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Modeling Siltation of River Channels Using the Physics-Informed Neural Networks Method and Numerical Simulation

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Abstract

In this study, we developed a Physics-Informed Neural Network (PINN) model integrated with the Navier-Stokes equations to simulate sediment transport and siltation in river channels. The model was designed to predict sediment deposition in complex hydrodynamic environments, using real-world data from the Syrdarya River and Shardara Reservoir and remote sensing data from Sentinel-1 and Sentinel-2 satellites. The PINN demonstrated a 10-15% reduction in computation time compared to traditional numerical methods like Ansys Fluent while maintaining high accuracy in predicting flow velocity, pressure, and sediment accumulation. By integrating physical laws and real-time data, this model has the potential to significantly improve flood management and river channel design, offering a faster, more adaptive approach to environmental hydrodynamic modeling.

Keywords: Physics-Informed neural networks; Numerical simulation; Navier-Stokes; Syrdarya river; Siltation and river pollution.
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1. Introduction

The erosion and transport of suspended nanoparticles are crucial processes in the dynamics of river channels. They significantly influence the formation of bedforms and currents and continuously alter the geomorphology of rivers by redistributing sediment and creating new channels and floodplains. This continuous movement of nanoparticles caused by erosion at the shoreline and river bed, as well as transport by the current, changes hydrodynamic conditions and can even lead to alterations in the river's course or reversal of the flow. It is essential to take this into account when managing water resources and designing hydrotechnical structures.[1] Consequently, the management of water resources has become a critical aspect of global concern. Issues such as pollution, flooding, and landslides are all linked to the contamination and siltation of river channels, which have a significant negative impact on the environment and human health. To address these issues, cutting-edge methods for modeling the transport of sediment deposits are being developed. With the advent of new technologies, remote sensing data, and machine learning techniques are being actively used. These innovative approaches allow for more accurate prediction and management of erosion and sedimentation processes, ensuring effective water resource management and preserving ecological balance in river systems.[2-4]

The main potential causes of deterioration in concrete retaining walls can be attributed to natural phenomena. These include flooding, landslides, earthquakes, and the degradation of heterogeneous foundations and building materials.[5] Therefore, the issue of the impact of dams on the environment and water resources is complex and depends on many factors, such as management, location, intended use, and environmental conditions. It is essential to conduct extensive studies and manage dams with consideration for their impact on the environment and human society.

The process of channeling is a highly unstable phenomenon.[6–8] This represents a significant risk to the infrastructure and environment, particularly in areas adjacent to the river bed. Meteorological catastrophes can potentially increase the risk of flooding in these rivers.[9] For example, the serious deepening of the rivers Koshi and Indin South Asia has resulted in the formation of extremely high loads, which in turn led to the failure of the barrage in 2008 and 2010. This caused significant damage to the downstream residential

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areas.[10] It is, therefore, of great importance to be able to manage newly formed rivers. This issue is relevant to researchers and other interested parties, such as politicians and environmental activists. However, further investigation and analysis are required to understand the issue better. The complexity of hydrodynamic processes makes forecasting the behavior of these nascent rivers difficult.[11] The current relevance of the issue stems from the increasing pressure on water resources due to accelerated industrialization, urban expansion, and climate change. Industrialization and urbanization lead to an increase in the release of pollutants into water sources. In contrast, climate change may lead to extreme weather conditions, such as higher levels of precipitation and higher temperatures, which can increase the risk of flooding.[12–14]

Researchers have noted that the use of intelligent data analysis techniques, such as machine learning and artificial neural networks, is an effective method for processing and analyzing large volumes of data collected from remote sensors. This allows for the creation of accurate and predictive models for transporting sedimentary deposits.[15-18]

Therefore, the development of models for the transportation of sedimentary deposits based on intelligent data analysis and remote sensing represents a significant area of research. In light of increasing environmental concerns and challenges associated with water resource management, this field of research is both relevant and in demand for forecasting and preventing potential threats to river channel contamination and siltation. This contributes to the resilience of aquatic ecosystems and the preservation of the natural environment.

The field experiments help to better understand the issue, and they are required to be performed in natural conditions. These experiments will allow us to study the movement of water and sedimentary layers under different conditions and provide us with real-time observations.[19–21] Even though empirical observations clearly illustrate the issue, they are often poorly documented. On the other hand, conducting experiments in specially constructed laboratories allows us to observe erosion and gullying processes directly. Many laboratory experiments have been conducted to study sedimentation phenomena in streams.[22–25] Nevertheless, comprehensive, real-world experiments investigating the maturation process are complex and require significant financial resources. Laboratory experiments are the most expensive and resource-intensive, and at the present time, numerical simulation represents the most accessible alternative to traditional experimentation. Although numerical simulation requires high-performance computers, it is less resource-intensive than laboratory experiments, and in many cases, an algorithm is validated using experimental data.[26] The study in Ref. [27] presents a laboratory experiment demonstrating morphological changes in the oral canal and riverbank erosion. The bottom and banks of the experimental channel were composed of homogeneous sand, and the cross-sectional profile of the experimental setup was that of a trapezoid. The article demonstrates the water flow behavior in an expanding installation over a homogeneous sand layer.[28] For a detailed examination of the design of land-based lakes, taking into account various criteria such as water circulation efficiency and economic efficiency of operation, It is proposed that the approach be based on the integration of modeling with the use of the Ansys Fluent software, multi-criteria optimization, and parallel.[29]

Significant advancements in artificial neural networks (ANN) have occurred in the last decade, leading to the rapid development of new approaches. The accuracy of the predictions depends on the amount of information in the training data, which is usually expressed as the sum of individual data sets. Training a neural network also involves minimizing the error function, also known as the loss function. However, there is often a lack of experimental data for neural networks in hydrodynamics.

