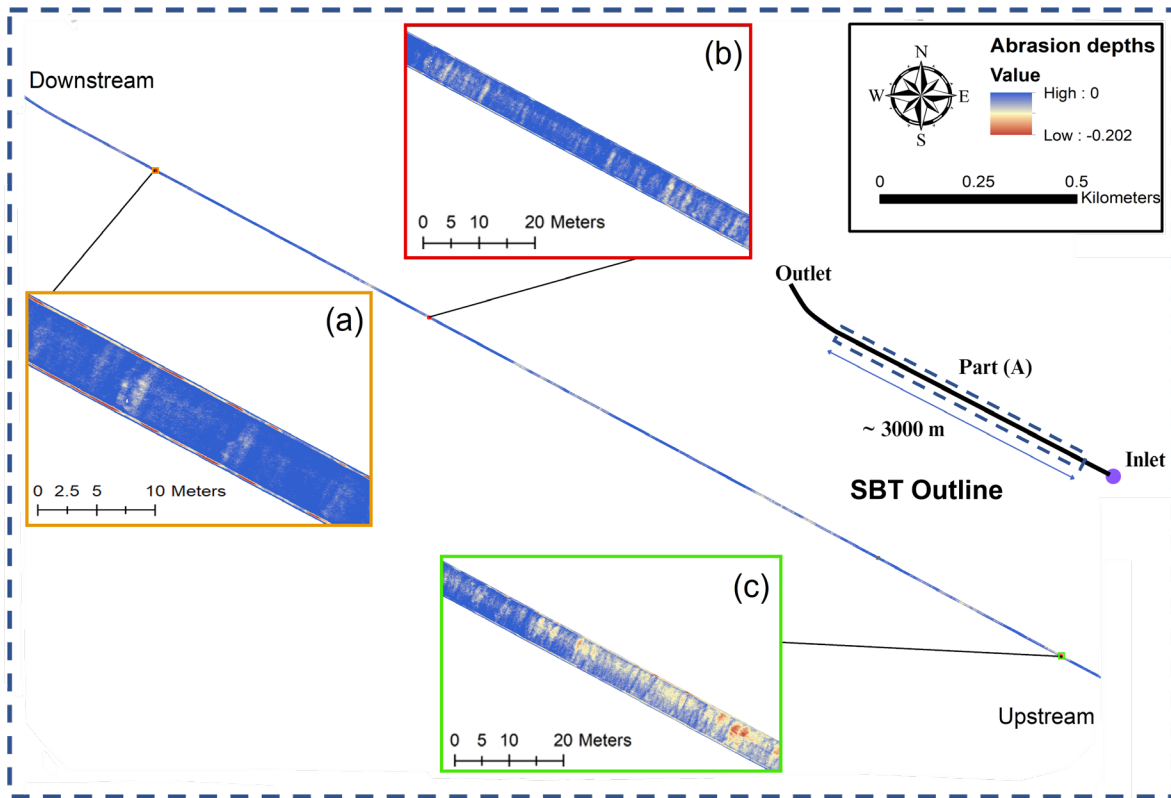


Fig (4) Abrasion laser scanning of SBT topography of part (A), a) the edged, b) wave-like, and c) scatter patterns.

Lastly, the skewed pattern observed in **Fig (5)** shows that the abrasion is present on only one side of the tunnel section, particularly in the curved section. This pattern is commonly observed in bends and has been reported in other tunnels, (Albayrak et al., 2024; Müller-Hagmann et al., 2020a; Nakajima et al., 2015). Several researchers have posited that secondary currents are the causative mechanism for this pattern. The straight part following a curve, despite being a straight section, is influenced by the preceding curvature, leading to an alternating pattern between wave-like and curved damage profiles. Typically, this formation of abrasion along the inner side can go further downstream of the bend but gradually re-distributes across the tunnel width downstream of the curve, as observed in some SBTs (Albayrak et al., 2024; Müller-Hagmann, 2018). However, in this case, the straight section is too short for that to happen.

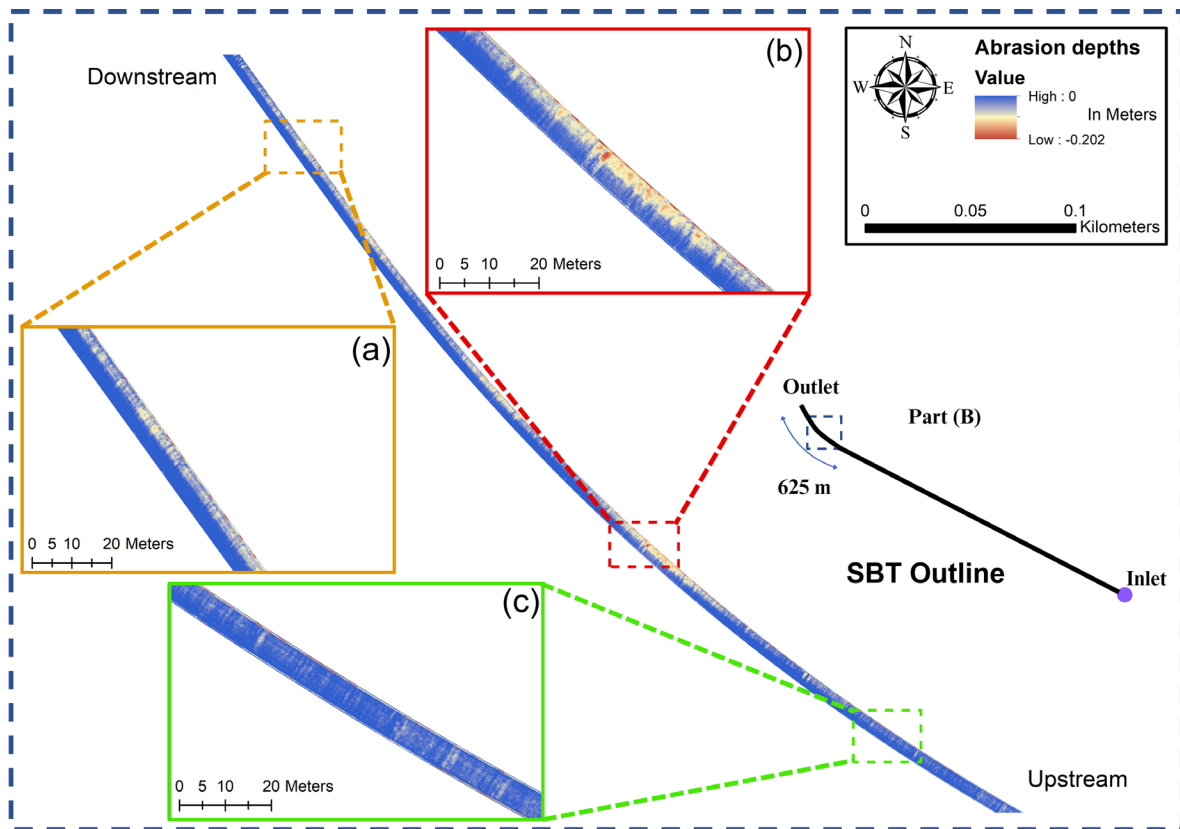


Fig (5) Abrasion laser scanning of SBT topography of part (B), a) after, b) center zone, and c) beginning of the curvature.

Overall, the previous damage patterns are compatible with the specified flow regimes within the tunnel, encompassing both shallow and deep open channel flows. Nevertheless, the diversity of discharge events, coupled with significant variations in hydraulic conditions and sediment transport dynamics, characterized by flow depths ranging from mere centimeters to several meters and particle sizes in transit from a few millimeters up to a quarter meter, (Koshiba, 2020; T.D.I.M Office, 2021), introduces complexity to the pattern formation. Additionally, some observed variations may be attributed to the overlay of different damage patterns from previous events. Certain tunnel sections may show an obvious pattern, whereas most topography shows a combination of these patterns. This complexity necessitates a comprehensive analysis, which is beyond the scope of this current study, which focuses on predictive modeling. The evaluation of such patterns warrants a separate assessment investigation.

3.2. Extreme Gradient Boosting (XGBoost) Modelling

A multi-parameter mathematical model is difficult to establish due to the complex influence of multiple sets of abrasion parameters. Fortunately, ML algorithms are an effective and feasible solution to address such complex multi-parameter nonlinear problems. XGBoost is an enhanced version and optimized type of gradient boosting algorithm, which generates and evolves a set of decision trees used as classifiers. The algorithm has recently gained popularity due to its speed, efficiency, and scalability, making it a highly effective method for classification and regression tasks (Chen & Guestrin, 2016). XGBoost excels at handling large datasets and complex data structures, which has led to its widespread adoption and numerous victories in data science competitions.

The system is designed to be highly scalable, and capable of handling sparse data efficiently with low computational resources. Therefore, the method has been successfully applied to various real-world predictions. For instance, in forest fire prediction, XGBoost has been applied to predict forest fire occurrences by analyzing environmental variables such as temperature, humidity, wind speed, and vegetation indices, (Hang et al., 2024). In earthquake hazard assessment, (Joshi et al., 2023) demonstrated its utility in predicting seismic events from historical data, underscoring the efficacy of deep learning models in such applications. The algorithm has also been recognized for its performance in flood susceptibility mapping (Abedi et al., 2022), and structural health monitoring, where (Yaghoubzadehfard et al., 2024) have showcased its effectiveness in detecting bridge damages. Similarly, (Kavzoglu & Teke, 2022) have employed XGBoost for landslide susceptibility mapping, highlighting its proficiency with complex environmental datasets.

This study uses the XGBoost algorithm as a classification model to predict abrasion in SBTs, marking a novel application for the algorithm. The choice of this algorithm was motivated by its proven track record and the need for a robust, scalable solution capable of managing high-dimensional data and delivering high performance in real-world scenarios.

XGBoost algorithm originated from the gradient tree boosting algorithm, which combines the outputs of weak learners sequentially to enhance predictive accuracy (Ramraj et al., 2016). The main objective is to minimize the loss function, which measures the difference between the predicted and actual outcomes. The model constructs an ensemble of decision trees, each of which tries to

correct the errors of the previous trees. The optimization problem can be formulated as follows (Chen & Guestrin, 2016):

The objective function L consists of the loss function l and a regularization term Ω :

$$L(\phi) = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (2)$$

where y_i is the true label (abraded or non-abraded), $\hat{y}_i$ is the predicted label, n is the number of samples, K is the number of trees, and f_k represents an individual tree in the model. The regularization term Ω controls the complexity of the model and helps prevent overfitting. The prediction for the i -th sample after t trees is given by:

$$\hat{y}_i^{(t)} = \sum_{k=1}^t f_k(x_i) \quad (3)$$

where x_i represents the input features (geometric and hydraulic parameters). The algorithm uses the first and second-order derivatives of the loss function to optimize the model and each tree f_k is added to minimize the following objective in the t -th iteration:

$$L^{(t)} = \sum_{i=1}^n \left[l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) \right] + \Omega(f_t) \quad (4)$$

The regularization term for a tree f_t is defined as:

$$\Omega(f_t) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2 \quad (5)$$

where T is the number of leaves in the tree, w_j are the leaf weights, and γ, λ are the regularization degrees. Any further elaboration about the concept of such an approach can be found in (Chen & Guestrin, 2016).

3.2.1 Accuracy Assessment

The accuracy assessment was done using a dual facilities approach: initially, statistical metrics were used as the primary evaluative criteria, followed by a visual interpretation of the outcomes. The forthcoming sections will detail the visual interpretation; presently, we show the statistical measures criteria as follows: Accuracy (ACC):

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

In this context, True Positive (TP) is the number of abraded points correctly classified as 1; True Negative (TN) is the number of non-abraded points correctly classified as 0; False Positive (FP) is the number of non-abraded points incorrectly classified as 1; and False Negative (FN) is the number of abraded points incorrectly classified as 0.

The model accuracy is not the only criterion to measure the model's efficiency; Other statistical measures are also computed: True Positive Rate or the Sensitivity (SEN) which represents the percentage of correctly classified positive observations, True Negative Rate or Specificity (SPE) that represents the percentage of correctly identified negative observations, Precision or Positive Predictive Value (PPV), and Negative Predictive Value (NPV), in the following manner:

$$SEN = \frac{TP}{TP+FN}, \quad SPE = \frac{TN}{TN+FP} \quad (7)$$

$$PPV = \frac{TP}{TP+FP}, \quad NPV = \frac{TN}{TN+FN} \quad (8)$$

4. Results and Discussion

4.1 Model accuracy

The previous metrics can reflect the algorithm's efficiency in distinct aspects. As mentioned before, the dataset contains around 1,161,352 data points distributed along the length of the study area of the tunnel. Half of these points are assigned to train the algorithm, and the other half are used to test the accuracy of the output classifier. **Table (3)** displays the outcome results of the XGBoost algorithm runs considering three experiments; Entire tunnel; Part (A); and Part (B).

For the entire tunnel, the performance of ASM is satisfying and achieves an accuracy of 0.872 in training and 0.856 in testing, leading to an overall accuracy of 0.864. The model also shows high sensitivity in both training and testing sets, with an overall value of 0.872. The same applies to the specificity, with an overall value of 0.860. These values suggest a balanced response to abraded and non-abraded areas. In terms of predictive values, the model demonstrates a high precision of NPV = 0.874 in the training set and NPV = 0.970 in the testing set, affirming the model's high ability to

identify the non-abraded areas. Still, it gives comparatively lower values of PPV = 0.869 in the training set and overall PPV = 0.754, which reflects a less robust ability to detect abraded regions. This observed behavior may be explained by the tunnel's geometry, which tends to be more of a 1D simulation than a 2D analysis due to its elongated shape. Also, high variation of the damage patterns affects the algorithm's ability to capture the abrasion's details, particularly in part (A), where the floor has more complex patterns.

The accuracy of the straight section, part (A), is the lowest among the three experiments, with testing and overall accuracy of 0.853 and 0.864, respectively. In terms of sensitivity, part (A) trail shows a slight increase compared to the entire tunnel, which is consistent with it being a more focused area. It also exhibits higher precision in the testing phase, with NPV = 0.971 than in the training phase, with NPV = 0.879.

Part (B) has the best accuracy of the three experiments with an overall accuracy of 0.901. It also has the highest sensitivity for abraded areas, with 0.919, and the highest specificity for non-abraded areas, with 0.896. This is logical as Part (B) has a distinct pattern and a lower length-to-width ratio, making the algorithm more efficient in dealing with this specific part, resulting in the most precise outcomes with more than 98 % in the testing phase.

Table (3) Evaluation metrics of the XGBoost algorithm for three experiments with 36 parameters.

Tunnel Parts	Dataset	Points	ACC	SEN	SPE	PPV	NPV
All	Training	580673	0.872	0.875	0.869	0.870	0.874
	Testing	580679	0.856	0.862	0.855	0.531	0.970
	All Data	1161352	0.864	0.872	0.860	0.754	0.932
Part (A): Straight Section	Training	500674	0.875	0.880	0.869	0.87	0.879
	Testing	500678	0.853	0.868	0.850	0.525	0.971
	All Data	1001352	0.864	0.877	0.857	0.752	0.934
Part (B): Curved Section	Training	79999	0.905	0.919	0.891	0.894	0.916
	Testing	80001	0.897	0.905	0.896	0.622	0.980
	All Data	160000	0.901	0.915	0.894	0.810	0.956

4.2 Abrasion Susceptibility Mapping (ASM)

4.2.1 Whole tunnel

As previously noted, the original floor topography was transformed into damaged and non-damaged areas via inventory data, yielding the resultant observed topography. This observed topography underwent a comparative analysis with the simulated outcomes of the ASM model to ascertain the model's validity in the final evaluation.

With an accuracy of 0.86, the critical question arises: Can the ASM model accurately distinguish the varying patterns of abrasion associated with Sections A and B? Essentially, the intent is to test the ASM model's ability to identify the areas of damage within these sections. Referencing **Fig (6)**, the ASM model has proven its efficacy in discerning between areas of abrasion and non-abrasion. It has successfully captured the various patterns of damage in Section A and has also accurately detected the unique damage profile of Section B. The forthcoming subsections will provide a comprehensive elaboration on the ASM model's behavior and its precision in damage pattern recognition.

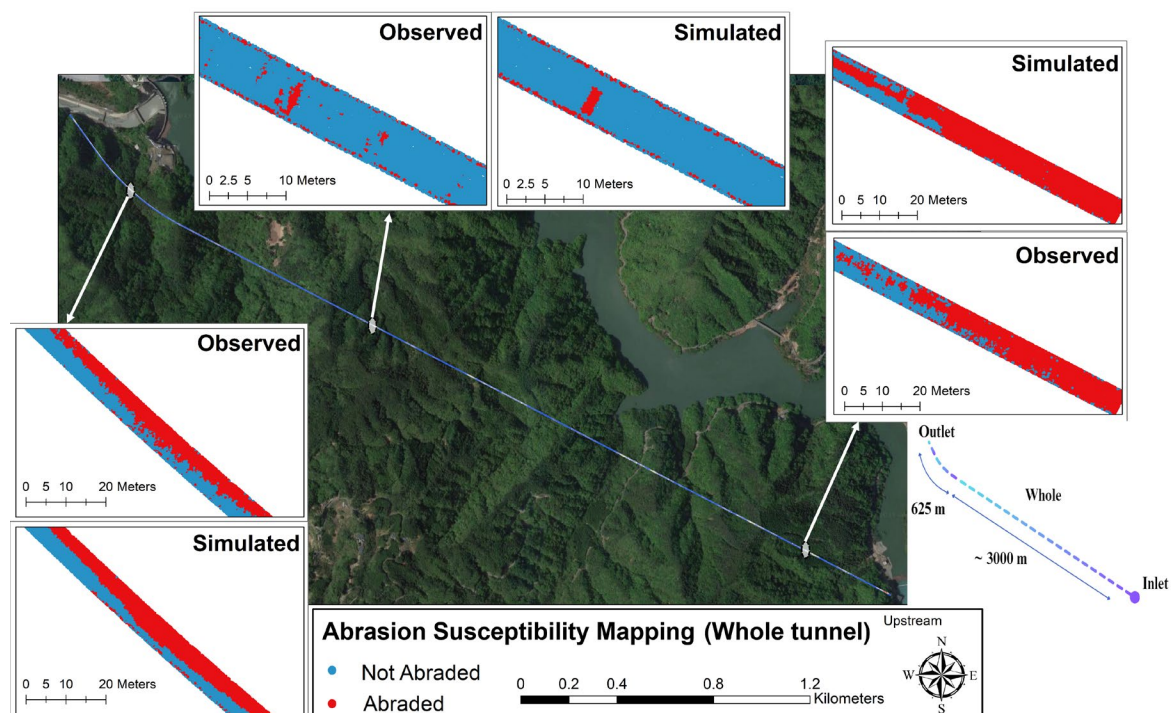


Fig (6) Comparative Analysis of Abrasion Susceptibility: Observed vs. Simulated Data for various patterns in the whole tunnel.

4.2.2 Straight section (Part A)

The inventory distribution of the XGBoost classifier, derived from the run of Part A, is illustrated in **Fig (7)**. Detailed topographic slots reveal the abrasion patterns in Part (A). **Fig (7-a)** shows the observed edged abrasion pattern of the straight section. **Fig (7-b)** indicates the wave-like abrasion pattern within the mid-region. **Fig (7-c)** displays the scatter damage area. It is important to note that whereas these patterns may overlap, as previously mentioned, the detailed views provided here clearly show each distinct type of abrasion pattern.

Figs (7-a', b', c') show the ASM's simulated projections. The comparison of observed measurements with simulation data highlights the algorithm's capability to accurately identify the most damaged areas along the various slots and expose different levels of performance:

- **Successful Detection Regions:** The model proficiently identified the damage along the edges and accurately assigned null values to the central area, **Fig (7-a')**, signifying minimal damage. The simulated results were consistent with the observations in these regions, even when it appeared as an isolated step-like shape on the left side. This accuracy is attributed to an obvious pattern over an extended distance, facilitating precise prediction. Similarly, when the damage exhibits a dominant scatter pattern **Fig (7-c)**, the model effectively recognizes and categorizes this region as significantly damaged, as demonstrated in **Fig (7-c')**.
- **Zones of Discrepancy:** The model exhibited limitations in certain zones, overclassifying intact sections as damaged, see **Figs (7-b, b')**. These areas presented a wave-like pattern with undamaged intervals among the abraded steps. The model's overestimation may stem from the tunnel's elongated dimensions relative to its width (4000 m to 7 m), suggesting a predominance of 1D analytical criteria over 2D. In other words, a more balanced ratio of areas could potentially enhance the model's precision in such patterns. For instance, a focused simulation conducted on a 500 m section of the tunnel, shown in **Fig (8)**, conducted under identical system configurations, resulted in a highly accurate delineation of the damaged areas, supporting this explanation.

4.2.3 Curved section (Part B)

Three topographical observation slots detail the abrasion patterns in Section B, see **Fig (9)**. **Fig (9-a)** illustrates the abrasion pattern of the straight section post-curvature, which is significantly influenced by the curvature effect, resulting in a skewed abrasion distribution. **Fig (9-b)** captures the abrasion within the mid-region of the curvature, highlighting the significant impact. **Fig (9-c)** presents the initial curvature region, delineating the transition in damage patterns from Section A to Section B.

Figs (9-a', b', c') depict the simulated outcomes of the ASM model. Comparative analysis between observations and simulation results reveals the algorithm's proficiency in identifying the most damaged regions across both the curvature and post-curvature sections. Section B demonstrates the highest fineness in the ASM's predictive capability, with accuracy surpassing 90% across training, validation, and overall assessment stages. Specifically, **Fig (9-a')** shows the ASM's adeptness in pattern recognition; it accurately identifies the damaged areas within the inner half of the section width. In **Fig (9-b')**, the ASM successfully locates all abrasion zones on the inner side and even discerns minor damages on the opposing outer side. Lastly, **Fig (9-c')** reveals a wave-like abrasion pattern, which the ASM model precisely maps. Despite a slight overestimation, the model effectively captures the distinct wave steps. Although this region exhibits a scattered damage pattern, the ASM effectively detects the most damaged areas. In the following section, we will explore the impact of the considered features.