A physics-informed neural network (PINN) emerged as a method based on artificial neural networks.[30,31] This method does not require big observational data for modeling physics through training artificial neural networks on randomly generated samples within a specified region. Additionally, they integrate well-known partial differential equation (PDE) models to constrain or regulate the training of neural networks with relatively limited data sets. Neural network training is conducted through the minimization of residuals of partial differential equations (PDEs), wherein the residual conditions are incorporated into the function of the PDEs, as well as the boundary and initial conditions of the PDEs. Therefore, PINN is a sparse network algorithm employing automatic differentiation (AD) to represent differential operators. These capabilities allow the overcoming of some of the limitations of simulation and the utilization of PINN for the resolution of inverse problems with the incorporation of observational data.[32–36]

A unified structure has been proposed as a solution to this problem. It combines computational fluid dynamics (CFD) modeling with deep neural networks (DNN) to utilize numerical simulation in a real-world context. This approach reduces the time required for calculations by incorporating mathematical modeling that considers the spatial dimensions of processes and dynamic and stationary forecasts of process variables. This method optimizes results while reducing calculation time and improving overall modeling efficiency.[37,38]

The relevance of this study stems from the need for precise and efficient methods for forecasting and modeling in the context of current ecological and hydrological challenges. Given the increasing human impact on natural water bodies, developing new approaches to assess and prevent flooding in river channels is crucial. Advanced machine learning techniques, such as PINNs, in conjunction with numerical simulation, represent a promising direction for future research. This approach allows for increased accuracy and speed in forecasting, facilitating effective management of aquatic resources.

The initial section II presents a test problem to evaluate the accuracy and precision of the PINN model. The main goal is to compare the results obtained from PINN with those from traditional numerical methods, such as the finite element and finite volume methods. The evaluation includes an analysis of errors and execution time, which allows us to identify this new approach's advantages and potential limitations.

In general, computational fluid dynamics and traditional numerical methods are mainly used to solve water resource problems, such as the siltation of rivers and river channels.[39] A distinctive feature of this work is the use of PINN in the process of river silting and channeling to increase calculation speed and gain time. PINN has been used in various applications, such as medicine, physics, atmospheric air pollution studies, oil production forecasting, *etc.*[40-42] This study considers the application of PINN to solving river channel silting problems.

In the second section III, we describe applying the PINN model for forecasting flood areas in a real-world geographical region. Using empirical data related to topography, hydrology, and meteorological conditions allows us to evaluate the accuracy and practicality of the model. The modeling process is illustrated with a conceptual diagram of the PINN model, providing a clear visual representation. We present modeling results using PINN and numerical simulation in a comparative analysis. We discuss the forecasting of floods in the context of their utility for planning and preventing flooding in challenging areas. The final section of the paper IV presents the conclusions drawn from the study.

It discusses the main conclusions and achievements obtained through the use of a combination of numerical simulation and the PINN methodology. The effectiveness and applicability of this combined approach are compared with traditional numerical simulations, and potential improvements to the method are identified based on future research directions.

2. The objective of the test is to ascertain the accuracy of the PINN model in comparison to traditional numerical modeling techniques

The experimental study used PINN to model the two-dimensional Navier-Stokes equation. This equation describes the velocity profile in a stream of parallel plates. To achieve this, we used the equation that describes the motion of a viscous, incompressible fluid. This equation is commonly used in hydrodynamics, as described below.[43–45]

$$u\frac{\partial u}{\partial x}+v\frac{\partial u}{\partial y}+\frac{1}{\rho}\frac{\partial P}{\partial x}=\nu\left(\frac{\partial^2 u}{\partial x^2}+\frac{\partial^2 u}{\partial y^2}\right) \tag{1}$$

$$u\frac{\partial v}{\partial x}+v\frac{\partial v}{\partial y}+\frac{1}{\rho}\frac{\partial P}{\partial y}=\nu\left(\frac{\partial^2 v}{\partial x^2}+\frac{\partial^2 v}{\partial y^2}\right) \tag{2}$$

$$\frac{\partial u}{\partial x}+\frac{\partial v}{\partial y}=0 \tag{3}$$

A geometric configuration was constructed with a length of 2m and a height of 1m. The boundary conditions and the complete dimensions of the region under investigation are presented in Fig. 1.

The upper and lower lateral walls served as boundaries for the structure, controlling access and egress points. In the next phase, to facilitate the training of neural networks using PINNs, the necessary points for solving the Partial differential equation (PDE) and a computational grid for numerical simulation were generated.

We obtained two data from two methods: numerical simulation and PINNs. Numerical simulation involves creating a data set that models the behavior of a real system using mathematical equations and physical laws, which serves as a benchmark for comparison. We then constructed a numerical simulation to obtain data about the behavior of the Syr Darya River under various conditions. After that, we created the PINN model, which was trained on real data and additional information, such as topography and meteorological data. Comparing the results from numerical simulation and PINN allowed us to evaluate the accuracy and reliability of our approach. Fig. 2 shows the contour plots of velocity and pressure values. There are differences in the numerical results when they are compared to the results of the PINN model. There are differences in the numerical results when they are compared to the results of the PINN model. These discrepancies are due to the differences in the approaches and methods used in traditional numerical simulation and the PINN method. Traditional numerical methods, such as finite difference or finite element methods,

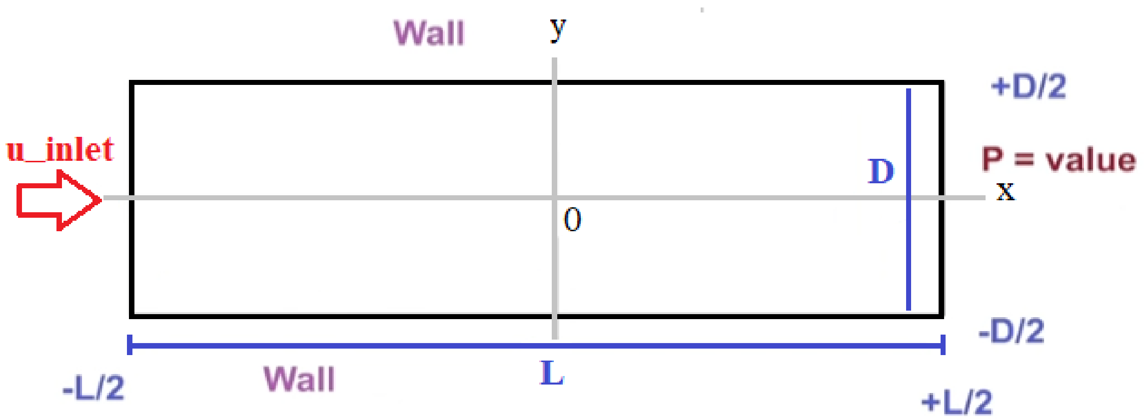


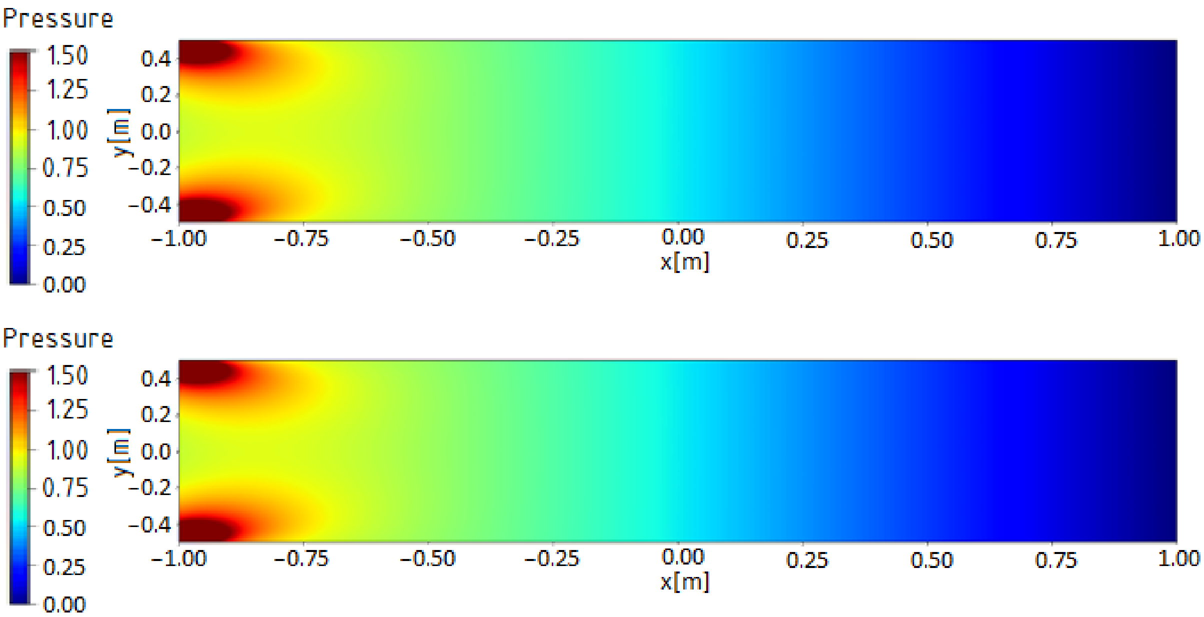
Fig. 1 Geometry and boundary conditions of the test problem for the PINN implementation.

may lead to approximations or simplifications of the equations and boundary conditions, which can affect the accuracy of the results. In contrast, the PINN model uses artificial neural networks to train models that can handle complex data and solve equations in their original forms. This difference in approach can lead to differences in the numerical solutions.

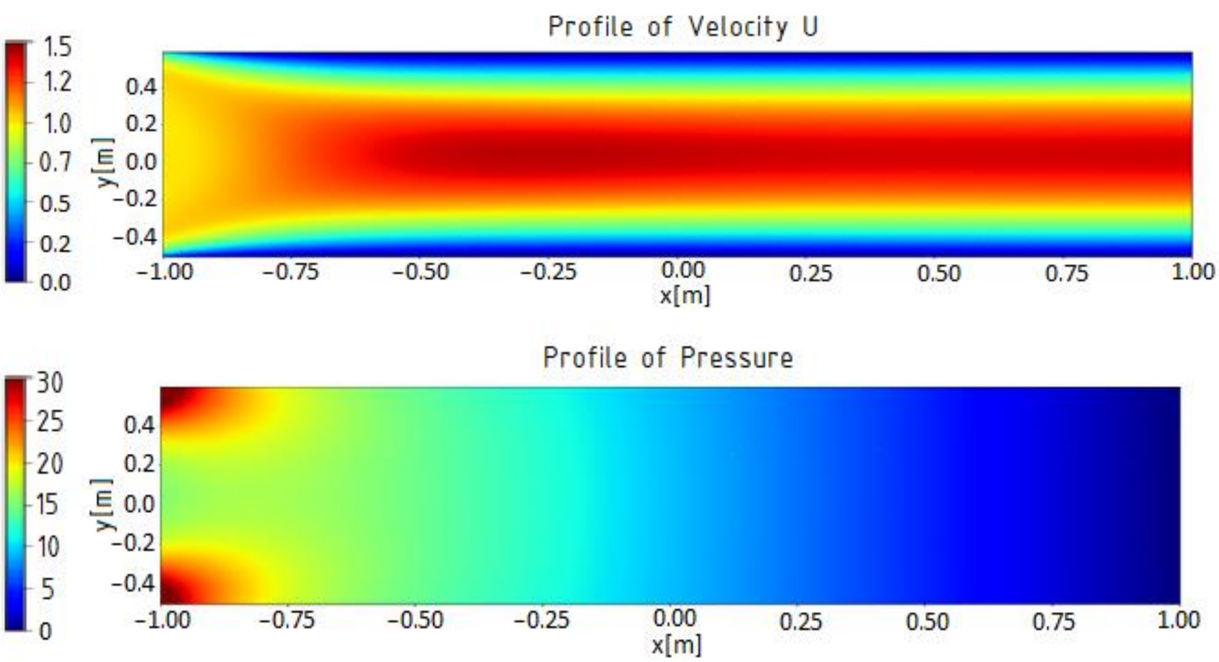
However, the results obtained from the velocity profile at the entrance to the system are in good agreement with the data presented in Fig. 3. PINN can calculate predicted values based on a limited data set, reducing the time required for these calculations. Therefore, it can be concluded that the PINN model can describe complex physical processes involving intricate differential equations.