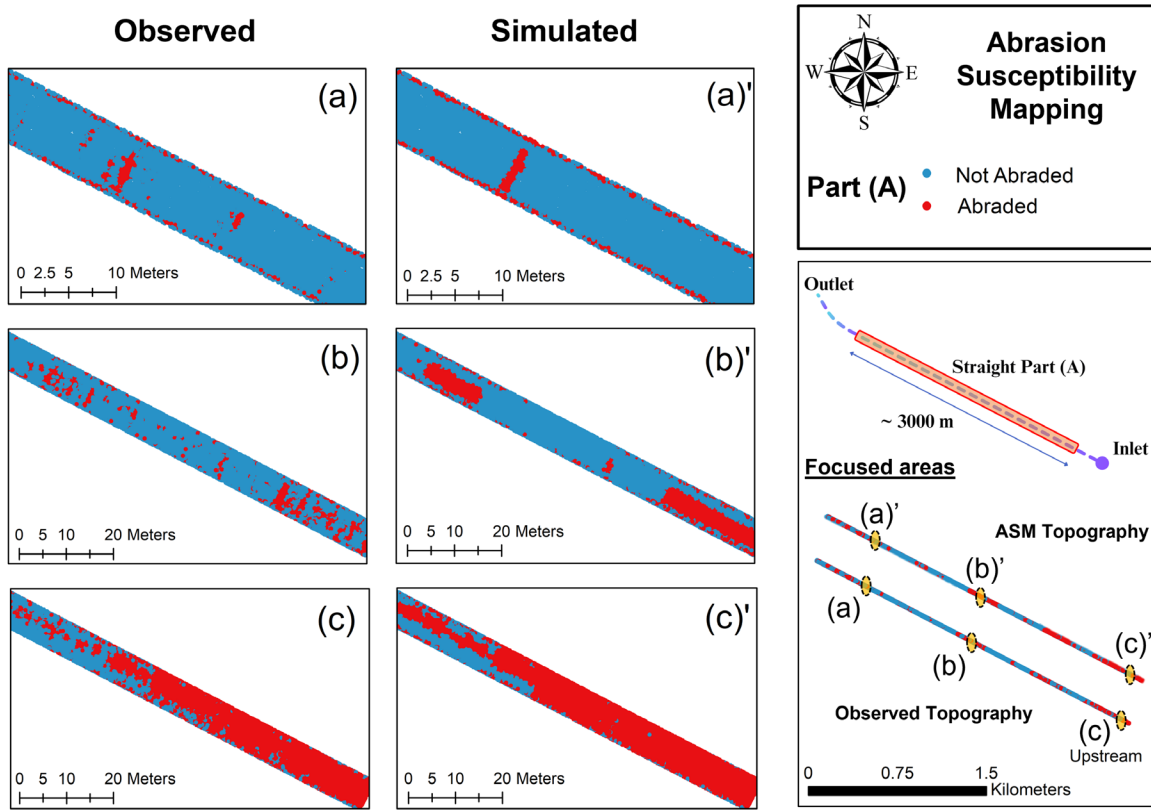


Fig (7) Comparative Analysis of Abrasion Susceptibility: Observed vs. Simulated Data for various patterns in part (A).

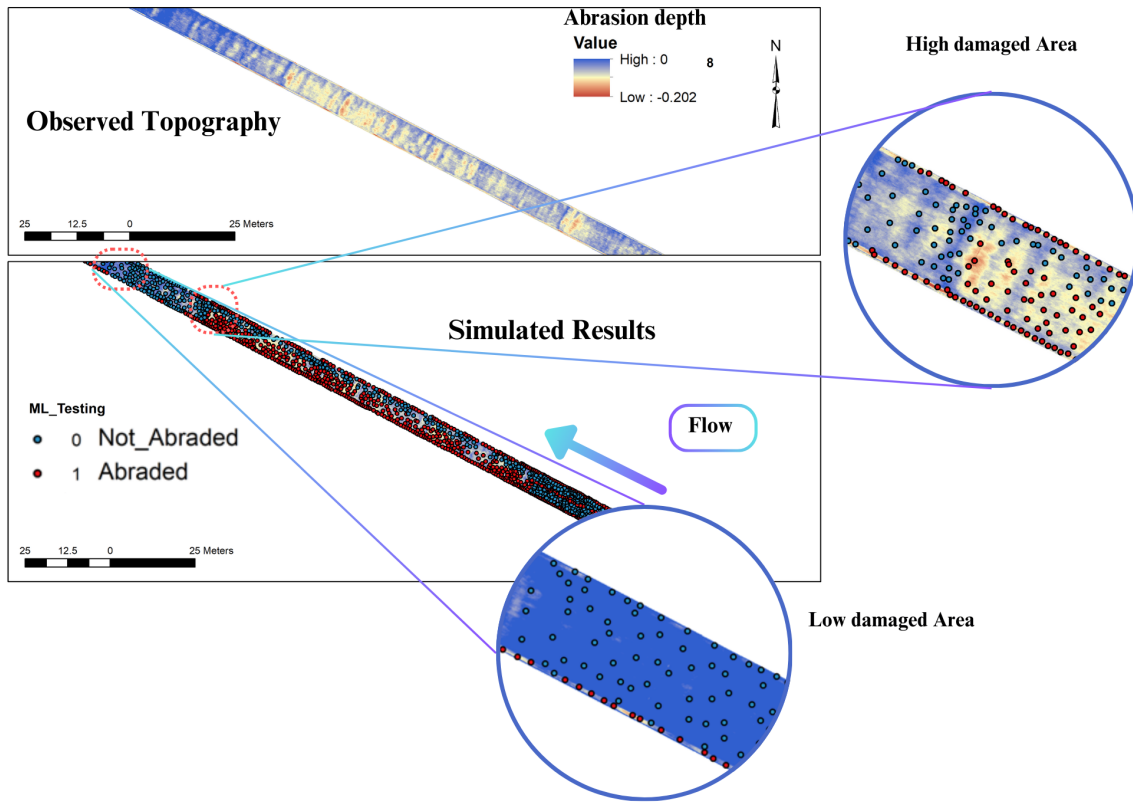


Fig (8) Abrasion prediction of a 500 m section of part (A) showing a very precise 2D abrasion prediction.

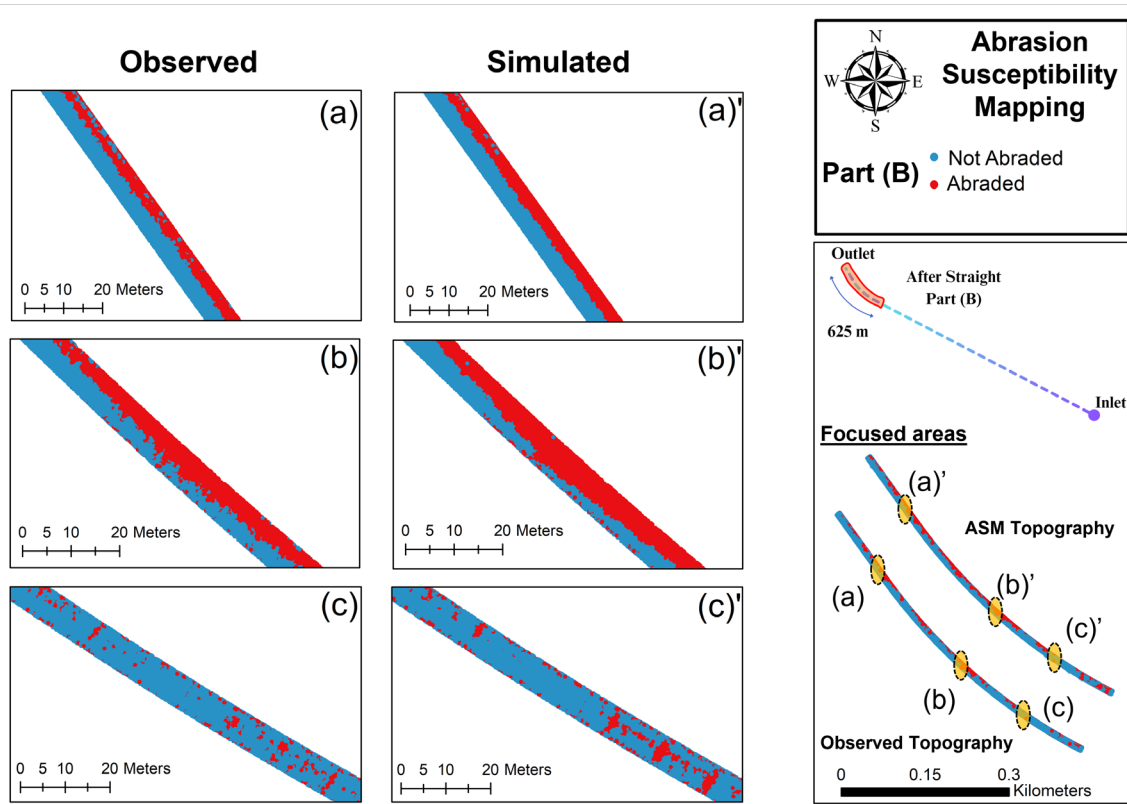


Fig (9) Comparative Analysis of Abrasion Susceptibility: Observed vs. Simulated Data for various patterns in part (B).

4.2.4 Input features influence

As mentioned before, the ASM model incorporates 36 input parameters: 4 geometric and 32 hydraulic, the latter corresponding to eight distinct events. To investigate the influence of input parameters on the model's performance, eight parameters were presented to assess the model's accuracy for the entire tunnel. These include the four fundamental geometric parameters and four representative hydraulic parameters. Each parameter corresponds to the respective values across all events. For instance, the 'water depth' parameter encapsulates the collective influence of water depths across all events. This aggregation method is applied to all hydraulic parameters, ensuring a comprehensive representation of the parameters while maintaining a manageable number of variables for analysis.

The analysis considered the individual impact of each parameter and the cumulative influence of all parameters excluding the one in question as shown in **Fig (10)**. The data indicates that hydraulic parameters exert an influence comparable to that of event time duration. This correlation is logical because hydraulic parameters are contingent upon flow discharges. The analysis suggests that three hydraulic parameters are sufficient for predictive modeling, as they maintain their predictive capability without the fourth parameter. However, when considering each parameter independently, velocities and water depths emerge as the most influential, with an accuracy of 80%. This observation is coping with extant scholarly research indicating that flow velocity exerts a more pronounced effect on the incidence of abrasion damage.

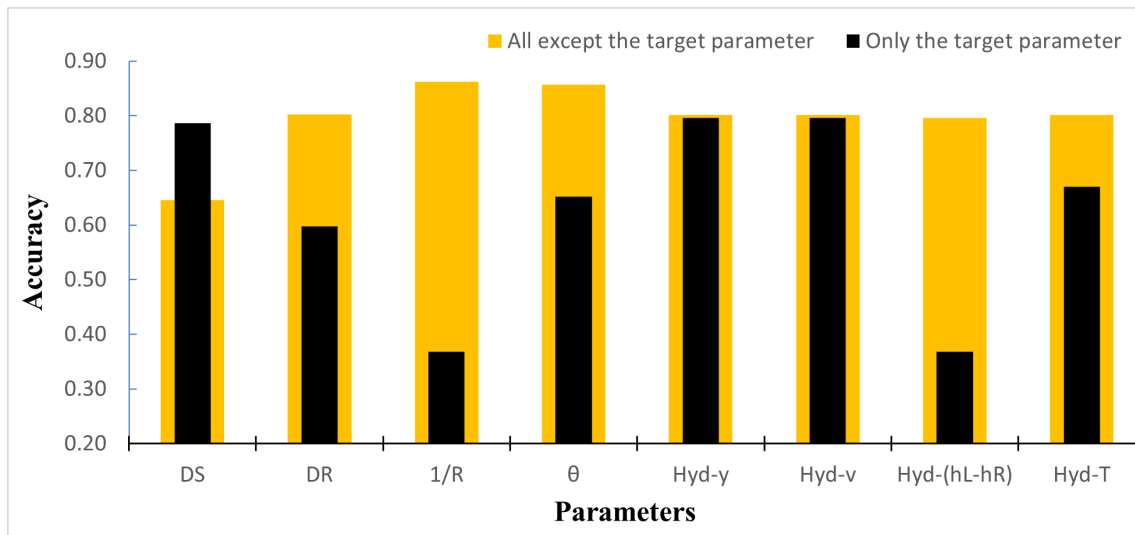


Fig (10) Parameter-based impact on ASM accuracy.

Conversely, water surface superelevation Δh demonstrates the least predictive power, with an accuracy below 40%. This diminished performance is attributed to its limited effect on tunnel curvature, as most of the tunnel is characterized by straight parts (with a ratio of 1 curvature to 10 straight sections). This observation is further corroborated by the geometric parameter Inverse R, which, along with water surface superelevation Δh , depends on the radius R, a measure directly associated with curvature.

When assessing the geometric parameters, the analysis reveals that all four parameters exert a substantial influence. Specifically, the parameter D_s is the most influential, affecting model

performance by over 75%. It is followed by the parameter theta at 65 %, D_R at 60%, and lastly, inverse R beneath 40%. This underscores the unique impact of each parameter, which cannot be substituted by the others. Notably, D_S is the singular parameter whose individual effect (only this parameter) surpasses the collective effect of the remaining parameters (all except this parameter), thereby emphasizing its significant influence. This may be attributed to the longitudinal characteristics of these structures which typically possess a greater length relative to their width. As a result, the model demonstrates a propensity to prioritize this 1D criterion in its evaluations.

The impact of each event is also evaluated, with the primary objective of assessing the potential effects of subsequent events, particularly from a hydraulic parameter perspective. To achieve that, the influence of the four geometric parameters is excluded from this analysis, focusing only on the four hydraulic parameters for each event. This approach enables a more effective assessment of parameter influence and facilitates a fundamental, in-depth analysis of the hydraulic dynamics.

Applying the same criteria to the events—both in isolation (only this event) and in combination (all except this event)—as depicted in **Fig (11)**, the precision of the outcome prediction varies with each event; for instance, Event 2, which had the smallest magnitude and shortest duration, yielded an accuracy of 72% (**Table (2)**), whereas Event 8, which was the most intense and had the longest duration, resulted in an accuracy of 78%. Even with a slight variance in model accuracy, it corresponds to the events' characteristics, thereby underscoring each event's significant role in the overall damage outcome. Moreover, the 'All except the event' analysis revealed a consistent accuracy of approximately 80%, highlighting the importance of event-based data in accurately tracking the resultant damage post-event.

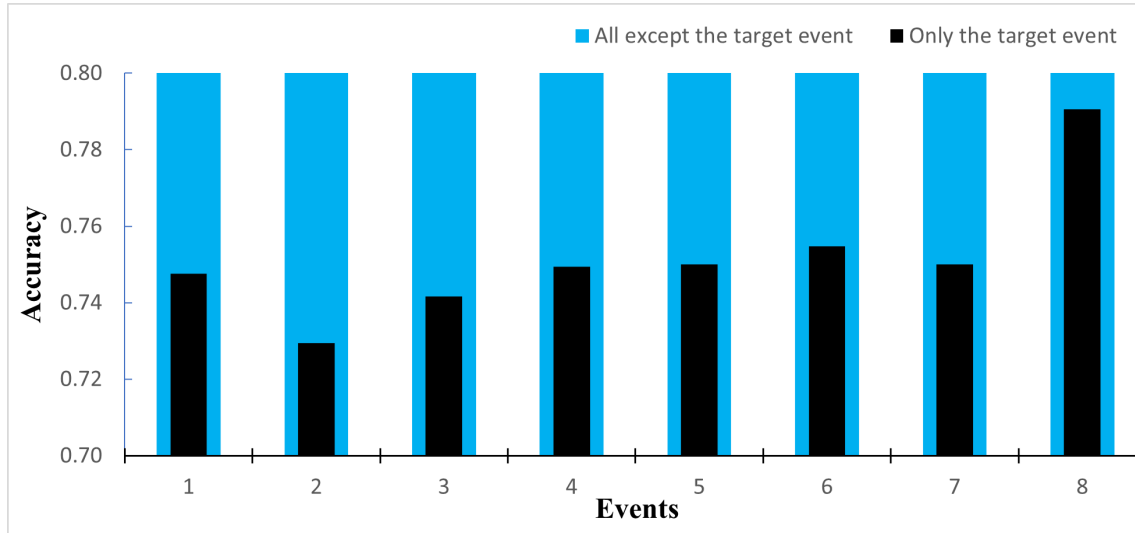


Fig (11) Event-based impact on ASM accuracy.

In summary, the recent revision aimed to improve clarity and precision in describing the performance of the ASM algorithm. The model effectively identifies abrasion damage in both straight sections with varying patterns and the unique pattern in the curved parts. The model's performance showcases its versatility in capturing complex abrasion patterns. However, attention to areas where the model exhibits some limitations is crucial for ongoing optimization, ensuring the continued accuracy and reliability of the susceptibility map across different conditions.

Whereas the ASM model provides valuable information related to 1D and 2D criteria that can identify different damage patterns, the quest for a precise methodology (tool) that can universally address cases remains unfulfilled. In a way of that, our introduction of ML classification represents a promising starting point. Also, for more consistency, there is a need for event-based data. With proper justification, these data can have the potential to link deeper between the abrasion damage and the principal causative factors providing us a comprehension understanding of this phenomenon.

5 Conclusion

The ASM model introduces an innovative ML-based approach for predicting spatial abrasion patterns on SBT floors. By employing the XGBoost algorithm and a comprehensive dataset of over one million data points, which integrates 32 hydraulic parameters from flood events along with 4

tunnel geometric features, the model offers both 1D and 2D characterizations of damaged areas. It captures various abrasion patterns with a remarkable overall accuracy of 0.864, even exceeding 0.9 in curved sections. The major findings of this research include:

- The ASM model effectively identifies abrasion damage in both straight sections with varying patterns and the unique pattern in the curved parts.
- The model exhibits high sensitivity and specificity, both exceeding 85 %, indicating strong predictive power in modelling.
- Some sections of the tunnel are prone to overestimation, likely due to the tunnel's elongated geometry (4000 m in length versus 7 m in width), suggesting that the model's 1D criteria may sometimes overshadow its 2D analysis. Focusing on more localized areas could enhance the model's accuracy in abrasion mapping.
- A limitation of the ASM model is its difficulty in detecting small, wave-like patterns, indicating a need for further refinement to balance the 1D and 2D analytical criteria.
- The abrasion patterns are significantly influenced by the flow regime within the tunnel, with 2D and 3D supercritical flows shaping different abrasion patterns. In the straight part, abrasion starts with scattered damage, which evolves into more defined edged patterns towards the downstream regions under 2D and 3D flows.
- The geometric configuration of the tunnel plays a critical role in abrasion mapping. In straight sections, the ASM model places significant importance on the longitudinal distance from the upstream boundary, while the curvature radius is a critical factor in curved sections.
- The analysis suggests that three out of four basic used hydraulic parameters are sufficient for effective predictive modeling, with water depth and velocity emerging as dominant factors influencing the model's accuracy.
- The performance of the ASM model highlights the value of event-based data, as it enables a more detailed understanding of the relationship between abrasion damage and the primary causative factors, providing a comprehensive insight into the abrasion process.

This study highlights the potential of integrating ML approach to improve the prediction and management of abrasion in SBTs. By implementing the hydraulic characteristics of upcoming flood events, the ASM model can evaluate the vulnerability of the tunnel to abrasion damage, contributing to more effective maintenance and operational strategies. This progress underscores the potential for developing more advanced models to offer detailed insights into tunnel damage patterns post-event. Future research directions could explore more additional influencing parameters and expanding to 3D criteria by implementing abrasion depths, which would represent a significant advancement over the current model.

6 Declaration of interest statement

The authors have no conflicts of state interest and affirm that this manuscript is not under consideration for publication elsewhere.