Despite the number of elements that can be used to resolve a task, advanced methodology can achieve reliable results and reduce calculation time. A comparison of the results and calculation times of PINN and numerical simulation methods can be presented in Table 1.

PINN 1 and PINN 2 are neural networks with differences in the number of neural network parameters used to train the model. PINN 1 uses a smaller number of elements (5000), allowing for faster calculations and less computational resources. Despite the smaller number of elements in the neural network, the results from PINN 1 simulations are in good agreement with experimental data, demonstrating the effectiveness of the model with a limited number of



(a) Numerical simulation with Ansys Fluent



(b) Simulation with PINN

Fig. 2 The results obtained from the trial simulation task are as follows.

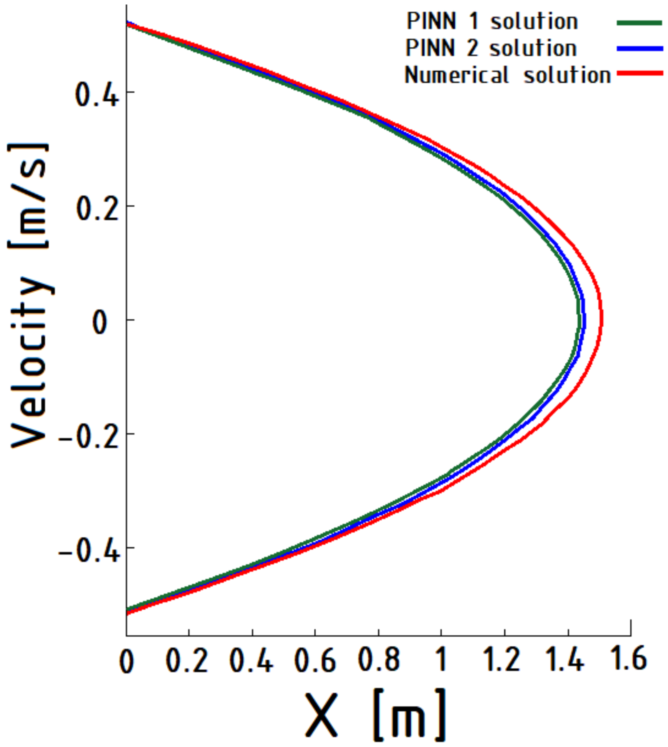


Fig. 3 A comparative analysis of the time required for the PINN method and numerical simulation.

parameters. On the other hand, PINN 2 uses the 500000 number of elements neural network, which may lead to accurate approximation but also increases the calculation time and resource requirements. Therefore, PINN 1 may be preferred in situations where a balance between speed and accuracy is required.

However, increasing the number of elements to 500,000 in PINN 2 increased the computational time, although it was still faster than numerical simulation using Ansys Fluent. Therefore, it can be concluded that a significant reduction in calculation time can be achieved when using Ansys for numerical simulation compared to traditional methods. This is especially true for smaller numbers of elements.

Despite the number of elements that can be used in resolving a crisis, it is possible to achieve more reliable results and reduce the calculation time by using a more advanced methodology. A comparison of the results and calculation times of PINN and numerical simulation methods can be presented in a table (Table 1). This allows us to evaluate the quality of the results and the efficiency of each calculation method. Therefore, despite the results of PINN 1 and PINN 2 modeling, it can be concluded that PINN 1 has the shortest calculation time and requires the minimum number of elements, demonstrating its effectiveness when a limited number of parameters is used. However, increasing the number of elements to 500,000 in PINN 2 increased the computational time, although it was still faster than numerical simulation using Ansys Fluent. Therefore, it can be concluded that a significant reduction in calculation time can be achieved when using Ansys for numerical simulation compared to traditional methods. This is especially true for smaller numbers of elements. In addition, the results show that PINN is more effective for simulation tasks that require fast and accurate forecasting, especially in situations with limited computational resources.

Table 1. Time comparison of the PINN method and numerical simulations.

Modelling	Time (s)	Number of elements(PINN), parameters(Ansys)
PINN 1 (CPU)	89,1	5 000
PINN 2 (CPU)	128,8	500 000
ANSYS (CPU)	154.4	1 570 000

3. Prediction of flood areas in river channels using the PINN model for a real-world area

The prediction of flooding areas using the PINN model and numerical simulations is a promising approach for solving problems related to pollution and flooding in river channels. The PINN model integrates physical principles expressed through Navier-Stokes and other equations with real-world data, allowing for more accurate and efficient predictions of flooding areas. To investigate the real-world area in greater detail, remote sensing data provides valuable imagery that contains information about the state of the land surface, including water bodies. This allows for the identification of siltation areas and the tracking of their changes over time.