7 Data Availability Statement

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

8 References

- Abedi, R., Costache, R., Shafizadeh-Moghadam, H., & Pham, Q. B. (2022). Flash-flood susceptibility mapping based on XGBoost, random forest and boosted regression trees. *Geocarto International*, 37(19), 5479–5496. <https://doi.org/10.1080/10106049.2021.1920636>
- Alamoudi, F., Saber, M., A. Kantoush, S., Boulmaiz, T., Abdrabo, K. I., Abdelmoneim, H., & Sumi, T. (2023). Stormwater management modeling and machine learning for flash flood susceptibility prediction in Wadi Qows, Saudi Arabia. *Hydrological Research Letters*, 17(3), 62–68. <https://doi.org/10.3178/hrl.17.62>
- Albayrak, I., Arnold, R., Demiral-Yüzügüllü, D., Maddahi, M., & Boes, R. M. (2024). Field monitoring and modelling of sediment transport, hydraulics and hydroabrasion at Sediment Bypass Tunnels. *Journal of Hydro-Environment Research*. <https://doi.org/10.1016/j.jher.2024.05.002>
- Ansari, A., Rao, K. S., Jain, A. K., & Ansari, A. (2023). Deep learning model for predicting tunnel damages and track serviceability under seismic environment. *Modeling Earth Systems and Environment*, 9(1), 1349–1368. <https://doi.org/10.1007/s40808-022-01556-7>
- Arnold, R., Albayrak, I., & Boes, R. (2020). *Field monitoring of sediment transport, hydraulics, and hydro-abrasion at Swiss sediment bypass tunnels* (SI/501609-01, SFOE) [Technical].
- Aubert, G., Langlois, V. J., & Allemand, P. (2016). Bedrock incision by bedload: Insights from direct numerical simulations. *Earth Surface Dynamics*, 4(2), 327–342.
- Auel, C. (2014). *Flow characteristics, particle motion and invert abrasion in sediment bypass tunnels* (p. 1 Band) [ETH Zurich; Application/pdf]. <https://doi.org/10.3929/ETHZ-A-010243883>
- Auel, C., Albayrak, I., Sumi, T., & Boes, R. M. (2017a). Sediment transport in high-speed flows over a fixed bed: 1. Particle dynamics. *Earth Surface Processes and Landforms*, 42(9), 1365–1383. <https://doi.org/10.1002/esp.4128>
- Auel, C., Albayrak, I., Sumi, T., & Boes, R. M. (2017b). Sediment transport in high-speed flows over a fixed bed: 2. Particle impacts and abrasion prediction. *Earth Surface Processes and Landforms*, 42(9), 1384–1396. <https://doi.org/10.1002/esp.4132>
- Auel, C., Boes, R. M., & Sumi, T. (2016). Invert abrasion prediction at Asahi sediment bypass tunnel, Japan. *Journal of Applied Water Engineering and Research*.
- Beer, A. R., & Lamb, M. P. (2021). Abrasion regimes in fluvial bedrock incision. *Geology*, 49(6), 682.
- Beer, A. R., & Turowski, J. M. (2015). Bedload transport controls bedrock erosion under sediment-starved conditions. *Earth Surface Dynamics*, 3(3), 291–309. <https://esurf.copernicus.org/articles/3/291/2015/>
- Chatanantavet, P., & Parker, G. (2009). Physically based modeling of bedrock incision by abrasion, plucking, and macroabrasion. *Journal of Geophysical Research: Earth Surface*, 114(F4).
- Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794. <https://doi.org/10.1145/2939672.2939785>

- Demiral, D., Albayrak, I., Turowski, J. M., & Boes, R. M. (2022). Particle saltation trajectories in supercritical open channel flows: Roughness effect. *Earth Surface Processes and Landforms*.
- Demiral, D., Boes, R. M., & Albayrak, I. (2020). Effects of Secondary Currents on Turbulence Characteristics of Supercritical Open Channel Flows at Low Aspect Ratios. *Water*, 12(11), Article 11. <https://doi.org/10.3390/w12113233>
- Demiral Yüzügüllü, D. (2021). *Hydro-abrasion processes and modelling at hydraulic structures and steep bedrock rivers* [PhD Thesis]. ETH Zurich.
- Fenton, J. D. (2010). Calculating resistance to flow in open channels. *Alternative Hydraulics*, 5.
- Ha, S., Kim, H., Kim, K., Lee, H., & Kim, H. (2017). Algorithm for Economic Assessment of Infrastructure Adaptation to Climate Change. *Natural Hazards Review*, 18(4), 04017007. [https://doi.org/10.1061/\(ASCE\)NH.1527-6996.0000247](https://doi.org/10.1061/(ASCE)NH.1527-6996.0000247)
- Hang, H. T., Mallick, J., Alqadhi, S., Bindajam, A. A., & Abdo, H. G. (2024). Exploring Forest Fire Susceptibility and Management Strategies in Western Himalaya: Integrating Ensemble Machine Learning and eXplainable AI for Accurate Prediction and Comprehensive Analysis. *Environmental Technology & Innovation*, 103655. <https://www.sciencedirect.com/science/article/pii/S2352186424001317>
- ISHIBASHI, T. (1983). A hydraulic study on protection for erosion of sediment flush equipments of dams. *Proceedings of the Japan Society of Civil Engineers*, 1983(334), 103–112. https://www.jstage.jst.go.jp/article/jscej1969/1983/334/1983_334_103/_article/-char/ja/
- Johnson, J. P. L. (2014). A surface roughness model for predicting alluvial cover and bed load transport rate in bedrock channels. *Journal of Geophysical Research: Earth Surface*, 119(10), 2147–2173. <https://doi.org/10.1002/2013JF003000>
- Joshi, A., Vishnu, C., Mohan, C. K., & Raman, B. (2023). Application of XGBoost model for early prediction of earthquake magnitude from waveform data. *Journal of Earth System Science*, 133(1), 5. <https://doi.org/10.1007/s12040-023-02210-1>
- Kavzoglu, T., & Teke, A. (2022). Predictive Performances of Ensemble Machine Learning Algorithms in Landslide Susceptibility Mapping Using Random Forest, Extreme Gradient Boosting (XGBoost) and Natural Gradient Boosting (NGBoost). *Arabian Journal for Science and Engineering*, 47(6), 7367–7385. <https://doi.org/10.1007/s13369-022-06560-8>
- Koshiba, T. (2020). *Improvement of Signal Analysis for Surrogate Bedload Monitoring at Sediment Bypass Tunnels* [Thesis, Kyoto University]. <https://repository.kulib.kyoto-u.ac.jp/dspace/bitstream/2433/253255/1/ykogk04680.pdf>
- Koshiba, T., & Sumi, T. (2020). Bedload transport and abrasion monitoring at the Koshibu Dam sediment bypass tunnel and proposing countermeasures against the abrasion problem. *Icold1st*, 13-49–19.
- Lague, D. (2014). The stream power river incision model: Evidence, theory and beyond. *Earth Surface Processes and Landforms*, 39(1), 38–61. <https://doi.org/10.1002/esp.3462>

- Lamb, M. P., Dietrich, W. E., & Sklar, L. S. (2008). A model for fluvial bedrock incision by impacting suspended and bed load sediment. *Journal of Geophysical Research: Earth Surface*, 113(F3), 2007JF000915. <https://doi.org/10.1029/2007JF000915>
- Lee, H.-Y., Lin, Y.-T., Yunyou, J., & Wenwang, H. (2006). On three-dimensional continuous saltating process of sediment particles near the channel bed. *Journal of Hydraulic Research*, 44(3), 374–389. <https://doi.org/10.1080/00221686.2006.9521689>
- Mitsubishi. (2013). *Consistently Accurate Measurement*. http://www.mitsubishielectric.co.jp/mms/pdf/mms_e.pdf
- MMS Website. (2024). *Mitsubishi Electric, Latest Version of GPS, MMS*. <http://www.mitsubishielectric.co.jp/mms/tokucho.html>
- Müller-Hagmann, M. (2018). *Hydroabrasion by high-speed sediment-laden flows in sediment bypass tunnels* [PhD Thesis]. ETH Zurich.
- Müller-Hagmann, M., Albayrak, I., Auel, C., & Boes, R. M. (2020a). Field Investigation on Hydroabrasion in High-Speed Sediment-Laden Flows at Sediment Bypass Tunnels. *Water*, 12(2), Article 2. <https://doi.org/10.3390/w12020469>
- Müller-Hagmann, M., Albayrak, I., Auel, C., & Boes, R. M. (2020b). Field Investigation on Hydroabrasion in High-Speed Sediment-Laden Flows at Sediment Bypass Tunnels. *Water*, 12(2), Article 2. <https://doi.org/10.3390/w12020469>
- Nakagawa, H. (2017). *Turbulence in open channel flows*. Routledge. <https://www.taylorfrancis.com/books/mono/10.1201/9780203734902/turbulence-open-channel-flows-hiroji-nakagawa>
- Nakajima, H., Otsubo, Y., & Omoto, Y. (2015). Abrasion and corrective measures of a sediment bypass system at Asahi Dam. *Proc. Int. Workshop on Sediment Bypass Tunnels*, 21–32.
- Nezu, I., & Nakagawa, H. (1993). Turbulence in open-channel flows, *iahr-monogr. Ser., A*, 1–281.
- Ramraj, S., Uzir, N., Sunil, R., & Banerjee, S. (2016). Experimenting XGBoost algorithm for prediction and classification of different datasets. *International Journal of Control Theory and Applications*, 9(40), 651–662. https://www.researchgate.net/profile/Shatadeep-Banerjee/publication/318132203_Experimenting_XGBoost_Algorithm_for_Prediction_and_Classification_of_Different_Datasets/links/595b89b0458515117741a571/Experimenting-XGBoost-Algorithm-for-Prediction-and-Classification-of-Different-Datasets.pdf
- Reinauer, R., & Hager, W. H. (1997). Supercritical bend flow. *Journal of Hydraulic Engineering*, 123(3), 208–218.
- Saber, M., Boulmaiz, T., Guermoui, M., Abdrabo, K. I., Kantoush, S. A., Sumi, T., Boutaghane, H., Hori, T., Binh, D. V., Nguyen, B. Q., Bui, T. T. P., Vo, N. D., Habib, E., & Mabrouk, E. (2023). Enhancing flood risk assessment through integration of ensemble learning approaches and physical-based hydrological modeling. *Geomatics, Natural Hazards and Risk*, 14(1), 2203798. <https://doi.org/10.1080/19475705.2023.2203798>
- Saber, M., Boulmaiz, T., Guermoui, M., Abdrabo, K. I., Kantoush, S. A., Sumi, T., Boutaghane, H., Nohara, D., & Mabrouk, E. (2022). Examining LightGBM and CatBoost models for wadi flash

- flood susceptibility prediction. *Geocarto International*, 37(25), 7462–7487. <https://doi.org/10.1080/10106049.2021.1974959>
- Scheingross, J. S., Brun, F., Lo, D. Y., Omerdin, K., & Lamb, M. P. (2014). Experimental evidence for fluvial bedrock incision by suspended and bedload sediment. *Geology*, 42(6), 523–526.
- Seidl, M. A., Dietrich, W. E., Schmidt, K. H., & De Ploey, J. (1992). The problem of channel erosion into bedrock. *Functional Geomorphology*, 23, 101–124. [https://books.google.com/books?hl=en&lr=&id=kTSBAAAAQBAJ&oi=fnd&pg=PT362&dq=Seidl,+M.A.+%26+Dietrich,+W.E.+\(1992\)+The+problem+of+channel+erosion+into+bedrock.+Catena+Supplement,+23,+101%E2%80%93124.&ots=KkNy-1M1lZ&sig=_WVCAv3durnocysG7Kg3uEd2-lU](https://books.google.com/books?hl=en&lr=&id=kTSBAAAAQBAJ&oi=fnd&pg=PT362&dq=Seidl,+M.A.+%26+Dietrich,+W.E.+(1992)+The+problem+of+channel+erosion+into+bedrock.+Catena+Supplement,+23,+101%E2%80%93124.&ots=KkNy-1M1lZ&sig=_WVCAv3durnocysG7Kg3uEd2-lU)
- Sklar, L. S., & Dietrich, W. E. (2001). Sediment and rock strength controls on river incision into bedrock. *Geology*, 29(12), 1087–1090. [https://doi.org/10.1130/0091-7613\(2001\)029<1087:SARSCO>2.0.CO;2](https://doi.org/10.1130/0091-7613(2001)029<1087:SARSCO>2.0.CO;2)
- Sklar, L. S., & Dietrich, W. E. (2004). A mechanistic model for river incision into bedrock by saltating bed load. *Water Resources Research*, 40(6). <https://doi.org/10.1029/2003WR002496>
- T.D.I.M Office. (2021). Tenryu River Dam Integrated Management Office. <https://www.cbr.mlit.go.jp/tendamu/>
- Turowski, J. M. (2009). Stochastic modeling of the cover effect and bedrock erosion. *Water Resources Research*, 45(3), 2008WR007262. <https://doi.org/10.1029/2008WR007262>
- Turowski, J. M. (2012). Semi-alluvial channels and sediment-flux-driven bedrock erosion. *Gravel-Bed Rivers: Processes, Tools, Environments*, 399–418.
- Turowski, J. M., & Hodge, R. (2017a). A probabilistic framework for the cover effect in bedrock erosion. *Earth Surface Dynamics*, 5(2), 311–330. <https://doi.org/10.5194/esurf-5-311-2017>
- Turowski, J. M., & Hodge, R. (2017b). A probabilistic framework for the cover effect in bedrock erosion. *Earth Surface Dynamics*, 5(2), 311–330. <https://esurf.copernicus.org/articles/5/311/2017/>
- Turowski, J. M., Lague, D., & Hovius, N. (2007). Cover effect in bedrock abrasion: A new derivation and its implications for the modeling of bedrock channel morphology. *Journal of Geophysical Research: Earth Surface*, 112(F4), 2006JF000697. <https://doi.org/10.1029/2006JF000697>
- Wang, X., Xiao, M., Liu, Y., Guo, J., Qin, Y., & Zhang, Y. (2024). A rapid and efficient method for flash flood simulation based on deep learning. *Engineering Applications of Computational Fluid Mechanics*, 18(1), 2407016. <https://doi.org/10.1080/19942060.2024.2407016>
- Yaghoubzadehfard, A., Lumantarna, E., Herath, N., Sofi, M., & Rad, M. (2024). Ensemble learning-based structural health monitoring of a bridge using an interferometric radar system. *Journal of Civil Structural Health Monitoring*. <https://doi.org/10.1007/s13349-024-00789-7>
- Zhang, T., Li, D., East, A. E., Kettner, A. J., Best, J., Ni, J., & Lu, X. (2023). Shifted sediment-transport regimes by climate change and amplified hydrological variability in cryosphere-fed rivers. *Science Advances*, 9(45), eadi5019. <https://doi.org/10.1126/sciadv.adi5019>

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CHAPTER 6

Advanced Abrasion Susceptibility and Depth Mapping [ASDM Model] (A Comprehensive Approach to Abrasion Prediction)

6.1. Summary

Building on the 2D framework, this study presents the first three-dimensional Abrasion Susceptibility Depth Model (ASDM) for SBTs, capable of predicting where and how deep abrasion will occur. Using the same Koshiibu tunnel, eight consecutive flood events were measured through laser scans at 2 cm resolution, resulting in over one million abrasion-depth measurements. A set of 36 static and event-based geometric and hydraulic features (e.g., local curvature gradients, peak flood velocities) was input into an XGBoost regression model, calibrated using a 50/50 train–test split. The ASDM achieved a Pearson correlation coefficient of 0.861 and a Nash–Sutcliffe Efficiency of 0.748 overall, with top segments surpassing $R > 0.90$ and $NSE > 0.85$ — highlighting its ability to reconstruct complex 3D damage geometries. By providing high-resolution depth maps, this model addresses the

long-standing need for spatially explicit wear-depth prediction, enabling real-time condition monitoring and improved design of SBTs.

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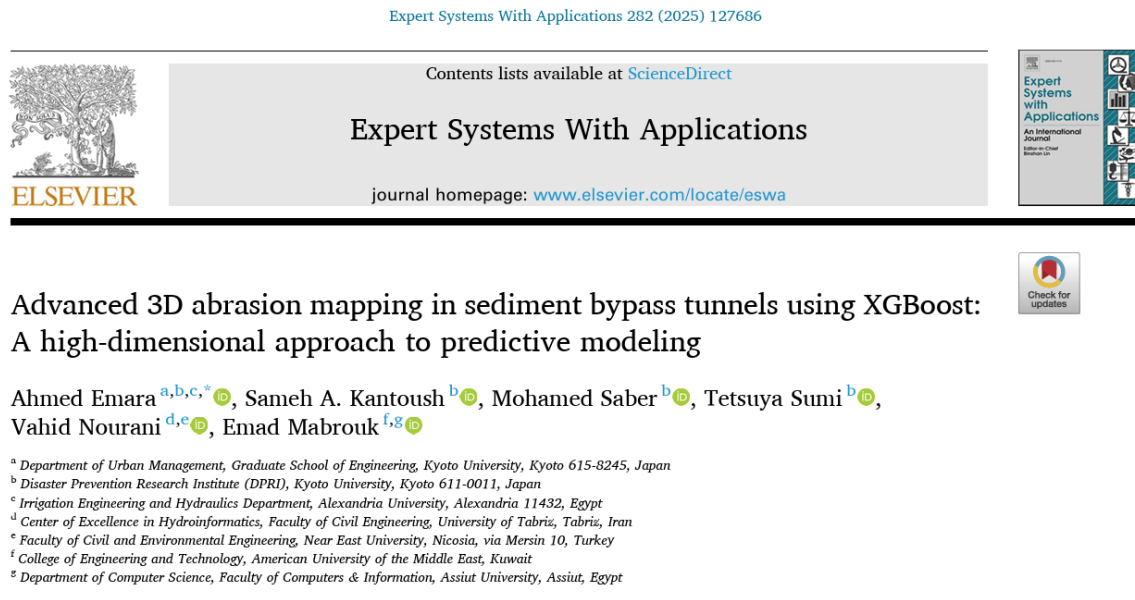


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6.2. Paper Content

Advanced 3D Abrasion Mapping in Sediment Bypass Tunnels Using XGBoost: A High-Dimensional Approach to Predictive Modeling

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Abstract

Reservoir sedimentation is mitigated by diverting sediment-laden floodwaters through Sediment Bypass Tunnels (SBTs). However, these tunnels face significant challenges due to hydro-abrasive damage, threatening their long-term sustainability. Predicting this abrasion is challenging due to the complex interactions between flow hydraulics and sediment transport, compounded by limited high-quality data. In this study, we investigate, for the first time, the potential of using the eXtreme Gradient Boosting (XGBoost) Machine Learning (ML) algorithm to predict both the spatial distribution and depths of abrasion throughout the tunnel. The Koshiyama tunnel in Japan, which spans approximately 4 km, was chosen as the case study. High-resolution field data were acquired using laser scanning with a spatial resolution of 2 cm. We evaluated three experimental scenarios: the entire tunnel, the straight section, and the curved section. Controlling factors for abrasion (36 variables) were derived from geometric and hydraulic features observed during eight flood events. The abrasion inventory map, with over 1 million data points indicating abrasion depths, was split equally for training and testing the XGBoost algorithm. Results suggest that the model effectively predicts spatial abrasion and depths within the tunnel, achieving an overall correlation coefficient (R) of 0.861 and a Nash-Sutcliffe Efficiency (NSE) of 0.748, with certain sections surpassing 0.90 and 0.85, respectively. Despite some limitations, the developed abrasion susceptibility model effectively presents various complex damage patterns throughout the tunnel. These findings highlight the potential of ML techniques in abrasion prediction and provide valuable insights for future research.

Keywords: Sediment Bypass Tunnels, Flood Event Hydrodynamics, Abrasion Inventory Mapping, Abrasion Damage 3D Prediction, Machine Learning in Hydraulics, Machine Learning for Spatial Prediction.

1. Introduction

Climate change exacerbates global sediment dynamics and reservoir sedimentation, leading to elevated sediment transport rates (Ha et al., 2017; Owens, 2020; Walling, 2009; Zhang et al., 2023). These heightened rates, in addition to accelerated flow velocities, result in bedrock incision within high-gradient mountain streams and significant hydro-abrasion and cavitation damage to hydraulic

structures, including dam outlets, weirs, sediment flushing channels, and, of particular interest, Sediment Bypass Tunnels (SBTs).

Advancing our comprehension of hydro-abrasion phenomena and developing predictive models is imperative for enhancing fluvial dynamics and landscape evolution forecasts. This progression in knowledge is also critical for the design and operational management of sustainable hydraulic structures capable of withstanding the multifaceted challenges posed by hydro-abrasion processes. Hydro-abrasion in SBTs is a complex phenomenon characterized by high-velocity, sediment-laden flows under typically supercritical conditions. This environment leads to high-energy particle impacts on the tunnel surfaces, resulting in significant structural damage.

The primary approach to understanding and quantifying this phenomenon has been experimental. These studies have yielded crucial formulas, forming the foundation of our knowledge of abrasion in SBTs. Notable contributions include work by (Auel et al., 2017a, 2017b; Demiral et al., 2020, 2022; ISHIBASHI, 1983; Scheingross et al., 2014; Sklar & Dietrich, 2001). Analytical and numerical methods are implemented in more limited and specific cases. These approaches, while valuable, have been constrained by the complexity of the phenomenon and computational limitations (Aubert et al., 2016; Johnson, 2014; Lee et al., 2006; Turowski, 2009; Turowski et al., 2007; Turowski & Hodge, 2017). A significant advancement came in 2020 when (Müller-Hagmann et al., 2020) introduced direct field measurements to calibrate the existing experimental formulas. This approach was further refined by (Albayrak et al., 2024), marking a crucial step in bridging the gap between laboratory findings and real-world applications.

The culmination of these efforts has led to the development of two predominant model types: (I) stream power incision models (Lague, 2014; Seidl et al., 1992), which correlate abrasion rates with flow discharges, and (II) mechanistic models (Albayrak et al., 2024; Auel et al., 2017b; Chatanantavet & Parker, 2009; Demiral et al., 2022; ISHIBASHI, 1983; Lamb et al., 2008; Sklar & Dietrich, 2004), which extend considerations to include the impact of sediment particles. While these models consider various parameters related to hydraulics, sediment, and material characteristics, they lack the incorporation of geometric features, as they provide bulk estimates (average values) for all tunnel abrasions. Although fundamental, these approaches do not extend to higher-dimensional representations (e.g., one-dimensional (1D), two-dimensional (2D), and three-dimensional (3D))

that would facilitate the detection of localized damage. The mechanistic and stream power models yield averaged abrasion volumes or rates, lacking the spatial resolution necessary to pinpoint critical damage zones. Mechanistic models suggest that as the bedload mass increases, the abrasion depths also increase, indicating a direct relationship between sediment load and damage volume. However, when damage thickness exceeds certain limits, these models become constrained, as the reliability of key parameters diminishes beyond specific thresholds (Auel et al., 2017b; Chatanantavet & Parker, 2009; Demiral et al., 2022; ISHIBASHI, 1983). Beyond their inability to account for localized effects, these models also show deviations due to uncertainties in parameter estimation. For instance, Auel et al., (2016) reported a 138% overestimation of tunnel abrasion volume compared to observed data; even after excluding some terms, the error persisted at 30%, which is still substantial. Similarly, Müller-Hagmann et al., (2020) discovered that uncertainties in one key parameter resulted in an 87–91% error in abrasion rate predictions, significantly affecting the final results. In a recent study by (Albayrak et al., 2024), refinements to this parameter successfully reduced the deviation to 45%. However, this discrepancy remains notable and highlights the need for further enhancements in model accuracy. These limitations underscore the urgent requirement for a more comprehensive approach to predict abrasion in 1D, 2D, and 3D contexts.

Developing a mathematical model that accurately describes the processes occurring within the tunnel has proven nearly impossible due to the complex interactions between flow hydraulics, sediment transport, geometry, and material properties. Consequently, statistical models and Machine Learning (ML) approaches have emerged as promising alternatives to unravel these complexities. The choice between traditional statistical models and ML algorithms for predictive modeling depends on the complexity of the data and the application's specific requirements. Traditional models, such as ordinary least squares and generalized linear models, are based on strong theoretical foundations, making them suitable for hypothesis-driven research. However, these models rely on strict assumptions, such as linearity, normality of residuals, and independence of observations, which often do not hold in real-world datasets (Hastie et al., 2009). In scenarios like abrasion prediction, where relationships are inherently nonlinear, traditional models fail to capture the underlying patterns effectively. This limitation highlights the need for more flexible approaches to manage complex, high-dimensional data. ML algorithms offer a more adaptable solution by minimizing assumptions about the data structure. These models are designed to learn patterns from

data automatically, excelling at capturing nonlinearities, interactions, and dependencies that traditional regression models struggle to address. Furthermore, Leo Breiman's influential concept of the "two cultures" in statistical modeling underscores the advantages of data-driven algorithmic approaches over traditional parametric methods, particularly when dealing with complex and poorly understood processes (Breiman, 2001). This perspective has been validated in numerous competitions and real-world applications, where ML models consistently achieve state-of-the-art results in classification and anomaly detection tasks. ML techniques have been widely applied to various real-world problems (Alzubi, 2025; Alzubi et al., 2022; An et al., 2025; Waqar, 2024). One notable application is in risk assessment, particularly regarding flood risk assessment and mitigation. Several ML algorithms have shown significant efficacy in generating flood susceptibility maps, as evidenced by recent studies (Abedi et al., 2022; Alamoudi et al., 2023; Saber et al., 2022, 2023). These investigations have consistently confirmed the high predictive accuracy of ML approaches in this field. Among various ML techniques, eXtreme Gradient Boosting (XGBoost) has emerged as a particularly powerful algorithm for predictive modeling. Several key features make XGBoost exceptionally well-suited for abrasion prediction. Firstly, it is optimized for handling large datasets with millions of records through parallel processing and out-of-core computation, ensuring scalability. Secondly, it effectively manages missing or sparse data, a common challenge in real-world applications. Thirdly, XGBoost incorporates regularization terms that help mitigate overfitting, a critical concern when working with high-dimensional datasets and complex feature interactions. Additionally, as part of the gradient-boosting family, it reduces prediction errors in regression modeling (Natekin & Knoll, 2013). Empirical studies consistently demonstrate that XGBoost outperforms other ML algorithms in terms of predictive accuracy and computational speed, making it an ideal choice for addressing complex phenomena (Ali et al., 2024; Demir & Şahin, 2022; Qi et al., 2025). Notable applications include flood susceptibility mapping (Abedi et al., 2022) and various environmental and engineering applications. The algorithm has also been recognized for its effectiveness in landslide susceptibility mapping (Kavzoglu & Teke, 2022) and forest fire prediction (Hang et al., 2024), showcasing its proficiency with complex environmental datasets. Extending its application to geohazard assessment, Joshi et al., (2023) employed XGBoost to predict seismic events using historical data, highlighting its potential in earthquake risk management. Notably, structural health monitoring (Yaghoubzadehfard et al., 2024) demonstrated XGBoost's robustness

by effectively forecasting bridge damages even when faced with incomplete modal parameters, a common challenge in real-world structural assessments. Despite the extensive application of ML techniques in various geohazard domains, their use in detecting abrasion damage in SBTs remains unexplored.

To address the earlier gaps, our previous work (Emara et al., 2025) introduced an abrasion susceptibility mapping approach utilizing ML. Considering both 1D and 2D criteria, this novel method defined and distinguished between damaged and non-damaged areas within SBTs, representing a significant step towards more localized mapping. Building upon this foundation, the present study advances the precision and applicability of abrasion prediction in SBTs. To the best of our knowledge, this study is the first to explore the application of the XGBoost algorithm for developing a 3D Abrasion Susceptibility and Depth Model (ASDM) in SBT floors. ML methods can articulate the complex relationships between abrasion damage and the key controlling factors, providing both general and localized insights. By overcoming the limitations of traditional models, our research introduces the innovative use of ML techniques in this field. The 3D aspect not only predicts the spatial distribution of abrasion throughout the tunnel but also the abrasion depths. This study employs the XGBoost algorithm as a regression model, representing a novel application of the algorithm in this context. The Koshibu SBT in Japan, approximately 4 km long, was selected as the case study. We evaluated three experimental scenarios: the entire tunnel, the straight section, and the curved section. Field data for the tunnel topography were measured at high resolution using laser scanning tools, achieving a spatial resolution of 2 cm × 2 cm. Our methodology integrated hydraulic characteristics from eight distinct flood events alongside geometric parameters as controlling factors. Additionally, we examined the influence of input parameters and consecutive flood events on model precision. This study highlights the potential of integrating ML approaches to enhance the prediction and management of abrasion in SBTs. The ASDM model can determine the tunnel's vulnerability to abrasion damage and depths by integrating the hydraulic characteristics of forthcoming flood events. This provides an accurate estimation of abrasion volumes at a general level and with localized scales, thereby enhancing the effectiveness of maintenance and operational strategies.

2. Koshiibu Case Study

The Koshiibu Dam, located in Nagano Prefecture, Japan, on the Koshiibu River—a left tributary of the Tenryu River—was constructed in 1969 and is managed by the Ministry of Land, Infrastructure, Transport, and Tourism (MLIT). Standing at a height of 105 meters, the dam’s catchment area spans 288 km², mostly covered by forest and sediment-prone regions. Consequently, the reservoir experiences significant and severe flooding, leading to a high sedimentation rate.

The Koshiibu SBT, which began its operation in 2016, plays a crucial role in mitigating the impact of sediment accumulation within the reservoir. The tunnel, extending approximately 3.982 kilometers, is strategically engineered to reroute high-sediment water flows, thereby preventing sediment accumulation in the associated reservoir, as illustrated in **Fig. (1)**.

Structurally, the Koshiibu SBT has a linear arrangement design; however, the section nearing the outlet, about 700 meters from it, transitions into a curved path that follows the orographic right with a curvature radius of 1000 meters. The tunnel’s cross-section measures 6.5 meters in width and 7.2 meters in height, with a maximum engineered discharge capacity of 370 cubic meters per second. The longitudinal gradient of the tunnel is characterized by an initial acceleration zone at the entrance, with a steep slope of 20%, which then gradually converted to a milder slope of 2% for the remainder of the tunnel. The first 50 meters of the tunnel, constituting the acceleration zone, are designed to impart sufficient kinetic energy to transport sediment-laden floodwater. Moreover, the inlet section is designed with an enlarged cross-sectional profile to maximize the entrance efficiency of sediment inflows. At the tunnel’s outlet, an array of instruments, including geophone plates, are installed to facilitate quantifying sediment properties (Koshiiba & Sumi, 2020).

2.1 Tunnel Divisions

Upon close visual examination of the tunnel topography, complex abrasion was observed through the tunnel length with notable intensity in the inlet and outlet regions. This is attributed to the unique geometrical features of the inlet zone and the measurement installations in the outlet zone, which amplify more turbulent variations in these areas. Therefore, these zones have been omitted from the current study to eliminate boundary effects on the results. The investigation involves a three-part analysis of the SBT system, including the entire tunnel (referred to as “all tunnel” and

combining Parts A and B), a straight section (Part A), and a curved section (Part B), as shown in **Fig. (1)**.

In the first division (Part A), the rectilinear expanse, measuring approximately 3000 meters, contains a variety of abrasion patterns. The second segment (Part B) begins with a curved section, with an arc length of 450 meters, followed by a straight section approximately 175 meters long. This segment features a distinct damage pattern, which will be discussed in more detail later.

3. Methodological Framework

The research methodology illustrated in **Fig. (2)** employs a systematic, multi-phase approach. The data acquisition stage is initially conducted, including topographic laser scanning and collecting valuable information about flood events that cause damage. This entails a preprocessing phase that involves the conversion of raw topographic data into 3D rendering format, followed by extracting abrasion inventory data and fundamental geometric and hydraulic variables. Data refinement procedures, including normalization and assembly, are then applied to ensure dataset consistency for ML algorithm implementation. The methodology progresses to the development and training of the ASDM model. Post-modeling phases incorporate both quantitative and qualitative assessments. Quantitative evaluation utilizes statistical analysis and validation metrics, while qualitative assessment involves comparative analysis between observed topography and model-simulated results. The details are explicated in the following.

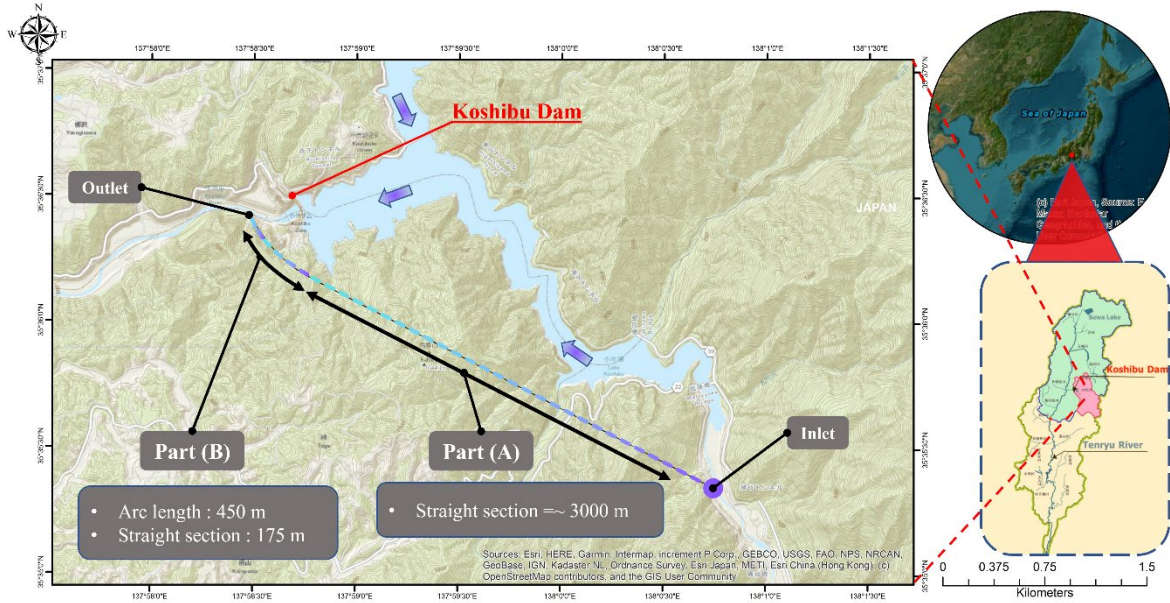


Fig. (12) Koshiyuu SBT case study having the parts under consideration.

3.1 Data Acquisition

The ASDM model development and validation required high-precision mapping of the tunnel floor's damaged surfaces. High-resolution 3D point clouds were obtained by laser scanning all tunnel floor locations. This topographic data, representing the damaged floor (designated as the abrasion map), encompasses two years. During this period, the tunnel experienced eight distinct flood events. Data processing and Digital Elevation Model (DEM) generation were executed using specialized geospatial software "ArcGIS and ParaView." The hydraulic characteristics are carefully adjusted to represent the eight flood events, and the geometrical features are precisely configured to reflect the conditions inside the tunnel. The details of these procedures are discussed in the following subsections.

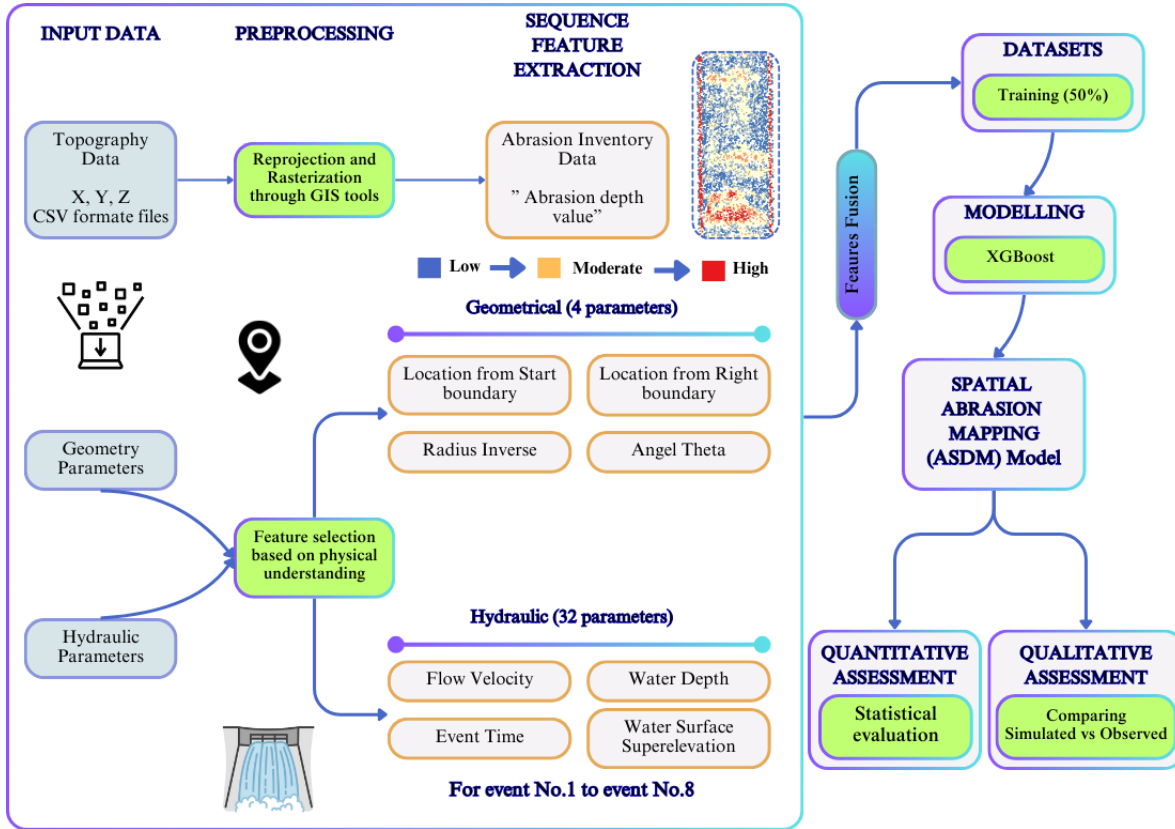


Fig. (13) Overall methodology implemented in this investigation.

3.1.1 Laser Scanning

The laser scanning dataset utilized in this analysis was procured via a Mitsubishi Mobile Laser Scanner (MMS), sourced from the Koshiu dam office (T.D.I.M Office, 2021). This MMS system is designed to integrate 3D laser point clouds with Geographic Information System (GIS) data, ensuring high precision in spatial measurements. This integration is particularly beneficial in complex infrastructures like bypass tunnels, where extended distances and various environmental factors could affect measurement accuracy. Calibration was conducted using the Flaechen Korrektur Parameter (FKP) method for enhancing GPS linking (Mitsubishi, 2013; MMS Website, 2024). The resultant dataset comprises a pixel resolution of 2 cm x 2 cm, derived from point clouds spaced at 2 cm intervals, facilitating the generation of a high-resolution DEM of the tunnel surface. The DEM demonstrates the extent of abrasion damage, with depth variations from the original floor surface

(0 cm) to over (20 cm) in certain areas, providing a foundational dataset for the ASDM's development and validation.

3.1.2 Abrasion Inventory Mapping

The algorithm employs DEM pixels to establish correlations between observed damage depths and various controlling factors. Each pixel is assigned a singular abrasion depth value derived from the abrasion inventory data. To generate this dataset, approximately 1,161,352 data points were systematically distributed throughout the tunnel's study area. Specifically, 1,001,352 data points were allocated for part (A) and 160,000 data points for part (B), as illustrated in **Fig. (3)**.

Given the high-resolution nature of the dataset, conversion of these data points to an interpolated surface would be counterproductive. Such a conversion might inadvertently alter some of the original topographic characteristics. So, a direct point-based classification approach was adopted to preserve data integrity and granularity while facilitating meaningful analysis.

To categorize abrasion severity, five distinct classes were established based on observed abrasion depths:

1. Not abraded: 0 m
2. Very low abrasion: ~ 0.01 m
3. Low abrasion: ~ 0.02 m
4. Moderate abrasion: ~ 0.03 m
5. High abrasion: ~ Maximum observed depth.

This categorization scheme was developed based on the depth distribution depicted in **Fig. (4)**. The data indicates that most abrasion depths are concentrated within the 0.05-meter range along the tunnel length. So, as mentioned above, the depth and ranges were chosen to represent the observed abrasion throughout the tunnel accurately.

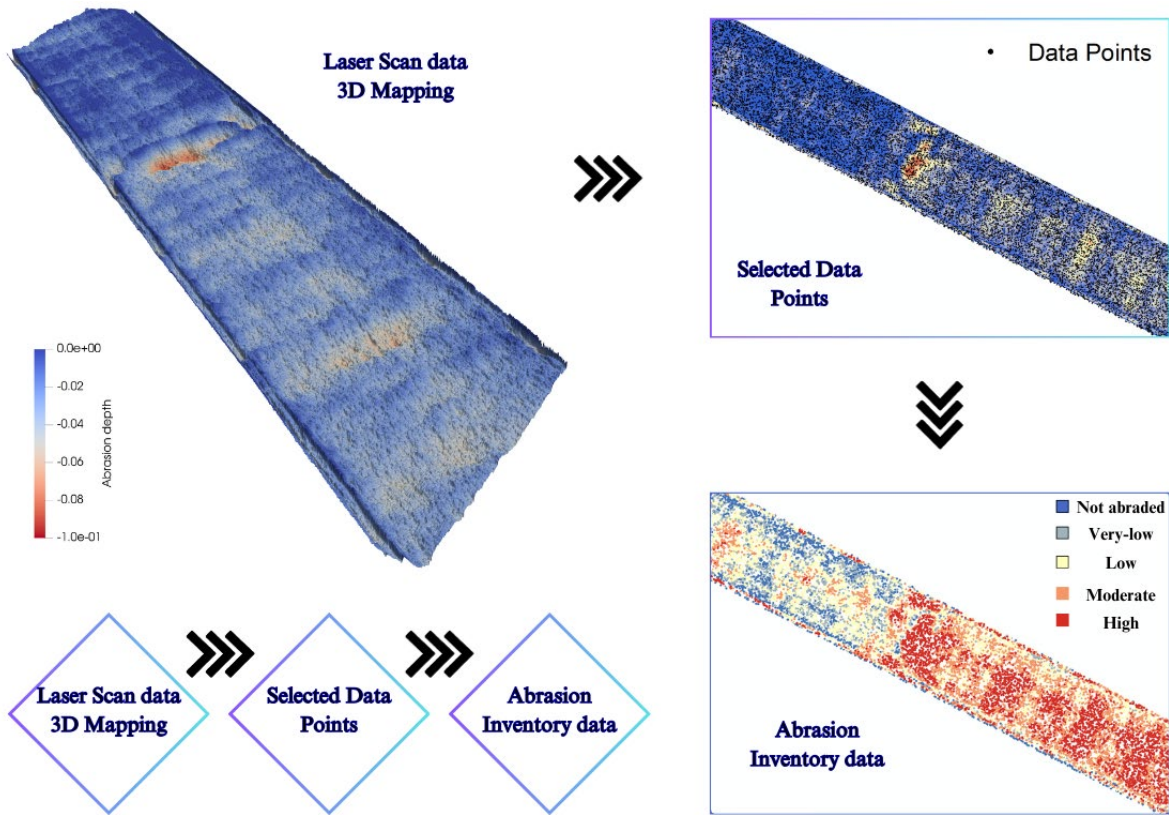


Fig. (14) Extraction of abrasion inventory data.