We used the PINN model to predict the siltation zone in the area around the dam on the Syrdarya River. To do so, we used a variety of data sources, including real-world data collected in the area, as well as topographic and weather information that was available. Additionally, we used remotely sensed data from satellites, such as Landsat and Sentinel-1/2, to increase the accuracy and detail of our model. Landsat satellites provided high-resolution multispectral imagery that allowed us to analyze changes in the landscape and water bodies in the area. Sentinel-1 used radar technology to gather data regardless of weather or time of day, which made it especially useful for monitoring water bodies. Data frequency is 6-12 day intervals depending on geographic location and latitude, but in some cases (especially in polar regions), it can update every 1-3 days. Sentinel-2 offered high temporal resolution imagery that helped us monitor dynamic changes in the region.[46,47] Data frequency is every 5 days, ensuring near-continuous monitoring over the exact location. These remotely sensed data were used to provide up-to-date and detailed information on topography, water regimes, and landscape changes. By combining these data with the PINN model and weather data, we were able to more accurately predict the area prone to flooding. The area of interest for our study is shown in Fig. 4. We defined the boundary conditions and created a geometry based on remote sensing images, as shown in Fig. 5.

Fig. 4 Schematic location of the study area of the dam on the Syrdarya River.

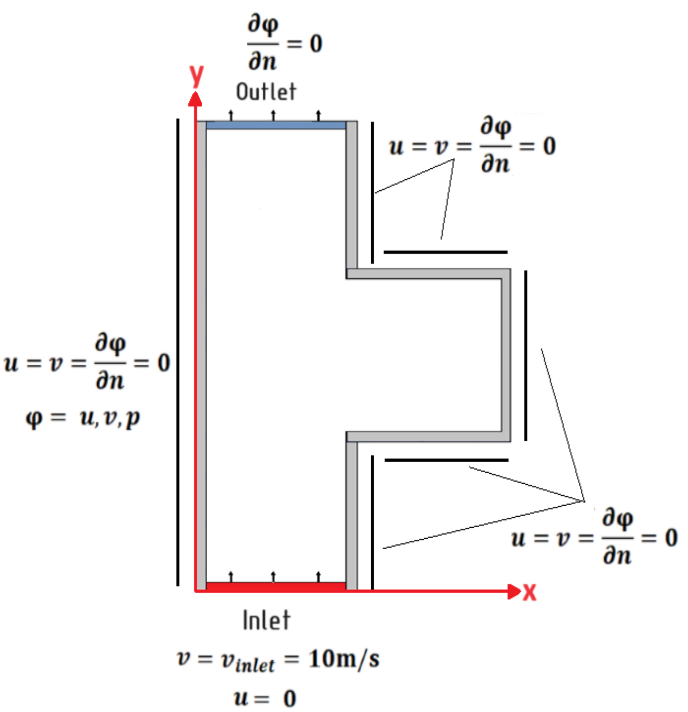


Fig. 5 Geometry and boundary conditions of the study area.

We then built a PINN model that combines remote sensing imagery with physical equations describing water flow in river channels. The model was trained on available data, using boundary and point conditions, to learn how to predict flood areas based on real-world data from the study area. Fig. 6 shows the points generated for calculating the partial differential equation (PDE) solution and the computational grid used for numerical simulation.

After that, once the grid has been created, we train the PINN model to obtain a forecast for predicting the flooding areas based on real data. This helps us to react to possible flooding threats and take appropriate precautions quickly. Fig. 7 illustrates the implementation of the PINN concept.

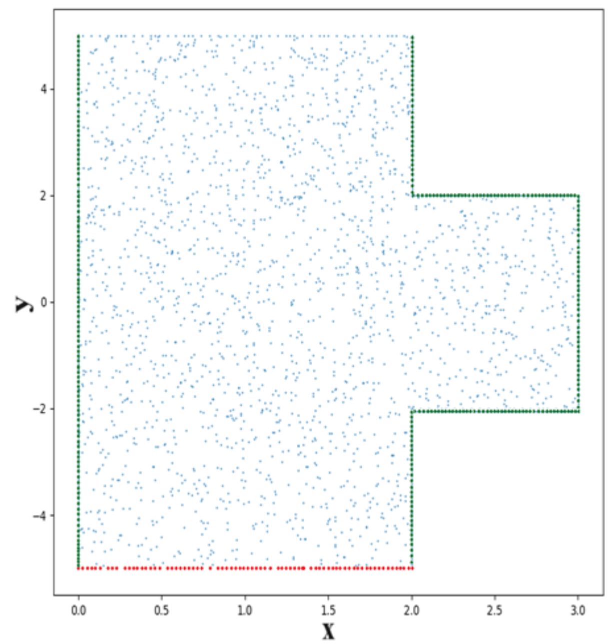


Fig. 6 Generated points for calculating the solution of the PDE and the computational grid for numerical simulation.

Neural networks for solving the Navier-Stokes equations can be implemented using different architectures and PINN models, where neural networks are trained to predict velocity and pressure fields corresponding to solutions of the Navier-Stokes equations. In the PINN method, differentiation within the neural network is performed automatically. In Python, with the deep learning library PyTorch, automatic differentiation is used to compute gradients of functions, including derivatives of the neural network parameters.

Once the conditions are defined, the PINN model is trained to satisfy the Navier-Stokes equations in the fluid volume and the boundary conditions on the object walls. The partitioning of the loss function into two parts in the PINN method is usually used to account for two aspects of the problem: the accuracy of the model prediction and the fit to the physical equations, the boundary conditions, the equation 4 shows the general loss function. The purpose of this part of the loss function is to minimize the prediction error of the model and ensure its accuracy on the training dataset.

Breaking the loss function into two parts allows for a balance between the accuracy of the model's prediction and its physical validity. This allows the PINN model to combine the advantages of neural networks for approximating complex functions with physical validity, making them effective tools for solving physics problems.