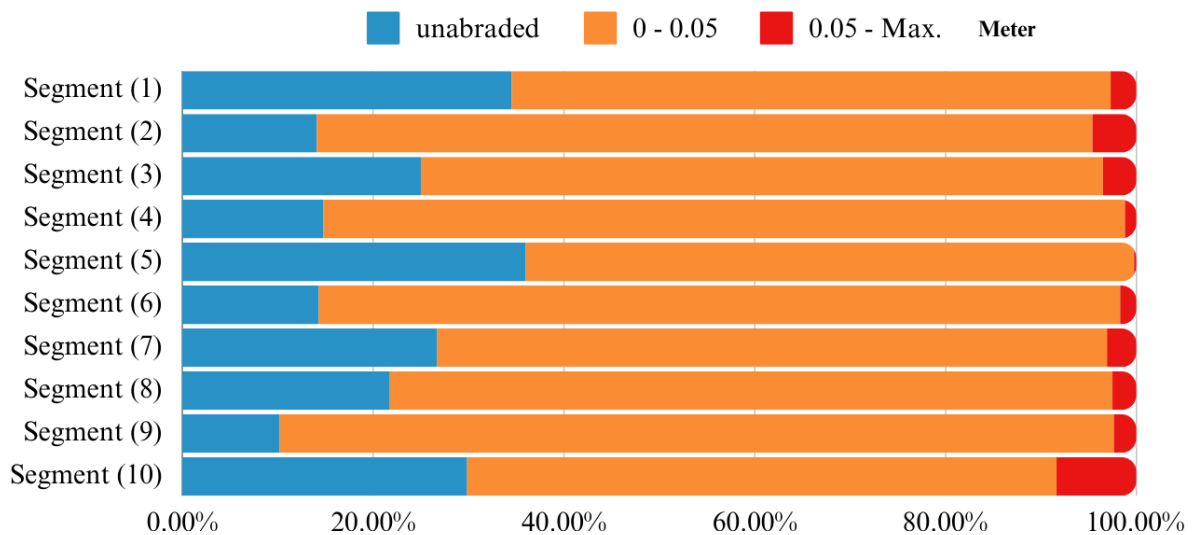


Fig. (15) Abrasion depth distribution along the tunnel length

3.1.3 Geometry Features and Hydraulic Characteristics

Despite its complex physical interactions, abrasion can be effectively represented through quantifiable parameters suitable for computational modeling. Integrating these parameters within an algorithmic framework can construct a predictive model. In this pioneering study, we employed ML methodology to forecast abrasion damage depths, thereby exploring the predictive potential of various input variables for the first time. Given the initial uncertainty regarding the most influential variables, we adopted an inclusive strategy by implementing a range of parameters, including hydraulic characteristics, sediment properties, floor material attributes, and the geometric configuration of the tunnel. The observed damage to the concrete floor, which accumulated over eight distinct operational flood events, suggests a cumulative impact where each event has contributed to the degradation process. Consequently, our analysis places particular focus on hydraulic characteristics derived from these events under established physical and hydraulic principles. Moreover, the study incorporates tunnel geometric features into the abrasion analysis, thereby offering a higher-dimensional perspective on the underlying processes. It is important to note that this investigation is confined to scenarios where floor abrasion is restricted to a single-material concrete slab. Thus, it does not account for potential influences arising from material heterogeneity. Furthermore, due to significant uncertainties in the in-situ variability of sediment properties within the tunnel, these factors were treated as a 'black box' and excluded from the current analysis. Recognizing that this research is an initial exploratory effort, our extensive parameter inclusion acts as a foundational baseline. Future studies could benefit from using feature selection techniques to identify the most relevant predictors from an even wider range of parameters set. Ultimately, the primary focus of this study is to highlight the interplay between hydraulic and geometric system characteristics. The resulting model correlates geometric factors with hydraulic data from eight distinct flood events and the subsequent topographic conditions, thereby quantifying abrasion depths as a measure of damage severity. A detailed summary of the critical determinants is included in **Table (1)**.

Table (1) The implemented Geometric and Hydraulic Parameters.

Parameter	Type	Unit	Case	Notes
Distance from Start boundary, D_S	Geometry	[m]	Laser scan data	1 value per pixel
Distance from Right boundary, D_R	Geometry	[m]	Laser scan data	1 value per pixel
Radius Inverse, $1/R$	Geometry	[1/m]	Laser scan data	1 value per pixel
Angel Theta, θ	Geometry	[degree]	Laser scan data	1 value per pixel
Flow Velocity, v	Hydraulic	[m/s]	Calculated	8 values per pixel
Water Depth, y	Hydraulic	[m]	Calculated	8 values per pixel
Event Time, T	Hydraulic	[hr]	Measured	8 values per pixel
Water Superelevation, Δh	Hydraulic	[m]	Calculated	8 values per pixel

Four geometric parameters are evaluated for each data point. The first two parameters (D_S and D_R) define the data point's position relative to the tunnel's start and right-hand boundaries. Given the tunnel's constant cross-sectional dimensions, these parameters adequately pinpoint the precise location of the data point under examination. The third and fourth parameters ($1/R$ and θ) are the inverse of radius and angle theta, respectively. These parameters are especially relevant to the curvature parts of the tunnel, as they primarily depend on the distance to the curvature center. These parameters are also applied within the straight parts; however, the radius is theoretically infinite, reducing it to zero, which enables the algorithm to differentiate between linear and curvilinear sections. The theta parameter θ represents the angle subtended from the data point's tangent in a counterclockwise direction relative to the primary direction of the straight section Part (A). Thus, theta values for data points of all Part (A) to the curvature's beginning is nearly null, exhibiting varied values throughout the curvature zone, reaching its maximum at the end of the curvature. For the section following the curvature, theta remains constant as it forms a fixed angle with Part (A). It is also noted that the longitudinal slope related to the tunnel floor remains invariant across the tunnel alignment under consideration. So, this parameter is excluded from the present analysis.

The hydraulic characteristics within the tunnel environment exhibit significant complexities in terms of system dynamics. Direct quantification of real-time hydraulic parameters using measurement devices within the tunnel during flood events is nearly impossible. However, it is feasible to derive certain hydraulic features along the tunnel length based on the recorded maximum discharge rates. Therefore, the maximum discharge rates of the Koshiu tunnel were utilized to derive the hydraulic characteristics associated with each event, as documented in **Table (2)**.

The hydraulic characteristics under consideration encompass four parameters for each data point across each discharge event: flow velocity, water depth, event duration, and water superelevation (defined as the differential in water levels across the tunnel's lateral span); see **Table (1)**. Event duration is directly measured for each flood occurrence. The remaining three parameters—flow velocities, water depths, and superelevation—are derived through backwater curve calculations employing the Darcy-Weisbach equation. This methodological approach for determining hydraulic characteristics is well-established in the literature, as evidenced by its application in multiple studies (Auel et al., 2016, 2017a; Demiral Yüzügüllü, 2021; Müller-Hagmann et al., 2020). The computational procedure is as follows:

The acceleration section's primary function is to impart sufficient momentum to the flow for downstream propagation. For computational simplicity, we assume that this section effectively achieves its purpose, allowing the flow to attain steady-state velocity at the end of this section. Under this condition, the Manning formula is applied, considering the acceleration section's steel lining. The parameters used in the calculations are as follows:

1. Manning coefficient for the acceleration section: $n = 0.015$
2. Roughness height of the SBT concrete bed: $k_s = 0.001 \text{ m}$

The Roughness Coefficient, $k_s = 0.001 \text{ m}$, was determined through backwater calculations for the design discharge and corresponding flow depths. The selected parameters are consistent with typical values for steel and concrete surfaces and are corroborated by experimental hydraulic simulations conducted by the dam authority (Fenton, 2010; T.D.I.M Office, 2021). The hydraulic analysis yields maximum flow velocities ranging from a lower bound of 17.4 m/s (Operation 2, $Q_2 = 60 \text{ m}^3/\text{s}$) to an upper bound of 26.6 m/s (Operation 8, $Q_8 = 200 \text{ m}^3/\text{s}$). These velocities are calculated

immediately downstream of the acceleration section. The flow characteristics exhibit an inverse relationship between velocity and aspect ratio (B/h), where B represents channel width and h denotes flow depth. The computed aspect ratios range from $B/h = 13$ to 6 , reflecting a shallow open channel flow regime (2D-flow) initially (Nakagawa, 2017; Nezu & Nakagawa, 1993). However, backwater curve computations reveal a longitudinal transition in the flow regime:

1. **Acceleration section downstream region:** Shallow open channel flow (2D-flow).
2. **Along the tunnel length:** Transition to a deep open channel flow regime (3D-flow) for all discharges except Q_2 .
3. **Exception:** $Q_2 = 60 \text{ m}^3/\text{s}$ maintains a shallow flow state throughout the tunnel length.
4. **General transition:** The transition from 2D to 3D flow regimes varies depending on the discharge under consideration. The critical limit distinguishing between 2D and 3D flows corresponds to an aspect ratio of approximately $B/h = 4$ to 5 (Nakagawa, 2017; Nezu & Nakagawa, 1993).

Therefore, this spatially varying transition from 2D to 3D flow regimes along the tunnel length allows for the calculation of velocity and water depth at each data point on the tunnel floor. Centrifugal forces affect the fourth parameter (water superelevation Δh) during the curvature section, which can be calculated using the following formula (Reinauer & Hager, 1997):

$$\Delta h = \frac{v^2 B}{Rg} \quad (1)$$

Where (v) is the velocity, (B) is the channel width, (R) is the radius of the data point from the curvature center, and (g) is the gravitational acceleration. Within the straight sections, the superelevation is nullified as the radius approaches infinity. Our analysis includes eight distinct discharge events, each characterized by four specific parameters. This results in 32 hydraulic features associated with each data point.

Table (2) The considered operations of Koshibu SBT from 2016 to 2018 (Koshiba & Sumi, 2020)

Operation	Date	Duration, T	Discharge, Q_{max}
No.	[-]	[hours]	[m ³ /s]
Op1	09/2016	16	80
Op2	09/2016	5.8	60
Op3	07/2017	3.1	120
Op4	10/2017	9.7	180
Op5	10/2017	48.8	90
Op6	07/2018	10.7	150
Op7	09/2018	44.2	175
Op8	10/2018	69.5	200

3.1.4 Tunnel Abrasion Map: Key Observations

In this section, we analyze the damage patterns observed within the tunnel and correlate these findings with existing literature to clarify the topographical characteristics. **Figures 5 and 6** illustrate the localized areas of damage within parts A and B of the tunnel, respectively.

The structural damage observed can be systematically classified into four primary patterns: (1) edged, (2) wave-like, (3) scattered (undefined), and (4) skewed. The first three patterns (edged, wave-like, and undefined) have been experimentally analyzed in previous studies. The fourth pattern (skewed) has been documented across various SBTs but lacks comprehensive experimental investigation.

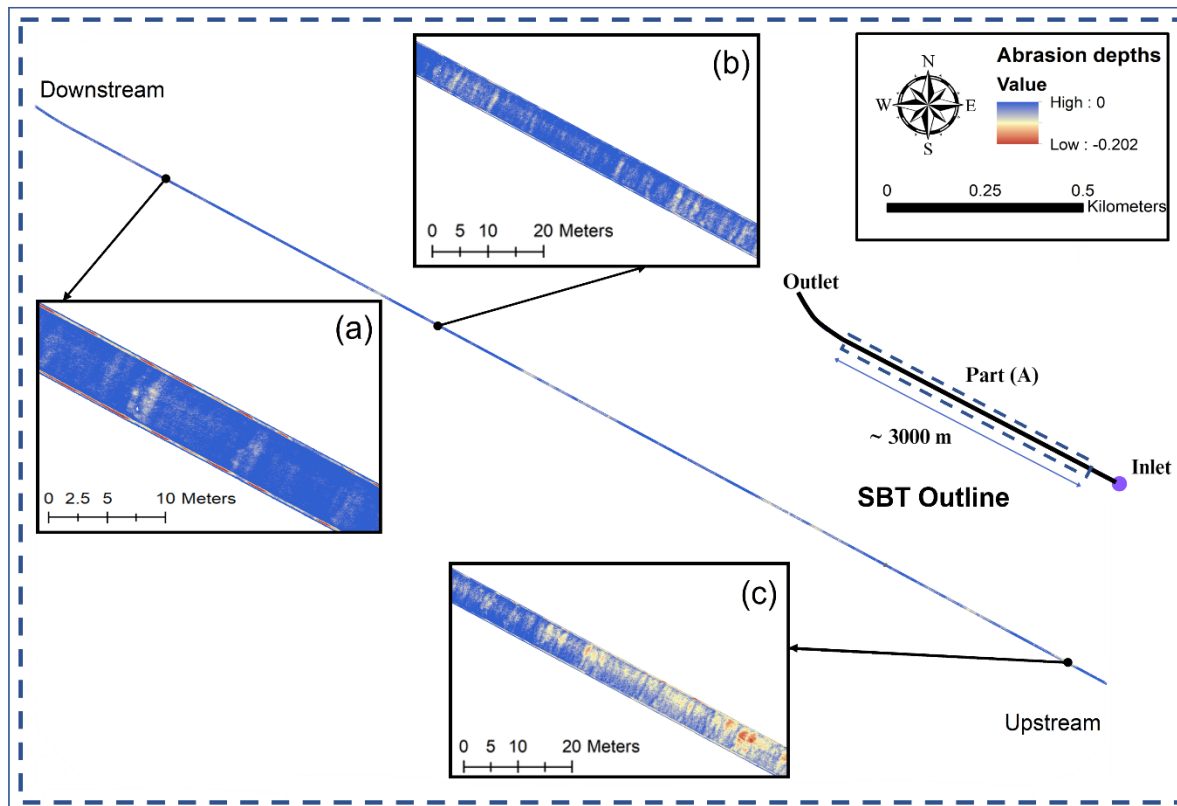


Fig. (16) Abrasion laser scanning of SBT topography of part(A), a) the edged, b) wave-like, and c) undefined patterns.

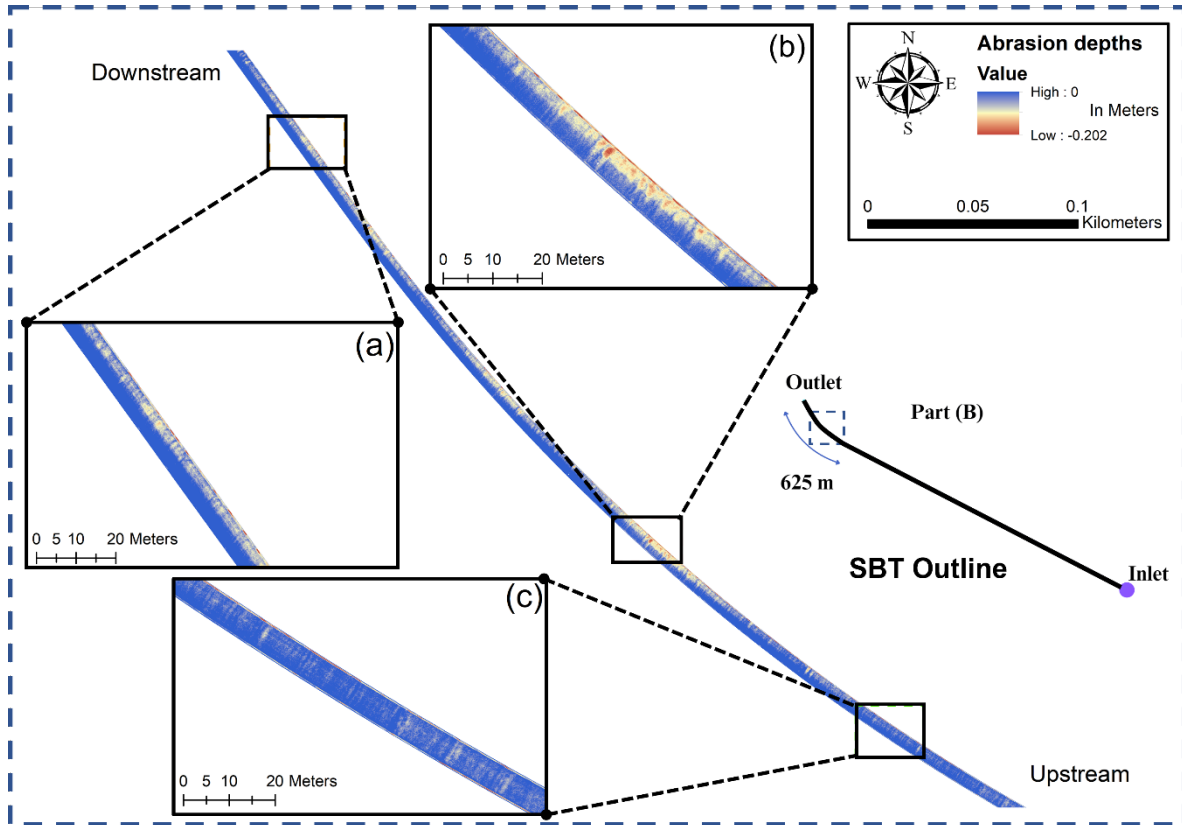


Fig. (17) Abrasion laser scanning of SBT topography of part(B), a) after, b) mid, and c) beginning of the curvature.

The edged pattern, characterized by concentrated damage along both lateral sides of the tunnel's cross-section (**Fig. (5-a)**), is particularly noticeable in the downstream regions of the straight Part (A), where 3D flow exists during various events. This observation aligns with experimental studies (Auel, 2014; Demiral Yüzügüllü, 2021), which attribute this phenomenon to intensified secondary currents and localized bed shear stress near the cross-section edges. The wave-like pattern (**Fig. (5-b)**), extending longitudinally throughout the tunnel, is typical due to the dominant saltation transport of sediment particles under various hydraulic conditions, as experimentally documented by (Auel, 2014). The undefined pattern, lacking an apparent shape (**Fig. (5-c)**), is particularly noted in the upstream segments of Part (A), where shallow (2D) flow prevails during most discharge events. This pattern was experimentally validated by (Demiral Yüzügüllü, 2021), who associated it with shallow flow regimes and significant influence from surface roughness.

Lastly, the skewed pattern observed in **Fig. (6)** reveals asymmetric abrasion predominantly on one side of the tunnel. This pattern is frequently observed in bends (Kadia et al., 2024) and reported in other tunnels (Albayrak et al., 2024; Müller-Hagmann et al., 2020; Nakajima et al., 2015). They attributed this behavior to the influence of secondary currents. Despite being linear, the straight part following the curve exhibits an alternating pattern of wave-like and skewed damage profiles due to the influence of upstream curvature. Typically, this abrasion along the inner side can extend further downstream of the bend but gradually redistributes across the tunnel width beyond the curve, as documented in some SBTs (Albayrak et al., 2024; Müller-Hagmann, 2018). However, in this case, the straight section is too short for redistribution.

In conclusion, the previously observed abrasion patterns correspond to the tunnel's specified flow regimes, including shallow and deep open channel flows. However, the formation of these patterns is characterized by significant complexity attributable to several factors. These include various discharge events, variations in hydraulic conditions, and diverse sediment transport dynamics. The hydraulic conditions span from shallow flows of a few centimeters to deep flows of several meters, while sediment sizes range from millimeters to approximately a quarter meter (Koshiba, 2020; T.D.I.M Office, 2021). This multifaceted variability in hydraulic and sediment characteristics introduces considerable complexity to the formation and evolution of abrasion patterns within the tunnel. Additionally, some variations result from superimposing different abrasion patterns from previous events. Certain tunnel sections may exhibit a distinct pattern, while most areas display a combination of these patterns. This complexity necessitates a comprehensive analysis, which is beyond the scope of this current study, which focuses on abrasion prediction. A separate assessment is required to evaluate these patterns thoroughly.

3.2 Application of XGBoost in ASDM Modeling

ML algorithms provide a practical and feasible solution for complex multi-parameter nonlinear problems. XGBoost, an enhanced and optimized version of the gradient boosting algorithm, is based on decision trees and used for classification and regression tasks. The algorithm has gained popularity due to its speed, efficiency, and scalability, making it highly effective for handling large datasets and complex data structures (Chen & Guestrin, 2016). The selection of this algorithm was motivated by its handling of high-dimensional data and delivering high performance in real-world

scenarios. In this study, XGBoost is employed as a regression model to spatially detect abrasion in SBTs in terms of extent and damage depth. This represents a novel application for the algorithm and introduces new criteria for evaluating such structures.

XGBoost is derived from the gradient tree boosting algorithm, which sequentially integrates the outputs of weak learners to improve predictive accuracy (Ramraj et al., 2016). The primary goal is to minimize the loss function and quantify the discrepancy between the predicted and actual outcomes. This model constructs an ensemble of decision trees, with each tree aiming to rectify the errors of its predecessors, **Fig (7)**.

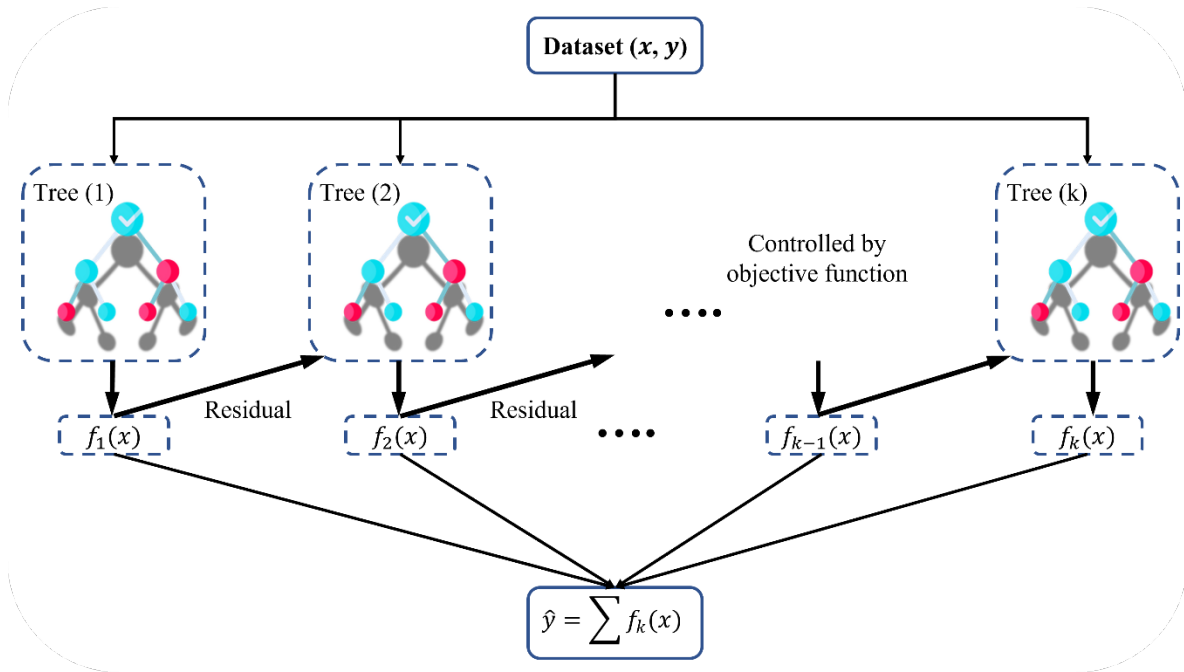


Fig. (18) A general architecture of the XGBoost algorithm

The optimization problem can be described as follows (Chen & Guestrin, 2016): the objective function (L) comprises the loss function (l) and a regularization term (Ω):

$$L(\phi) = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{i=1}^n \Omega(f_k) \quad (2)$$

where (y_i) is the true label (actual abrasion depth), ($\hat{y}_i$) is the predicted value, n is the number of samples, (f_k) represents an individual tree, and (K) is the number of trees in the model. The

regularization term (Ω) manages the model's complexity and aids in preventing overfitting. The prediction for the (i)-th sample after (t) trees is given by:

$$\hat{y}_i^{(t)} = \sum_{k=1}^t f_k(x_i) \quad (3)$$

where x_i represents the controlling features (geometric and hydraulic parameters). The algorithm optimized the model by using the first and second-order derivatives of the loss function. In each iteration (t), a new tree (f_k) was added to minimize the objective function:

$$L^{(t)} = \sum_{i=1}^n [l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i))] + \Omega(f_t) \quad (4)$$

The regularization term for a tree (f_t) is defined as:

$$\Omega(f_t) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2 \quad (5)$$

Where (T) represents the number of leaves in the tree, w_j is the leaf weight, and (γ, λ) are the regularization parameters. For more details, refer to (Chen & Guestrin, 2016).