We used the input parameters that are derived from a combination of real-world data. The spatial coordinates x and y, it is derived from geographic data, such as topographical maps, remote sensing data or digital elevation models. Time t is an essential input, especially when the model aims to predict the dynamic evolution of the system, such as changes in sediment deposition or water flow over time. Time-based observational data, such as historical river flow rates or weather data.

The layers and neurons in each layer between input and output make up the structure of the neural network. The automatic differentiation method calculates the physical loss function, and the velocity components u and v on the training data are calculated by minimizing the loss function, equation 4.

$$\mathcal{L}_{total}(W,b) = \frac{1}{N_u}\sum_{i=1}^{N_u}\left|u\left(t_u^i, x_u^i\right) - u^i\right|^2 + \frac{1}{N_f}\sum_{i=1}^{N_f}\left|\frac{\partial u}{\partial t} + (u\cdot\nabla)u + \frac{1}{\rho}\nabla p - \nu\nabla^2 u + b_f\right|^2 + \frac{1}{N_f}\sum_{i=1}^{N_f}|\nabla u|^2 \quad (4)$$

The total loss function $\mathcal{L}_{total}(W,b)$ consists of the prediction error L_{MSE}, the deviation from the Navier-Stokes equation L_{NS}, and an additional regularization term L_V.

The first part is the initial and boundary conditions:

$$L_{MSE} = \frac{1}{N_u}\sum_{i=1}^{N_u}\left|u\left(t_u^i, x_u^i\right) - u^i\right|^2 \quad (5)$$

where N_u is the number of data points used for the computation, $u\left(t_u^i, x_u^i\right)$ is the neural network prediction for the fluid velocity at the space-time point t_u^i, x_u^i is the flow velocity at point u^i. Here, the mean square error (MSE) between the neural network predictions and the actual data is minimized.

The second part finds the deviation from the solution of the Navier-Stokes equation:

$$L_{NS} = \frac{1}{N_f}\sum_{i=1}^{N_f}\left|\frac{\partial u}{\partial t} + (u\cdot\nabla)u + \frac{1}{\rho}\nabla p - \nu\nabla^2 u + b_f\right|^2 \quad (6)$$

where N_f is the number of points used for the Navier-Stokes equation, $\frac{\partial u}{\partial t}$ the partial derivative of velocity with respect to time, $(u\cdot\nabla)u$ is the convective term for nonlinear changes in velocity, $\frac{1}{\rho}\nabla p$ is the pressure gradient divided by density, ν is the kinematic viscosity, $\nabla^2 u$ is the diffusion term, b_f represents external forces.

The third part helps minimize the velocity gradients in the system:

$$L_V = \frac{1}{N_f}\sum_{i=1}^{N_f}|\nabla u|^2 \quad (7)$$

where ∇u is the velocity gradient.

The optimization is defined as:

$$W^*, b^* = argmin_{W,b},\ \mathcal{L}_{total}(W,b) \quad (8)$$

where W and b are the weights and biases of the neural network, u-flow velocity, p- pressure, ρ-fluid density, t-time, x-spatial coordinates, W^*, b^* optimal values of the weights W and biases b of the neural network.

For this problem, the following hyperparameters were selected to minimize the loss function. The main hyperparameters of the PINN architecture are presented in Table 2. We used the 7 hidden layers and 30 neurons per layer. The total number of parameters of PINN is 5,732. The outputs are the velocity in direction (u) and pressure (p). The loss function analysis demonstrated that the model successfully trained over 7500 training iterations. A significant decrease in loss values indicates improvement in the model's performance and ability to predict data accurately. Although there were some fluctuations, the overall decreasing trend in losses suggests a well-tuned model with appropriate training parameters. Fig. 8 shows the PINN model's learning progress for 7500 epochs. Our model reaches an acceptable loss function value after 3000 epochs, after which the loss function plateaus and stops improving significantly over successive epochs.

Table 2. Main hyperparameters of the PINN architecture.

Parameters	PINN
Number of layers	7
Activation function	Tanh
Optimiser	Adam
Number of epochs	7500
Learning rate	0.001
Loss function	MSE

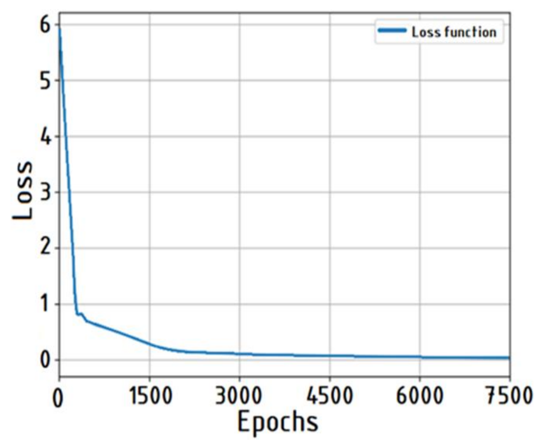
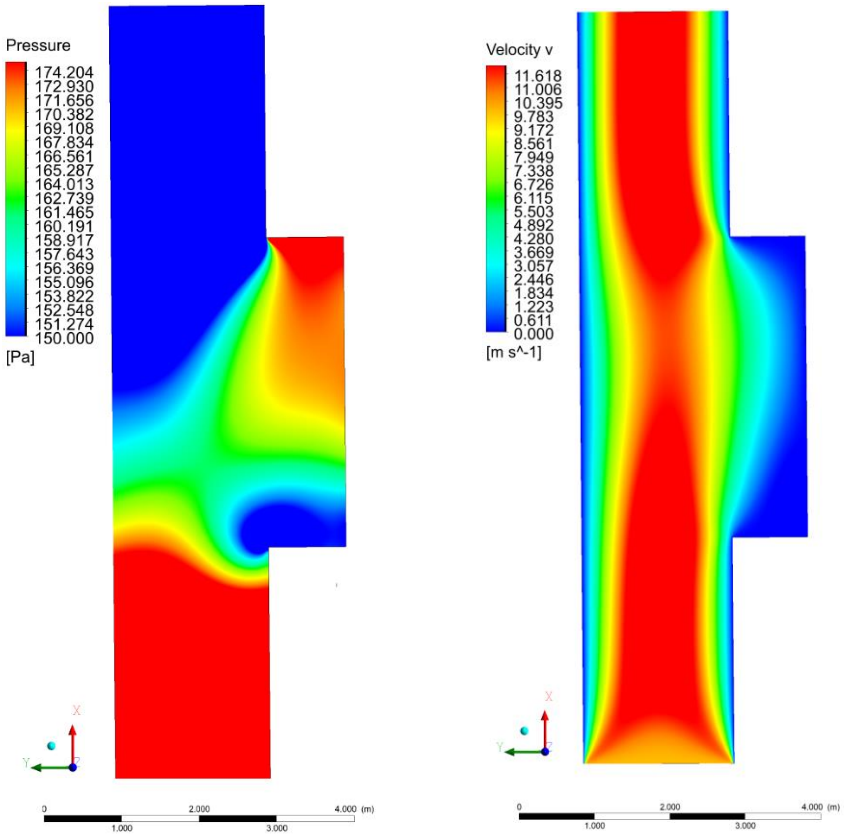


Fig. 8 Loss Function over Epochs for the PINN model.



(a) (b)

Fig. 9 Contour plots of the study area based on numerical simulation: (a) pressure profile; (b) velocity profile.

To verify the accuracy of our results, we compared them with those obtained from numerical simulation. We also generated contour plots of the velocity and pressure changes in the area under study, which are shown in Fig. 9.

As the water moves along the selected path, its velocity varies depending on the geometry of the 'T' shape, where there is friction of the canal wall due to the change in depth. The velocity will be highest at the entrance to the canal (where the water enters) and gradually decrease as it moves along the canal.

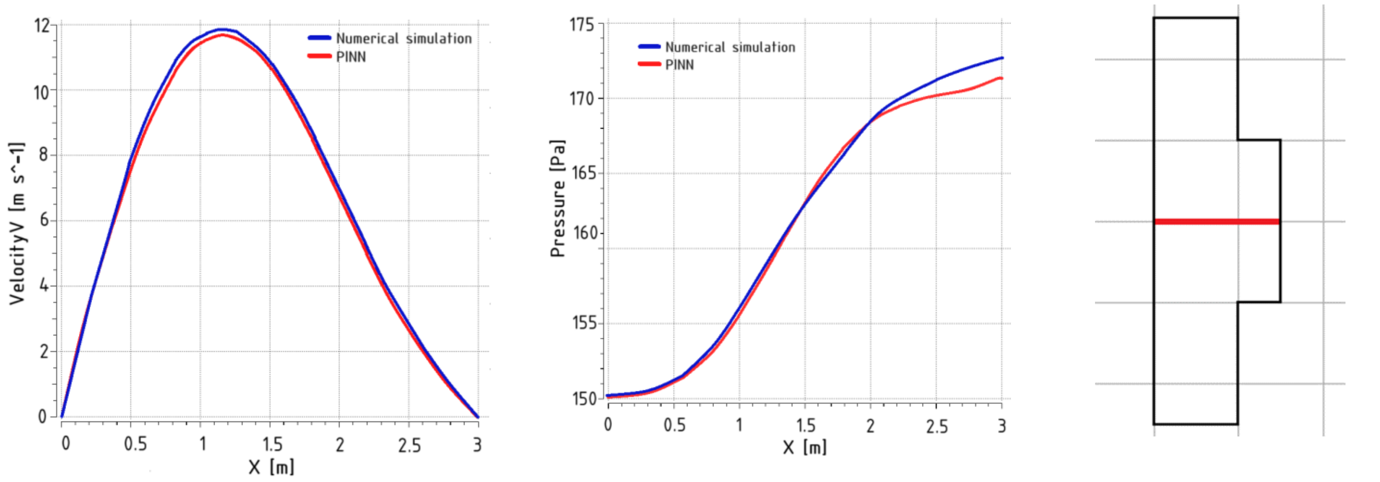
Pressure can also vary along the path of the water. As the water moves through the channel, the pressure can fluctuate due to changes in velocity and water elevation, affecting the geometry of the channel. In areas of increased velocity, the pressure also increases; in the pocket area, a decrease in pressure can be seen. The results presented in Fig. 10 demonstrate the significant impact of the study area's geometry on velocity and pressure profiles. In Fig. 10(a), the velocity profile illustrates the distribution of velocities along the reference line as obtained through numerical simulation and PINNs. The close agreement between these two methods highlights the effectiveness of PINN in accurately representing the velocity field. In Fig. 10(b), the pressure profile along the reference line shows results derived from both numerical simulation and PINN, with a comparison revealing minor deviations. These deviations indicate the sensitivity of pressure predictions to computational and modeling nuances while still maintaining a general consistency in the trend.

Thus, it can be noted that the results obtained from the numerical simulation and PINN model agree well, showing the validity of the obtained results using the PINN model.

Predicting flooding areas using the PINN model and numerical simulation to verify the accuracy of the predictions has the potential to improve water management and protect the environment from potential flooding risks. The use of a PINN model, based on neural networks, can adapt to complex nonlinear dependencies in flow data and accurately predict flooding areas in river channels.

Remote sensing of Earth provides valuable information on surface water, including river flow, water quality, and pollution. Integrating this data with the PINN model can lead to more accurate predictions of flooding and better assessment of environmental risks.