3.2.1 Statistical Assessment

The accuracy of the ASDM model was evaluated through a two-step process. First, a quantitative assessment was conducted using statistical metrics. This quantitative analysis was then complemented by a qualitative evaluation involving a visual comparison between the observed topography and the model results. In the following sections, we will elaborate on the visual analysis; for now, the key statistical measures used to assess the model's performance are presented in **Table (3)**:

Table (3) Mathematical representation for model performance metrics.

Measure	Formula		Variable description
Mean Squared Error (MSE)	$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$	n	Number of observations
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$	y_i	The observed abrasion depth
Mean Absolute Error (MAE)	$MAE = \frac{1}{n} \sum_{i=1}^n y_i - \hat{y}_i $	$\hat{y}_i$	The predicted abrasion depth
Mean Bias Error (MBE)	$MBE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)$	$\bar{y}$	The mean of the observed abrasion depths
Correlation Coefficient (R)	$R = \frac{\sum_{i=1}^n (y_i - \bar{y})(\hat{y}_i - \bar{y})}{\sqrt{\sum_{i=1}^n (y_i - \bar{y})^2 \sum_{i=1}^n (\hat{y}_i - \bar{y})^2}}$		
Nash-Sutcliffe Efficiency (NSE)	$NSE = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$		

The Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) provide measures of the average magnitude of prediction errors. The Mean Absolute Error (MAE) offers a similar interpretation but is less sensitive to outliers. The Mean Bias Error (MBE) helps identify any systematic bias in the predictions, indicating whether the model tends to overestimate or underestimate the observed values. A negative MBE indicates overestimation, while a positive MBE indicates underestimation. The Correlation Coefficient (R) measures the strength and direction of the linear relationship between the predicted and observed values. It ranges from -1 to 1, with 1 indicating a perfect positive linear relationship, -1 indicating a perfect negative linear relationship, and 0 indicating no linear relationship. The Nash-Sutcliffe Efficiency (NSE) ranges from $-\infty$ to 1, where 1 indicates an ideal match between predictions and observations, zero suggests that the model predictions are as accurate as the mean of the observed data, and less than zero occurs when the observed mean is a better predictor than the model. These indices collectively evaluate our model's performance and assess its accuracy, precision, and reliability in predicting abrasion depths.

By employing multiple metrics, we gain a more detailed understanding of the model's strengths and limitations, which is essential for its practical application in SBTs.

4. Results and Discussion

4.1 Quantitative Assessment

The performance of the XGBoost algorithm is evaluated using four geometric parameters and 32 hydraulic parameters as controlling factors. As mentioned before, the dataset contains around 1,161,352 data points distributed along the length of the study area of the tunnel. Half of these points are assigned to train the algorithm, while the other half are used to test the accuracy of the output regression model. **Table (4)** displays the outcome results of the XGBoost algorithm runs considering three experiments: All tunnel, Part (A), and Part (B).

For the all-tunnel scenario, the model's performance is satisfactory, achieving an RMSE of 0.0399 during training and 0.0406 during testing, leading to an overall RMSE of 0.0403. The model also shows a high R in both training and testing sets, with an overall value of 0.861. The MAE is consistently low, with an overall value of 0.0285. These indicate that the model can accurately predict abrasion depths across the tunnel. Further, the model demonstrates a high NSE of 0.752 in the training set and 0.744 in the testing set, which indicates the model's high ability to capture variability in abrasion depths.

The performance metrics for the straight section, Part (A), are lower than those for Part (B), with a testing RMSE of 0.0395 and an overall R of 0.863. Regarding MAE, Part (A) shows a slight decrease compared to the all-tunnel case, which is consistent with its more focused area. It exhibits approximately the same NSE, indicating that most depth variations exist in Part (A). Regarding Part (B), the R-value exceeds 0.90, reflecting excellent correlation. It shows the best performance of the three experiments. It also has the lowest MSE (0.0012) and MAE (0.0228), indicating high accuracy in predicting abrasion depths. The NSE for Part (B) is the highest at 0.870. This superior performance is reasonable since Part (B) has a distinct pattern and a lower length-to-width ratio, making the algorithm more efficient in dealing with this specific part and resulting in the most precise outcomes.

Overall, the three experiments reflect the model's ability to handle different scales of abrasion depths effectively. The MBE is notably low for all cases at 0.0001, suggesting a slight tendency

towards underprediction. This minor bias could be attributed to the significant variation in damage depths, which challenges the algorithm's capability to capture the fine details of the abrasion.

To conduct a comprehensive statistical analysis of the results beyond basic error metrics, a paired t-test was performed to determine whether the differences between the model's predicted values and the actual values are statistically significant. The null hypothesis of the paired t-test states that the mean difference between predicted and observed values is zero, implying no significant discrepancy. Conversely, the alternative hypothesis asserts that the mean difference is not zero. If the p -value of the t-test is less than 0.05, the null hypothesis is rejected, indicating a statistically significant difference between the predicted and observed values. However, if the p -value is greater than 0.05, the null hypothesis cannot be rejected, suggesting that the mean difference is zero.

Table (4) presents the p -values of the t-test for each experiment in this study. In most cases, the p -value exceeds 0.05, indicating no statistically significant difference between the predicted and observed values at the 95% confidence level. However, for the "Testing" dataset in the first experiment, where all points of the tunnel are considered, the p -value = 0.0245 is below 0.05, signifying a significant difference between predicted and observed values. This result suggests that the tunnel comprises two sections with different abrasion patterns, making it challenging for the model to predict values accurately across both sections in one experiment. This conclusion is further supported by the model's performance when independently evaluating Part (A) and Part (B). Additionally, the p -value for the "All Data" dataset of the tunnel, along with the statistical metrics for the "Testing" dataset, falls within an acceptable range. This reflects an overall acceptable model performance despite some significant differences observed in certain datasets.

Table (4) Evaluation metrics and p-values of the paired t-test for the XGBoost algorithm across three experiments with 36 parameters.

Tunnel Parts	Dataset	MSE	RMSE	MAE	MBE	R	NSE	p-value t-Test
All	Training	0.0016	0.0399	0.0283	0.0001	0.864	0.752	0.9999
	Testing	0.0017	0.0406	0.0287	0.0001	0.859	0.744	0.0245
	All Data	0.0016	0.0403	0.0285	0.0001	0.861	0.748	0.1084
Part (A): Straight Sec.	Training	0.0015	0.0391	0.0282	0.0001	0.866	0.751	0.9999
	Testing	0.0016	0.0399	0.0286	0.0001	0.860	0.742	0.4247
	All Data	0.0016	0.0395	0.0284	0.0001	0.863	0.747	0.5684
Part (B): Curved Sec.	Training	0.001	0.0322	0.0219	0.0001	0.940	0.885	0.9999
	Testing	0.0013	0.0366	0.0237	0.0001	0.922	0.855	0.7208
	All Data	0.0012	0.0345	0.0228	0.0001	0.931	0.870	0.7883

4.2 Qualitative Assessment (ASDM Mapping)

This section presents a qualitative assessment of the ASDM model. First, it compares the model's performance against the observed topography for the three experiments. Then, we examine the controlling factors and their influence on detecting abrasion depths.

4.2.1 All Tunnel

The ASDM model demonstrates acceptable performance, achieving RMSE = 0.0403 and R = 0.861. These metrics prompt crucial questions: How effectively can the model capture the tunnel's diverse abrasion patterns and depths? Can it successfully differentiate between various tunnel parts? Our main goal here is to assess the model's capability to quantify the extent of damage across these different sections.

Referring to **Fig. (8)**, the ASDM model is proficient in estimating abrasion depths throughout the tunnel floor. It successfully replicates the complex patterns in Part (A) and accurately represents Part (B)'s unique abrasion profile characteristic.

A closer examination indicates a slight tendency towards underestimation compared to the observed topography. This underestimation is quantitatively confirmed by the MBE of 0.0001. The model predicts slightly lower abrasion depths than those observed in the topography. However, it is essential to note that this underestimation is minimal, representing only a tiny fraction of the typical abrasion depths. Generally, the model performs better upstream, offering more detailed predictions than it does in downstream areas. In the downstream sections, especially in the straight parts, the model tends to create bulkier zones when defining abrasion patterns. Overall, the model effectively captures various abrasion patterns and, more importantly, differentiates between abrasions in parts (A) and (B).

The following sections will comprehensively examine the ASDM model's behavior and precision in quantifying abrasion patterns and depths. We will explore how the model's predictions align with observed data across different parts of the tunnel and discuss the implications of these results.

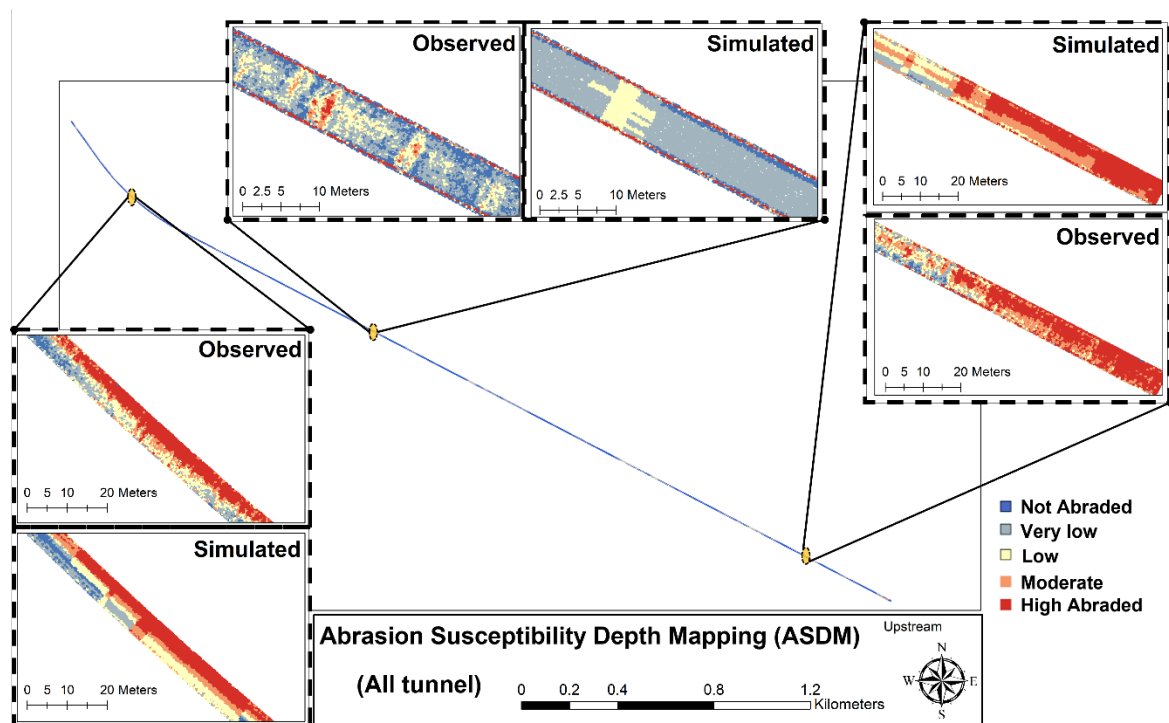


Fig. (19) Comparative Analysis of abrasion Susceptibility: Observed vs. Simulated Data for various patterns in All Tunnel.

4.2.2 Straight Section (Part A)

Three observed slots detail the abrasion patterns in Part (A); see **Fig. (9)**. **Figure (9-a)** shows the edged abrasion pattern of the straight section, **Fig. (9-b)** highlights the small wave-like pattern within the mid-region, and **Fig. (9-c)** presents the undefined damage area upstream of the tunnel. **Figures (9-a', b', and c')** display the simulated outcomes of the ASDM model. A comparative analysis between the observed and simulated results demonstrates the model's proficiency in accurately identifying and detecting the most damaged regions.

When comparing slots (a and a'), the model accurately captures the edged pattern, even with its fluctuations in depths. This accuracy may be attributed to a clear pattern over a long distance, which aids in making precise predictions. However, it is noted that the model underpredicts the damage in the center area, as confirmed before by the statistical analysis. The model shows some limitations in this area, as it struggles to capture all variations in depth values, especially the low to moderate abrasion ranges concentrated in wave steps. Additionally, the model has difficulty perfectly capturing the highly abraded isolated step-like shape and handling it more broadly. This limitation is discussed in detail at the end of the section.

Focusing on slots (b and b'), the model captures all depth ranges and shows a steep variation in depths, starting from unabraded to the low abraded range. It also accurately captures the downstream reach, including the two highly abraded wave steps. However, for the upstream highly abraded waves, the model generally represents it with less detailed accuracy and underestimation. Regarding slots (c and c'), located upstream of the tunnel, despite the undefined pattern, the model almost captures all depth variations perfectly, including both highly and moderately abraded areas, though there is some underestimation in the downstream region.

4.2.3 Curved section (Part B)

In this section, three high-resolution inventory maps provide a detailed view of the abrasion patterns in Part (B). **Figure (10-a)** shows the abrasion pattern in the straight section after the curve, showing the high influence of the curvature effect. **Figure (10-b)** highlights the uneven abrasion pattern in the middle of the curve, illustrating the localized impact. **Figure (10-c)** presents the beginning of the curve, showing the transition in damage patterns from Part (A) to Part (B).

As noted before, Part (B) demonstrates the highest fineness in the ASDM's predictive capability, with accuracy surpassing 90% across training, validation, and overall assessment stages. When comparing model results to observed topography, the model shows significant mapping details, perfectly capturing the extent and depth of abrasion. Slot (a') mirrors slot (a), proving the model's ability to distinguish between unabraded and highly abraded sides and the moderately abraded line in between, which the model captures well and even discerns minor damages on the outer side. Slot (b') captures the full details of the abraded area, beginning with the highly abraded area in the curvature and accurately transitioning to moderate zones both upstream and downstream and towards the outside of the curvature. Slot (c') also presents an excellent representation. Despite the complex pattern and wide range of depths in this area, the model captures almost all types of damage depths, especially the highly abraded range, though some underestimation is noted. Moreover, the model shows effective mapping, particularly in the transition from unabraded to moderately abraded ranges, and accurately captures the wave steps.

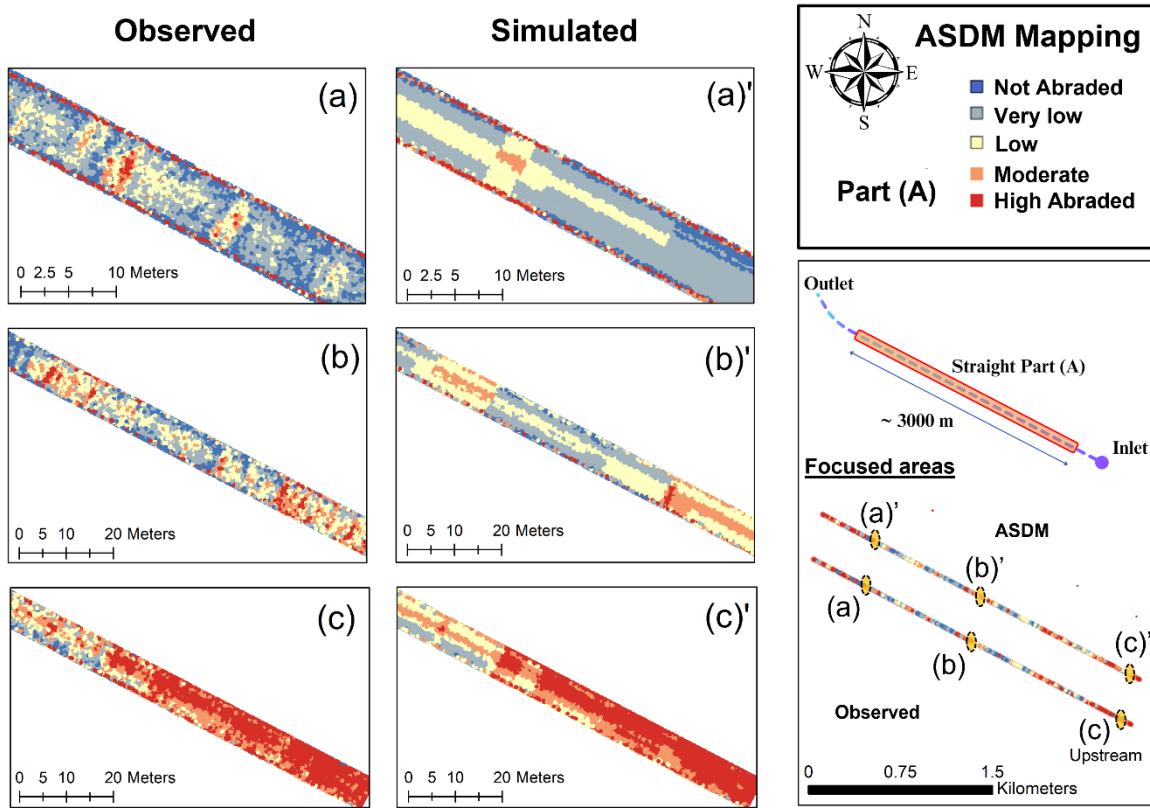


Fig. (20) Inventory mapping compares observed and simulated data for different patterns of part (A).

In general, across all scenarios, the model effectively maps various types of abrasion, spatially and in-depth, throughout the tunnel. However, it exhibits a slight tendency towards underprediction. Upstream, the model's detailed performance accurately captures all abrasion ranges, including steep variations. Conversely, downstream, the model's behavior becomes less precise. This can be attributed to specific patterns in certain regions, which the model handles well over long distances (e.g., edged patterns). However, the model tends to generalize when encountering sudden, steep variations such as step-like shapes, revealing some limitations. Despite this, the model performs better in upstream regions with multiple steep variations.

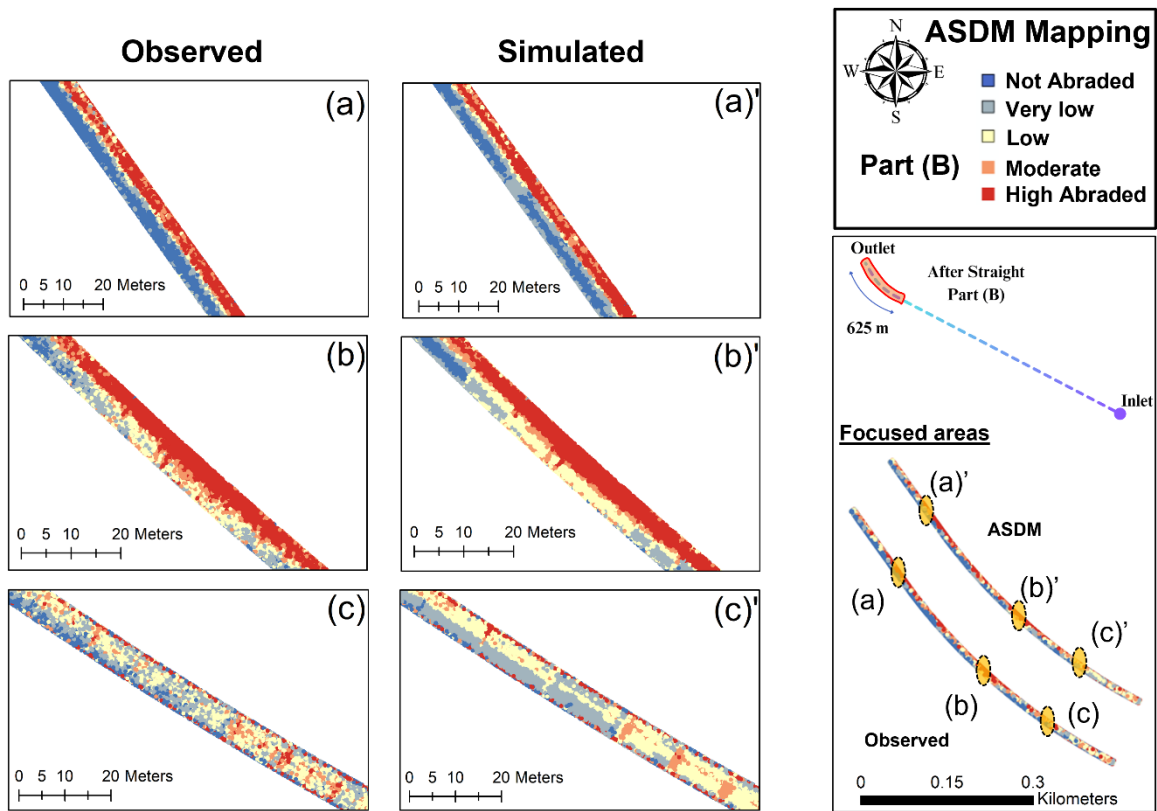


Fig. (21) Inventory mapping for comparing observed data and simulated ones for different zones in part (B).