However, verification and validation of the results are also necessary to ensure the reliability and accuracy of predictions. Numerical simulation is used to verify the consistency of PINN model predictions with real data and physical laws. To verify the correctness of the results, experimental data or special solvers are usually used to describe the flow of fluid, which is solved using the Navier-Stokes equation. In our case, we use the Ansys Fluent numerical solver software package. The use of numerical simulation allows us to conduct additional analysis and adjust the PINN model parameters to



(a) (b) (c)

Fig. 10 Comparative results of numerical simulation and the PINN on the reference line: (a) pressure profile; (b) velocity profile; (c) location of the reference line.

obtain the best results.

The combination of the PINN model and numerical simulation is a powerful tool for predicting flooding in river channels. It provides accurate and reliable results, contributing to efficient water management and environmental protection. For a more in-depth analysis and to draw valid conclusions from the data presented in Tables 3 and 4, it is essential to consider both the technical specifications of the resources used and the results of a comparative analysis between the PINN model and traditional numerical methods in terms of runtime and accuracy.

The system used for the calculations is equipped with an Intel Core i9-9900K processor with a clock speed of 3.6 GHz, which offers high-performance thanks to its 10 cores, 20 threads and 64 GB of RAM. Additionally, the 64-bit operating system and x64 architecture ensure optimal use of available resources and compatibility with modern software solutions. Table 3 presents a comparison between the execution time of the PINN approach and traditional numerical simulations. The PINN model demonstrates the following outcomes:

Table 3. Time comparison of PINN method and numerical simulations.

Simulation	Time (s)	Number of elements (PINN)	Percentage of elements(PINN) to number of parameters(Ansys mesh=6,698,266)
PINN 1 (CPU)	94.06	50 000	≈1%
PINN 2 (CPU)	143.8	250 000	3.7%
PINN 3 (CPU)	180.4	500 000	7.5%

PINN 1 on the CPU takes 143.8 seconds to process 50,000 elements, which is approximately 1% of the total number of parameters used in the Ansys mesh (6,698,266 elements). PINN 2 on the CPU takes 180 seconds to process 250,000 elements (3.7% of the Ansys mesh). PINN 3 on the CPU processes 500,000 elements, which is 7.5% of the Ansys mesh. From this data, it can be seen that the processing time increases as the number of elements in the PINN model increases, but the method can significantly reduce the number of parameters compared to full numerical simulation, which can reduce the computational cost when the number of elements increases. Table 4 shows a comparison of Root Mean Square Error (RSME) and Mean Squared Error (MSE) metrics for velocity and pressure obtained from numerical simulation and the PINN method.

Table 4. Comparison of metrics for the results obtained: Comparison of numerical simulation and PINN results for velocity and pressure.

Metrics	RSME	MSE
Speed	0.6838	4.8969
Pressure	0.6838	0.4676

The RSME for velocity and pressure is the same: 0.6838, which indicates the standard deviation of the predicted values from the real values.

The MSE for velocity is significantly higher (4.8969) than the MSE for pressure (0.4676), which may indicate the greater accuracy of pressure predictions by the PINN method compared to velocity.

Based on the analysis of the presented data, it can be concluded that the PINN method shows high efficiency in reducing the number of computational elements required while maintaining acceptable prediction accuracy, especially for pressure. This makes it promising for applications where fast processing of large data is required with limited computational resources. However, further optimization of the model may be required to improve accuracy for complex parameters such as velocity.

4. Discussion

As observed in our results, even slight differences in accuracy between PINNs and traditional methods can have significant implications in real-world applications. For instance, in flood management, minor inaccuracies in predicting flood-prone areas could lead to suboptimal resource allocation or infrastructure planning. The PINN's ability to integrate real-world data, including satellite imagery and meteorological information, enables more refined predictions in dynamic environments like river channels. While traditional methods remain highly accurate, the PINN's real-time data integration may offer improved compute cost and time efficiency in adaptive management scenarios, allowing for better preparation and mitigation strategies in the face of unexpected hydrological events.

The general frequent updates from Sentinel-1 and Sentinel-2 are 5-12 days. The frequent data update enables more accurate real-time predictions, better adaptability to environmental changes, and the capacity to support critical decision-making processes in river management and flood prevention. The PINN model benefits from continuous retraining with updated remote sensing data. Therefore, we proposed to use two satellite images to decrease the update interval of data. However, there may still be challenges during rapid changes or cloud cover events requiring using other data acquisition strategies.

While it is true that PINNs may show marginal differences in accuracy compared to traditional methods, in flood prediction, where conditions can change rapidly, having a slightly faster, real-time prediction model can lead to better, more informed decisions, even if the accuracy is slightly less than that of traditional simulations. This allows for more frequent and iterative simulations that can better adapt to changing environmental conditions, which is vital during emergency flood scenarios.

5. Conclusions

In this study, a numerical simulation was developed using the Navier-Stokes equations. The simulation results were compared with experimental data and showed good agreement, confirming the model's validity for the complex domain under study.

An important aspect of this research is using PINN compared to traditional numerical simulation. PINN analyzes flow characteristics such as velocity, pressure, and density. PINN was faster for the test area, about two times faster than Ansys (PINN 89.1 sec, Ansys 154.4 sec). The results obtained using PINN were compared to those obtained using Ansys, a standard numerical method. The two methods produced similar results, except when shock effects were present. PINN was able to model these conditions, while traditional methods struggled to do so accurately. The use of remote sensing data, including multilayer imagery and geodetic data, has improved the accuracy of modeling input data. This allows for a detailed analysis of topographic features in the study area and enables the application of this information in accurately modeling hydrological processes.

In further research, we would like to consider the hybrid modeling approach, the integration of traditional numerical methods (finite element models) with the Deep Learning approach to achieve a hybrid model that leverages the strengths of both techniques for increased accuracy and flexibility in different scenarios. Additionally, we are considering extending our result for 3D modeling to capture more complex hydrodynamic processes; we will extend the model to support three-dimensional simulations, allowing for a better representation of the vertical flow and sediment deposition.

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Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

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