This limitation may be due to the elongation ratio related to the tunnel geometry (length measured in kilometers and width in several meters). For instance, when comparing the all-tunnel case (**Fig. (8)**) with Part (A) (**Fig. (9)**), the all-tunnel case tends to be bulkier than Part (A) in the same slots. This is because Part (A) focuses on a more specific area compared to the entire tunnel. Another example is when the model maps Part (B), it accurately captures nearly all patterns and depths, including the wave-like pattern (**Fig. (10-c)**), which was challenging to capture in the other two scenarios. Therefore, a more balanced ratio of areas could potentially enhance the model's precision in capturing abrasion patterns and depths.

4.2.4 Controlling Factors Influence

A lot of information can be extracted from the ASDM model. This model allows us to investigate how the controlling factors, represented by geometric and hydraulic parameters, are linked to

abrasion damage throughout the tunnel. For instance, which factors have the most influence, and how do they impact the model's predictive performance? To address these questions, we have conducted a two-faced analysis. Initially, a parameter-based analysis is performed, followed by an event-based analysis for further investigation. These two analytical criteria are applied to the experiments: the All tunnel, Part (A), and Part (B).

I. Parameter-based Analysis

The ASDM model utilizes 36 input parameters: 4 geometric and 32 hydraulic, each associated with eight distinct events. To evaluate the influence of these controlling variables on the model's performance, a subset of 8 parameters was presented, including the four geometric parameters and four aggregated hydraulic parameters. The 32 hydraulic parameters are encapsulated into 4 for simplicity. For example, the 'water velocity' parameter represents the collective influence of water velocities across all events. This approach allows for a systematic evaluation of parameter influence on ASDM performance while balancing analytical complexity. The analysis evaluated the individual impact of each parameter as well as the cumulative influence of all parameters, excluding the target one, using the R coefficient, as illustrated in **Fig. (11)**.

I.1 All tunnel Scenario

Examining the hydraulic parameters, the (All except this parameter) dataset reveals that the four hydraulic parameters exert an equal influence, with $R = 80\%$. This is logical, given that hydraulic parameters depend on flow discharges, suggesting that three hydraulic parameters are sufficient for high predictive modeling, maintaining their predictive capability without the fourth parameter. However, when considering each parameter independently, velocities (v) and water depths (h) emerge as the most influential, with $R = 60\%$, while event time (T) does not affect predictions. This observation aligns with existing literature, indicating that flow velocity significantly impacts abrasion damages, making it a principal determinant. Additionally, water superelevation (Δh) shows low predictive power, with $R = 20\%$, due to its limited effect on tunnel curvature, as most of the tunnel consists of straight sections (with a ratio of 1 curvature to 8 straight).

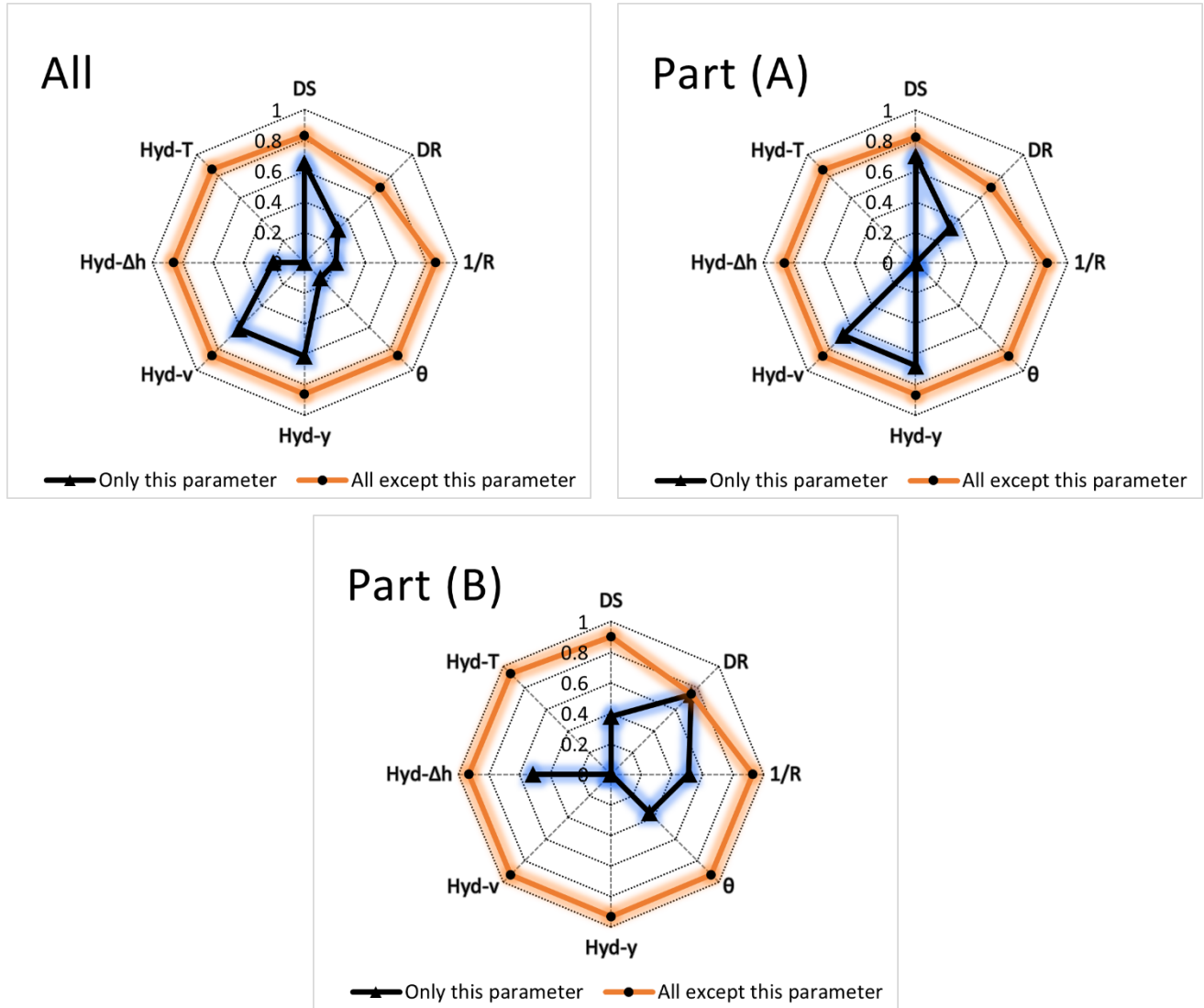


Fig. (22) The Influence of Each Parameter on the ASDM Model Performance (Correlation Coefficient, R) for All Tunnel, Part (A), and Part (B) Cases.

Evaluating the geometric parameters and considering (All except this parameter) data, the analysis shows that all four parameters exert a substantial influence. However, only the Distance from Right boundary (D_R) parameter has an R-value of less than 70%, highlighting its importance due to significant variations in abrasion depths across the tunnel width. In the (only this parameter) set, the Distance from the Start boundary (D_S) parameter is the most influential, affecting model performance by over 65%, the highest among all parameters. It is followed by the D_R parameter at 30%, inverse radius ($1/R$) at 20%, and theta (θ) below 15%. This observation is consistent, as

parameters $1/R$ and θ have the least overall effect, given their maximum influence in the curvature part, which is a small portion compared to the whole tunnel. In contrast, the D_s parameter has the highest impact, as the abrasion pattern changes progressively downstream from reach to reach. Some parameters are more related to changes in abrasion patterns, such as D_s , while others are related to transverse variation, such as D_R , and some to curvature, such as θ . This underscores the critical combination of these parameters in abrasion mapping and prediction.

I.2 Part (A) Scenario

When analyzing the hydraulic parameters, the (All except this parameter) criteria demonstrate that the four hydraulic parameters exert an equal influence, indicating that only three out of the four should be included in the predictive model. However, when each parameter is considered independently, velocities and water depths emerge as the most influential, with no significant contribution from water superelevation and event time. This suggests that either velocities or water depths should be included in the model due to their importance along the tunnel length and their variations with damage depths. The lack of effect from Δh is logical, as it only impacts curved sections, whereas the current analysis is related to straight sections only.

Regarding the geometric parameters and considering the (All except this parameter) data, the results indicate that all four parameters have a significant impact, with D_R having the lowest R-value among them. This highlights its importance due to the high variations in abrasion depths across the tunnel width. In the (only this parameter) dataset, the D_s parameter has the most contribution, affecting model performance by 70%, which is the highest among all parameters. This is followed by D_R at 30%, with no effect from the other parameters. This result underscores the importance of D_s , as abrasion depths and patterns change progressively downstream from reach to reach and vary across the tunnel width, emphasizing the relevance of D_R . The lack of effect from parameters $1/R$ and θ is understandable, as their influence is confined to curved sections.

I.3 Part (B) Scenario

By focusing on the hydraulic parameters, the analysis of (All except this parameter) result indicates that three hydraulic parameters are sufficient for high predictive modeling, as previously mentioned. However, in the (only this parameter) dataset, only Δh exhibits a significant effect, with a relative influence exceeding 50%. This suggests that not just any three out of the four parameters can be

considered; it is imperative to include parameters that are functions of the curvature radius, such as Δh , due to its critical role in curved sections.

When assessing the geometric parameters and considering the (All except this parameter) set, the analysis demonstrates that all four parameters play a significant role, with R values exceeding 90% for three parameters. However, the D_R parameter has an R-value of less than 75%, highlighting its importance. This is particularly evident in the unique variation in abrasion depths across the tunnel width, especially from a pattern perspective.

This observation is further corroborated when considering the (only this parameter) information, where the D_R parameter shows the same predictive power as the combined other parameters and is regarded as the highest among all parameters. This may be attributed to the unique damage pattern associated with the tunnel width, occurring predominantly on one side. Additionally, the D_s parameter shows one of the lowest effects, indicating minimal changes in the damage pattern along the longitudinal direction, as confirmed by the maps. Similarly, the θ parameter has a low effect, likely due to its role in distinguishing between curved and straight sections. However, since the damage pattern continues from the curve through the straight section without change, its effect is reduced in this context.

II. Event-based Analysis

The ASDM model derives most of its controlling factors from hydraulic parameters across eight events, each with its own set of parameters. The key questions are: How do these subsequent events affect the ASDM model? What is the contribution of each event to the performance? The main goal is to evaluate the potential impacts of subsequent events, especially from the perspective of hydraulic parameters. To accomplish this, the analysis excludes the influence of the four geometric parameters, focusing solely on the effect of hydraulic parameters. This method allows for a more precise assessment of parameter influence and supports a detailed analysis of hydraulic dynamics. The evaluation here considers the three experiments; see **Fig. (12)**.

Applying the same criteria to the events—both in isolation (only this event) and in combination (all except this event)—as depicted in **Fig. (12)**, it is noted that the behaviors of the All tunnel case and Part (A) exhibit approximately the same model influences under several events. Reviewing these

two figures and considering (only this event), it becomes evident that the precision of the outcome prediction varies with each event. There is a linear correlation between the event discharge magnitude and the model performance; for instance, Event 2, which had the smallest magnitude and relatively shorter duration, yielded an R of 45%, whereas Event 8, which was the most intense and had the most extended duration, resulted in an R exceeding 65%. These findings underscore the influence of individual events on the overall damage. Moreover, the 'All-except-this-event' analysis revealed a consistent R of approximately 67%, highlighting the need for more topographical data with corresponding events (event-based data) to accurately track the resultant damage post-event.

Considering the Part (B) dataset, there is no influence on the model performance with changing events. The results for (All except this event) equal (Only this event) with $R \approx 50\%$. This indicates that successive events do not have any effect; one event has the same influence as eight events. One explanation is that this region has a pronounced pattern, and the model considers only hydraulic parameters, excluding geometry, which lacks significant variations in this part. This behavior suggests that the model requires more relevant data to establish such linkages. For more consistency, it is essential to implement event-based data. With proper justification, these data can potentially connect the abrasion damage and the main drivers, providing a deeper understanding of this phenomenon.

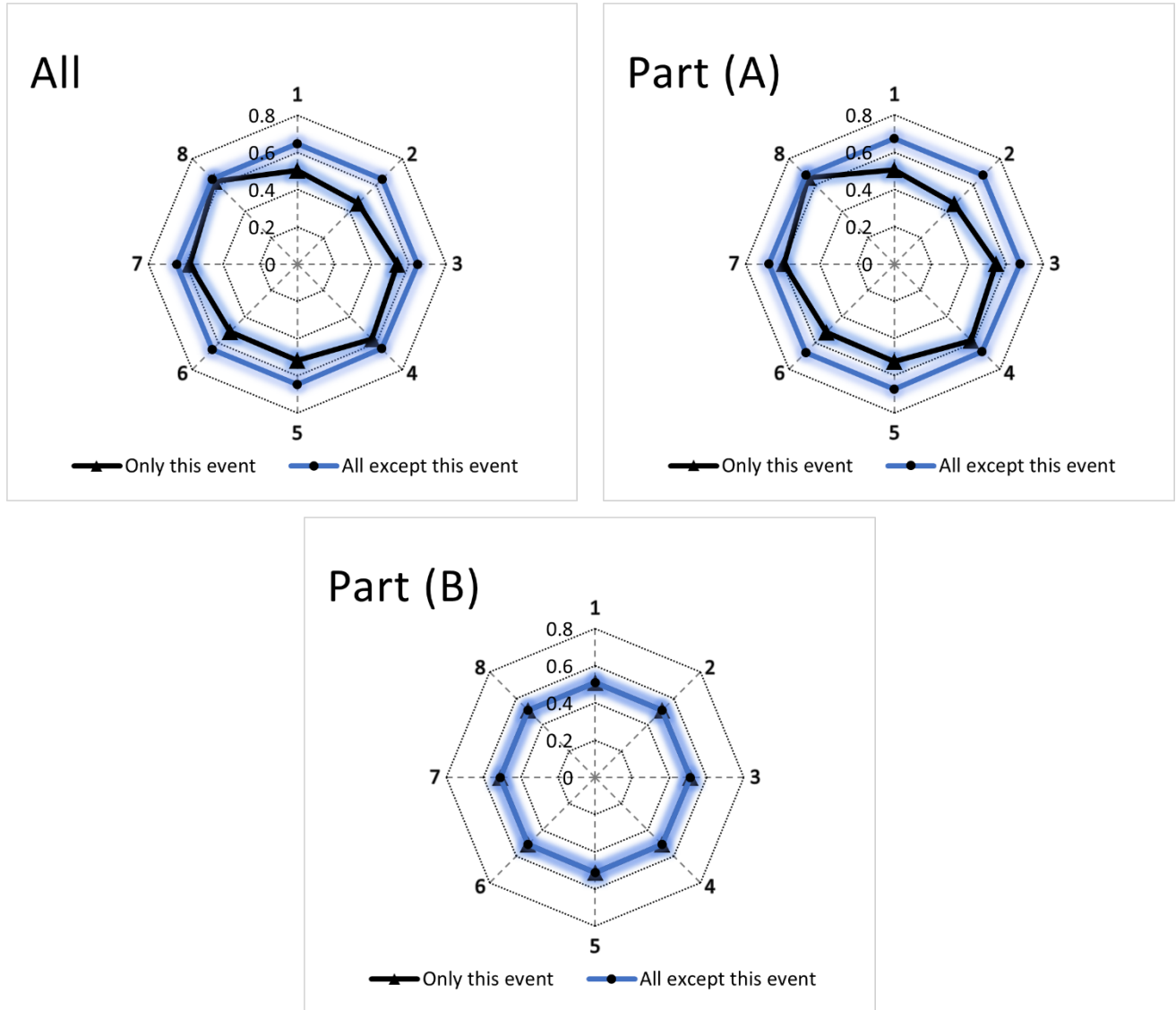


Fig. (23) The Influence of Each Event on the ASDM Model Performance (Correlation Coefficient, R) for All Tunnel, Part (A), and Part (B) Cases.

4.2.5 The Model Limitation

As previously mentioned, the model showed limitations in certain areas. We attributed these limitations to the elongation ratio related to tunnel geometry, where length is measured in kilometers and width in several meters. A more balanced focus ratio could enhance the model's precision. Additionally, uncertainty in input data, such as laser scanning or hydraulic measurements,

could propagate into the predictions, further contributing to these limitations. For example, the MMS laser scanner was equipped with a dual-axis compensator that automatically corrects for tilt, ensuring consistent vertical accuracy, which is critical in environments with uneven surfaces (Mitsubishi, 2013). However, after further calibration, we discovered that the bias was approximately 10% (T.D.I.M Office, 2021). Moreover, the limitations may be linked to the XGBoost algorithm's ability to predict abrasion. The high variability in abrasion depths, combined with the high dimensionality of the trained data, presents challenges for any algorithm to achieve satisfactory results. Even though XGBoost typically excels at capturing complex patterns, it may struggle with the highly nonlinear relationships in abrasion phenomena. Despite this, we could utilize a larger portion of the training set, such as 70% or 80%, to potentially improve results. However, we opted to use only 50% to avoid possible overfitting, which may compromise reliability. Additionally, using a smaller portion helps to reduce computational time due to the extensive datasets involved. Our approach demonstrates that even with a limited dataset, which is typical in such infrastructures, the model can still yield satisfactory results. Overall, the focus is on evaluating the effectiveness of the ML technique in predicting such complicated phenomena, utilizing physical and hydraulic parameters. Consequently, the ASDM model, which maps abrasion along the entire 4 km tunnel length with 3D criteria (abrasion depths), achieves an accuracy exceeding 80% and, in some sections, surpasses 90%. This outcome is considered extraordinary and represents a significant advancement in this field.

5 Model Application

To effectively apply the ASDM model, it is essential to collect relevant information about expected discharges entering tunnels from future flood events. This information can be obtained through hydrological simulations and ML models (Saber et al., 2025). Furthermore, the Internet of Things (IoT) can be utilized for real-time data collection, enhancing monitoring as a flood event approaches (Prakash et al., 2023). By implementing hydraulic features from these events, using the developed methodology, and incorporating established tunnel geometric characteristics (which require input only during the training phase), we can create a comprehensive dataset. This fused information serves as input features for the model, enabling it to generate high-resolution abrasion susceptibility maps, as previously trained. In the early stages, these maps can help identify critical zones that

require reinforcement, which is particularly valuable from a cost perspective. During an impending flood, the model can evaluate the potential damage throughout the tunnel, allowing stakeholders to make informed decisions about whether to open the tunnel gates based on the anticipated risk. This strategy contributes to more effective maintenance and operational efficiency.

6 Conclusion

The ASDM model, a novel ML-based tool, marks a significant advancement in the prediction of tunnel abrasion. By utilizing the XGBoost algorithm and a robust dataset comprising over one million data points, the model integrates 32 hydraulic parameters derived from flood events along with four geometric features of the tunnel. This integration enables the model to generate 3D characterizations of floor areas, including both the abrasion extent and depth. The model demonstrated strong predictive performance, achieving a correlation coefficient $R=0.861$ and a Nash-Sutcliffe efficiency $NSE=0.748$ across the tunnel length, with certain sections attaining values of 0.93 and 0.87, respectively, highlighting its accuracy. The key findings of this research include:

1. **High Capability in Identifying Abrasion Patterns:** The model effectively distinguishes a wide range of abrasion patterns in both straight and curved tunnel sections, capturing the full range of abrasion depths from undefined to skewed patterns. This indicates the model's ability to recognize various abrasion profiles across diverse tunnel geometries.
2. **Strong Predictive Power in Curved Sections:** The model shows a high correlation (exceeding 90%) in curved tunnel sections, achieving the lowest root mean square error (RMSE) of 0.0345 compared to all tunnel sections. This indicates the model's superior accuracy in predicting abrasion damage in curved areas, where complex geometric factors play a significant role.
3. **Model Limitations:** Despite its high predictive accuracy, the model has some limitations. First, it exhibits a slight tendency towards underprediction. Second, it tends to provide bulkier estimations, particularly as the analysis progresses downstream. This may be due to the tunnel's greater length than its width, indicating that a more balanced length-to-width ratio could improve precision. Additionally, input data uncertainties and the model's complex relationships may contribute to these issues.

4. **Influence of Geometrical and Hydraulic Parameters:** The ASDM's performance underscores the critical role of the controlling factors implemented in the model and highlights the impact of specific parameters. Among the geometric parameters, the elongated distance (length) exerted the most significant influence on predictive power, especially in straight sections. In contrast, the transverse distance (width) plays a more substantial role in curved sections. Hydraulically, the model finds that three of the four fundamental hydraulic parameters are sufficient, with water velocity and depth having the most significant impact, particularly in straight tunnel parts. However, it is essential to include at least one curvature-dependent parameter incorporating the curvature radius in curved sections due to its critical role in improving abrasion mapping.
5. **Importance of Event-Based Data:** The model's performance suggests that implementing event-based data is crucial for obtaining more relevant correlations between abrasion and controlling factors, thereby enhancing the model's predictive capabilities.

This study illustrates the potential of ML-based approaches to enhance the prediction and management of abrasion in SBTs. By incorporating hydraulic characteristics from anticipated future flood events, the ASDM model can evaluate tunnel vulnerability to abrasion with high precision, offering detailed estimates of abrasion depth that enhance maintenance and operational effectiveness strategies. This progress represents a significant step toward developing advanced models capable of providing deeper insights not only into tunnel abrasion but also in managing bedrock incisions that face similar challenges. Future research could explore testing alternative algorithms for deeper insights, integrating real-time and event-based data, considering additional influencing factors such as the geological foundations of tunnels and material properties, developing hybrid models, utilizing transfer learning to adapt the model to various tunnel environments, and extending this methodology to other infrastructure systems affected by abrasion phenomena.

7 Declaration of Interest Statement

The authors have no conflicts of state interest and affirm that this manuscript is not under consideration for publication elsewhere.

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9 Declaration of generative AI in scientific writing

During the preparation of this work, the author(s) used Copilot to improve language and readability. After using this tool, the author(s) reviewed and edited the content as needed and took(s) full responsibility for the publication's content.

10 Data Availability Statement

The data supporting this study's findings are available from the corresponding author, [Ahmed Emara], upon reasonable request.

11 References

- Abedi, R., Costache, R., Shafizadeh-Moghadam, H., & Pham, Q. B. (2022). Flash-flood susceptibility mapping based on XGBoost, random forest and boosted regression trees. *Geocarto International*, 37(19), 5479–5496. <https://doi.org/10.1080/10106049.2021.1920636>
- Alamoudi, F., Saber, M., A. Kantoush, S., Boulmaiz, T., Abdrabo, K. I., Abdelmoneim, H., & Sumi, T. (2023). Stormwater management modeling and machine learning for flash flood susceptibility prediction in Wadi Qows, Saudi Arabia. *Hydrological Research Letters*, 17(3), 62–68. <https://doi.org/10.3178/hr.17.62>
- Albayrak, I., Arnold, R., Demiral-Yüzügüllü, D., Maddahi, M., & Boes, R. M. (2024). Field monitoring and modelling of sediment transport, hydraulics and hydroabrasion at Sediment Bypass Tunnels. *Journal of Hydro-Environment Research*. <https://doi.org/10.1016/j.jher.2024.05.002>
- Ali, Y., Hussain, F., & Haque, M. M. (2024). Advances, challenges, and future research needs in machine learning-based crash prediction models: A systematic review. *Accident Analysis & Prevention*, 194, 107378. <https://doi.org/10.1016/j.aap.2023.107378>
- Alzubi, O. A. (2025). BotNet Attack Detection Using MALO-Based XGBoost Model in IoT Environment. *Proceedings of Third International Conference on Computing and Communication Networks*, 679–690. https://doi.org/10.1007/978-981-97-2671-4_50
- Alzubi, O. A., Alzubi, J. A., Alazab, M., Alrabea, A., Awajan, A., & Qiqieh, I. (2022). Optimized Machine Learning-Based Intrusion Detection System for Fog and Edge Computing Environment. *Electronics*, 11(19), Article 19. <https://doi.org/10.3390/electronics11193007>
- An, S., Oh, T.-J., Sohn, E., & Kim, D. (2025). Deep learning for precipitation nowcasting: A survey from the perspective of time series forecasting. *Expert Systems with Applications*, 268, 126301. <https://doi.org/10.1016/j.eswa.2024.126301>
- Aubert, G., Langlois, V. J., & Allemand, P. (2016). Bedrock incision by bedload: Insights from direct numerical simulations. *Earth Surface Dynamics*, 4(2), 327–342.
- Auel, C. (2014). *Flow characteristics, particle motion and invert abrasion in sediment bypass tunnels* (p. 1 Band) [ETH Zurich; Application/pdf]. <https://doi.org/10.3929/ETHZ-A-010243883>
- Auel, C., Albayrak, I., Sumi, T., & Boes, R. M. (2017a). Sediment transport in high-speed flows over a fixed bed: 1. Particle dynamics. *Earth Surface Processes and Landforms*, 42(9), 1365–1383. <https://doi.org/10.1002/esp.4128>
- Auel, C., Albayrak, I., Sumi, T., & Boes, R. M. (2017b). Sediment transport in high-speed flows over a fixed bed: 2. Particle impacts and abrasion prediction. *Earth Surface Processes and Landforms*, 42(9), 1384–1396. <https://doi.org/10.1002/esp.4132>
- Auel, C., Boes, R. M., & Sumi, T. (2016). Invert abrasion prediction at Asahi sediment bypass tunnel, Japan. *Journal of Applied Water Engineering and Research*, 6(2), 125–138. <https://doi.org/10.1080/23249676.2016.1265470>

- Breiman, L. (2001). Statistical modeling: The two cultures (with comments and a rejoinder by the author). *Statistical Science*, 16(3), 199–231. <https://projecteuclid.org/journals/statistical-science/volume-16/issue-3/Statistical-Modeling--The-Two-Cultures-with-comments-and-a/10.1214/ss/1009213726.short>
- Chatanantavet, P., & Parker, G. (2009). Physically based modeling of bedrock incision by abrasion, plucking, and macroabrasion. *Journal of Geophysical Research: Earth Surface*, 114(F4).
- Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794. <https://doi.org/10.1145/2939672.2939785>
- Demir, S., & Şahin, E. K. (2022). Liquefaction prediction with robust machine learning algorithms (SVM, RF, and XGBoost) supported by genetic algorithm-based feature selection and parameter optimization from the perspective of data processing. *Environmental Earth Sciences*, 81(18), 1–17. <https://doi.org/10.1007/s12665-022-10578-4>
- Demiral, D., Albayrak, I., Turowski, J. M., & Boes, R. M. (2022). Particle saltation trajectories in supercritical open channel flows: Roughness effect. *Earth Surface Processes and Landforms*, 47(15), 3588–3610.
- Demiral, D., Boes, R. M., & Albayrak, I. (2020). Effects of Secondary Currents on Turbulence Characteristics of Supercritical Open Channel Flows at Low Aspect Ratios. *Water*, 12(11), Article 11. <https://doi.org/10.3390/w12113233>
- Demiral Yüzügüllü, D. (2021). *Hydro-abrasion processes and modelling at hydraulic structures and steep bedrock rivers* [PhD Thesis]. ETH Zurich.
- Emara, A., Kantoush, S. A., Saber, M., Sumi, T., Nourani, V., & Mabrouk, E. (2025). Machine learning approach for 2D abrasion mapping in Sediment Bypass Tunnels: A case study of Koshibu SBT, Japan. *Engineering Applications of Computational Fluid Mechanics*, 19(1), 2444419. <https://doi.org/10.1080/19942060.2024.2444419>
- Fenton, J. D. (2010). Calculating resistance to flow in open channels. *Alternative Hydraulics*, 5.
- Ha, S., Kim, H., Kim, K., Lee, H., & Kim, H. (2017). Algorithm for Economic Assessment of Infrastructure Adaptation to Climate Change. *Natural Hazards Review*, 18(4), 04017007. [https://doi.org/10.1061/\(ASCE\)NH.1527-6996.0000247](https://doi.org/10.1061/(ASCE)NH.1527-6996.0000247)
- Hang, H. T., Mallick, J., Alqadhi, S., Bindajam, A. A., & Abdo, H. G. (2024). Exploring Forest Fire Susceptibility and Management Strategies in Western Himalaya: Integrating Ensemble Machine Learning and eXplainable AI for Accurate Prediction and Comprehensive Analysis. *Environmental Technology & Innovation*, 103655. <https://www.sciencedirect.com/science/article/pii/S2352186424001317>
- Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning*. Springer. <https://doi.org/10.1007/978-0-387-84858-7>
- ISHIBASHI, T. (1983). A hydraulic study on protection for erosion of sediment flush equipments of dams. *Proceedings of the Japan Society of Civil Engineers*, 1983(334), 103–112. https://www.jstage.jst.go.jp/article/jscej1969/1983/334/1983_334_103/_article/-char/ja/

- Johnson, J. P. L. (2014). A surface roughness model for predicting alluvial cover and bed load transport rate in bedrock channels. *Journal of Geophysical Research: Earth Surface*, 119(10), 2147–2173. <https://doi.org/10.1002/2013JF003000>
- Joshi, A., Vishnu, C., Mohan, C. K., & Raman, B. (2023). Application of XGBoost model for early prediction of earthquake magnitude from waveform data. *Journal of Earth System Science*, 133(1), 5. <https://doi.org/10.1007/s12040-023-02210-1>
- Kadia, S., Larsson, I. A. S., Billstein, M., Rüther, N., Lia, L., & Pummer, E. (2024). Investigating supercritical flow characteristics and movement of sediment particles in a narrow channel bend using PTV and video footage. *Advances in Water Resources*, 104827. <https://doi.org/10.1016/j.advwatres.2024.104827>
- Kavzoglu, T., & Teke, A. (2022). Predictive Performances of Ensemble Machine Learning Algorithms in Landslide Susceptibility Mapping Using Random Forest, Extreme Gradient Boosting (XGBoost) and Natural Gradient Boosting (NGBoost). *Arabian Journal for Science and Engineering*, 47(6), 7367–7385. <https://doi.org/10.1007/s13369-022-06560-8>
- Koshiba, T. (2020). *Improvement of Signal Analysis for Surrogate Bedload Monitoring at Sediment Bypass Tunnels* [Thesis, Kyoto University]. <https://repository.kulib.kyoto-u.ac.jp/dspace/bitstream/2433/253255/1/ykogk04680.pdf>
- Koshiba, T., & Sumi, T. (2020). Bedload transport and abrasion monitoring at the Koshibu Dam sediment bypass tunnel and proposing countermeasures against the abrasion problem. *Icold1st*, 13-49–19.
- Lague, D. (2014). The stream power river incision model: Evidence, theory and beyond. *Earth Surface Processes and Landforms*, 39(1), 38–61. <https://doi.org/10.1002/esp.3462>
- Lamb, M. P., Dietrich, W. E., & Sklar, L. S. (2008). A model for fluvial bedrock incision by impacting suspended and bed load sediment. *Journal of Geophysical Research: Earth Surface*, 113(F3), 2007JF000915. <https://doi.org/10.1029/2007JF000915>
- Lee, H.-Y., Lin, Y.-T., Yunyou, J., & Wenwang, H. (2006). On three-dimensional continuous saltating process of sediment particles near the channel bed. *Journal of Hydraulic Research*, 44(3), 374–389. <https://doi.org/10.1080/00221686.2006.9521689>
- Mitsubishi. (2013). *Consistently Accurate Measurement*. http://www.mitsubishielectric.co.jp/mms/pdf/mms_e.pdf
- MMS Website. (2024). *Mitsubishi Electric, Latest Version of GPS, MMS*. <http://www.mitsubishielectric.co.jp/mms/tokucho.html>
- Müller-Hagmann, M. (2018). *Hydroabrasion by high-speed sediment-laden flows in sediment bypass tunnels* [PhD Thesis]. ETH Zurich.
- Müller-Hagmann, M., Albayrak, I., Auel, C., & Boes, R. M. (2020). Field Investigation on Hydroabrasion in High-Speed Sediment-Laden Flows at Sediment Bypass Tunnels. *Water*, 12(2), Article 2. <https://doi.org/10.3390/w12020469>

- Nakagawa, H. (2017). *Turbulence in open channel flows*. Routledge. <https://www.taylorfrancis.com/books/mono/10.1201/9780203734902/turbulence-open-channel-flows-hiroji-nakagawa>
- Nakajima, H., Otsubo, Y., & Omoto, Y. (2015). Abrasion and corrective measures of a sediment bypass system at Asahi Dam. *Proc. Int. Workshop on Sediment Bypass Tunnels*, 21–32.
- Natekin, A., & Knoll, A. (2013). Gradient boosting machines, a tutorial. *Frontiers in Neurorobotics*, 7, 21. <https://www.frontiersin.org/articles/10.3389/fnbot.2013.00021/full>
- Nezu, I., & Nakagawa, H. (1993). Turbulence in open-channel flows, *IAHR-Monogr. Ser., A*, 1–281.
- Owens, P. N. (2020). Soil erosion and sediment dynamics in the Anthropocene: A review of human impacts during a period of rapid global environmental change. *Journal of Soils and Sediments*, 20(12), 4115–4143. <https://doi.org/10.1007/s11368-020-02815-9>
- Prakash, C., Barthwal, A., & Acharya, D. (2023). FLOODWALL: A Real-Time Flash Flood Monitoring and Forecasting System Using IoT. *IEEE Sensors Journal*, 23(1), 787–799. *IEEE Sensors Journal*. <https://doi.org/10.1109/JSEN.2022.3223671>
- Qi, Z., Feng, Y., Wang, S., & Li, C. (2025). Enhancing hydropower generation Predictions: A comprehensive study of XGBoost and Support Vector Regression models with advanced optimization techniques. *Ain Shams Engineering Journal*, 16(1), 103206. <https://doi.org/10.1016/j.asej.2024.103206>
- Ramraj, S., Uzir, N., Sunil, R., & Banerjee, S. (2016). Experimenting XGBoost algorithm for prediction and classification of different datasets. *International Journal of Control Theory and Applications*, 9(40), 651–662. https://www.researchgate.net/profile/Shatadeep-Banerjee/publication/318132203_Experimenting_XGBoost_Algorithm_for_Prediction_and_Classification_of_Different_Datasets/links/595b89b0458515117741a571/Experimenting-XGBoost-Algorithm-for-Prediction-and-Classification-of-Different-Datasets.pdf
- Reinauer, R., & Hager, W. H. (1997). Supercritical bend flow. *Journal of Hydraulic Engineering*, 123(3), 208–218.
- Saber, M., Boulmaiz, T., Guermoui, M., Abdrabo, K. I., Kantoush, S. A., Sumi, T., Boutaghane, H., Hori, T., Binh, D. V., Nguyen, B. Q., Bui, T. T. P., Vo, N. D., Habib, E., & Mabrouk, E. (2023). Enhancing flood risk assessment through integration of ensemble learning approaches and physical-based hydrological modeling. *Geomatics, Natural Hazards and Risk*, 14(1), 2203798. <https://doi.org/10.1080/19475705.2023.2203798>
- Saber, M., Boulmaiz, T., Guermoui, M., Abdrabo, K. I., Kantoush, S. A., Sumi, T., Boutaghane, H., Nohara, D., & Mabrouk, E. (2022). Examining LightGBM and CatBoost models for wadi flash flood susceptibility prediction. *Geocarto International*, 37(25), 7462–7487. <https://doi.org/10.1080/10106049.2021.1974959>
- Saber, M., Furuie, R., Emara, A., Kantoush, S. A., Sumi, T., Kobayashi, S., & Mabrouk, E. (2025). Real-Time Prediction of Suspended Sediment Concentration Using Machine Learning: Case Study of Miwa Reservoir, Tenryu River in Japan. *Journal of JSCE*, 13(2). <https://doi.org/10.2208/journalofjsce.24-16055>

- Scheingross, J. S., Brun, F., Lo, D. Y., Omerdin, K., & Lamb, M. P. (2014). Experimental evidence for fluvial bedrock incision by suspended and bedload sediment. *Geology*, 42(6), 523–526.
- Seidl, M. A., Dietrich, W. E., Schmidt, K. H., & De Ploey, J. (1992). The problem of channel erosion into bedrock. *Functional Geomorphology*, 23, 101–124. [https://books.google.com/books?hl=en&lr=&id=kTSBAAAAQBAJ&oi=fnd&pg=PT362&dq=Seidl,+M.A.+%26+Dietrich,+W.E.+\(1992\)+The+problem+of+channel+erosion+into+bedrock.+Catena+Supplement,+23,+101%E2%80%93124.&ots=KkNy-1M1lZ&sig=_WVCAv3durnocysG7Kg3uEd2-lU](https://books.google.com/books?hl=en&lr=&id=kTSBAAAAQBAJ&oi=fnd&pg=PT362&dq=Seidl,+M.A.+%26+Dietrich,+W.E.+(1992)+The+problem+of+channel+erosion+into+bedrock.+Catena+Supplement,+23,+101%E2%80%93124.&ots=KkNy-1M1lZ&sig=_WVCAv3durnocysG7Kg3uEd2-lU)
- Sklar, L. S., & Dietrich, W. E. (2001). Sediment and rock strength controls on river incision into bedrock. *Geology*, 29(12), 1087–1090. [https://doi.org/10.1130/0091-7613\(2001\)029<1087:SARSCO>2.0.CO;2](https://doi.org/10.1130/0091-7613(2001)029<1087:SARSCO>2.0.CO;2)
- Sklar, L. S., & Dietrich, W. E. (2004). A mechanistic model for river incision into bedrock by saltating bed load. *Water Resources Research*, 40(6). <https://doi.org/10.1029/2003WR002496>
- T.D.I.M Office. (2021). Tenryu River Dam Integrated Management Office. <https://www.cbr.mlit.go.jp/tendamu/>
- Turowski, J. M. (2009). Stochastic modeling of the cover effect and bedrock erosion. *Water Resources Research*, 45(3), 2008WR007262. <https://doi.org/10.1029/2008WR007262>
- Turowski, J. M., & Hodge, R. (2017). A probabilistic framework for the cover effect in bedrock erosion. *Earth Surface Dynamics*, 5(2), 311–330. <https://esurf.copernicus.org/articles/5/311/2017/>
- Turowski, J. M., Lague, D., & Hovius, N. (2007). Cover effect in bedrock abrasion: A new derivation and its implications for the modeling of bedrock channel morphology. *Journal of Geophysical Research: Earth Surface*, 112(F4), 2006JF000697. <https://doi.org/10.1029/2006JF000697>
- Walling, D. E. (2009). *The impact of global change on erosion and sediment transport by rivers: Current progress and future challenges*. <https://books.google.com/books?hl=en&lr=&id=zwhpknVKEsQC&oi=fnd&pg=PA1&dq=Global+sediment+dynamics+and+reservoir+sedimentation+are+intensifying+under+the+influence+of+climate+change,+leading+to+increased+sediment+transport+rates&ots=L0K-EJXnnh&sig=ssCgjr-wvSwo1o6RpuAjYfdrUMM>
- Waqar, A. (2024). Intelligent decision support systems in construction engineering: An artificial intelligence and machine learning approaches. *Expert Systems with Applications*, 249, 123503. <https://doi.org/10.1016/j.eswa.2024.123503>
- Yaghoubzadehfard, A., Lumantarna, E., Herath, N., Sofi, M., & Rad, M. (2024). Ensemble learning-based structural health monitoring of a bridge using an interferometric radar system. *Journal of Civil Structural Health Monitoring*. <https://doi.org/10.1007/s13349-024-00789-7>
- Zhang, T., Li, D., East, A. E., Kettner, A. J., Best, J., Ni, J., & Lu, X. (2023). Shifted sediment-transport regimes by climate change and amplified hydrological variability in cryosphere-fed rivers. *Science Advances*, 9(45), eadi5019. <https://doi.org/10.1126/sciadv.adi5019>

CHAPTER 7

Conclusion and Outlook (Key Findings and Future Directions)

7.1. Key Conclusions

This research advances the state of SBT abrasion prediction through comprehensive analysis and modeling. Key contributions are summarized as follows:

Literature Review (Chapter 2): The survey of sedimentation and SBT design highlighted critical gaps: most Hydro-abrasion models assume constant parameters and produce only lumped estimates. We emphasized the need to account for localized detection, justifying a high-resolution, data-driven approach.

Abrasion Drivers & Foundation Effects (Chapter 3): Abrasion in the Koshiu SBT progresses primarily via depth growth rather than expansion of worn area, with tunnel foundation type dictating where maximum damage occurs. This highlights the need to consider foundation characteristics at the design stage.

Mechanistic Model Calibration (Chapter 4): The coefficient of variation (COV) for the abrasion coefficient K_v increases from 13 % in low-damage (scatter) zones to 30 % in high-

damage (after-curvature) reaches, indicating rising heterogeneity with severity. Yet, the mean K_v across regions remains within $\pm 5\%$ of the overall average ($\sim 3.95 \times 10^4$), refuting the idea of large regional shifts in mean abrasion intensity.

ASM Model (1D/2D Susceptibility Mapping) (Chapter 5): Training XGBoost on over one million labeled points achieved an overall accuracy of 0.864 (with a value above 0.90 in the curved part), along with sensitivities and specificities above 85%. The model performs well at identifying high-risk zones but tends to overpredict on long, straight reaches and can miss fine “wave-like” abrasion patterns, indicating a need to better balance one-dimensional and two-dimensional criteria.

ASDM Model (3D Depth Prediction) (Chapter 6): The three-dimensional model achieved a correlation of $R = 0.861$ and a Nash–Sutcliffe Efficiency of 0.748 overall, peaking at 0.93/0.87 in curved sections. Water depth and hydraulic velocity emerged as dominant drivers, although the model slightly underpredicts depth, especially further downstream.

Introducing Novel ML-Based Models for Field-Scale Abrasion Prediction (Thesis): The ASM and ASDM frameworks greatly surpass traditional approaches. Importantly, our models are entirely data-driven; they do not rely on pre-existing assumptions of constant coefficients, but instead learn abrasion behavior directly from spatiotemporal data. The feature analysis confirms that the ML algorithms recognize physically meaningful controls (e.g., higher velocity increases abrasion, and both longitudinal and transverse distances influence damage patterns). In this way, our work introduces a new integration of ML algorithms into the field of hydraulic abrasion science.

7.2. Design & Operational Recommendations

1. Integrate foundation assessments

Incorporate detailed foundation-type assessments into early SBT design to predict and reduce peak abrasion zones.

2. Utilize Kv variability to enhance safety margins

Use region-specific COVs (13 %–30 %) as safety factors in mechanistic models, while adopting the overall mean Kv ($\sim 3.95 \times 10^4$) as a simplified baseline to streamline calibration.

3. Deploy ML models for forecasting & maintenance

Implement ASM/ASDM outputs in real-time flood forecasting, maintenance planning, and early warning systems to prioritize inspection and repair of vulnerable tunnel areas.

7.3. Future Outlook

Building on these advances, several directions emerge:

Integrated Flow–Sediment Feedback: Develop upstream–downstream models (e.g., SPH-based) that simulate how curvature-induced abrasion propagates upstream, closing the loop between flow and evolving bed topography.

Methodological Extensions & Validation: Test ASM/ASDM on other abrasion-prone structures (bedrock channels, weirs) and explore hybrid ML architectures (including neural networks) to benchmark and enhance performance. Broader cross-validation across multiple tunnels will establish model generalizability.

Expanded Data & Real-Time Adaptation: Integrating live sensor data (e.g., real-time cameras) with pre-trained ML models could enable online prediction of abrasion during flood events, leading to proactive maintenance actions.

Design Guidelines and Policy: The insights from this work should inform updates to engineering standards for SBTs. We recommend that hydraulic infrastructure policies incorporate multidimensional abrasion assessments and encourage high-frequency monitoring. Ultimately, linking ML-based predictions to regulatory frameworks will help ensure resilient infrastructure in the face of evolving sediment challenges.