Article Type: Research

Predicting Flood Energy Attenuation in Vegetated Rivers using Artificial Neural Networks (ANN)

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Received: 03 September 2025 / Accepted: 25 September 2025 / Published: 19 October 2025

Abstract: Flood energy attenuation in vegetated rivers is a critical factor in flood management and riverine ecosystem stability. This study develops an Artificial Neural Network (ANN) model to predict flood energy reduction using a dataset of 760 rivers in Iran. The dataset was divided into 70% for training and 30% for testing. A multi-layer perceptron (MLP) ANN was implemented in Python to establish the relationship between key hydraulic and vegetation parameters and energy dissipation. The input variables included the Froude number (F_r), vegetation density and thickness (D_v), and relative backwater rise (Δr), while the output parameter was energy reduction (ΔE). The model's performance was evaluated using statistical metrics, achieving a high correlation ($R^2 = 0.92$) and a low mean absolute error (MAE = 0.025 and RMSE = 0.012), demonstrating the ANN's strong predictive capability. Results indicate that vegetation characteristics significantly influence energy dissipation, with denser and thicker vegetation leading to greater flood energy reduction. Sensitivity analysis further highlighted the dominant role of Δr in determining energy loss. The ANN model outperformed traditional empirical methods in accuracy, proving its reliability for practical applications in flood risk assessment. These findings suggest that ANN-based modeling can be a valuable tool for hydrologists and engineers in optimizing river management strategies. Future research should focus on expanding the dataset and integrating additional hydraulic parameters to further refine prediction accuracy.

Keywords: Flood energy, Vegetated rivers, Artificial neural networks, Flood prediction, Hydraulic modeling.

I. INTRODUCTION

Flood periods play a key role in shaping river systems by altering their morphology, sediment transport dynamics, and ecological conditions (Yan et al., 2022). During high-flow events, rivers experience increased discharge, which enhances erosion, sediment deposition, and channel migration (Nanehkaran et al., 2023). These processes contribute to the long-term evolution of river systems, influencing their width, depth, and meandering patterns (Gergel et al., 2002). The frequency and intensity of floods determine the extent of these changes, with more extreme events leading to significant alterations in river structure (Tockner & Stanford, 2002). One of the most important effects of flood periods is sediment transport and deposition (Syvitski et al., 2012). When river discharge increases, the flow gains the capacity to carry larger sediment loads downstream (Banach et al., 2009). As floodwaters recede, the reduced flow velocity causes sediment to settle, leading to the formation of natural levees, sandbars, and floodplains (Lewin & Ashworth, 2014). Over time, these deposits contribute to the development of diverse river landscapes, supporting both aquatic and terrestrial ecosystems (Tockner & Stanford, 2002).

Flood periods also influence the connectivity between the main river channel and its floodplain (Kiedrzyńska et al., 2015). During flooding, water spreads over adjacent low-lying areas, replenishing floodplain wetlands and groundwater reserves. This hydrological exchange is essential for maintaining habitat diversity and ensuring the survival of species adapted to flood-driven environments (Habersack et al., 2015). Many fish species rely on floodplain inundations for breeding and feeding, making floods a critical ecological process (Castellarin et al., 2011). The impact of flood periods on river development varies depending on local geological conditions, vegetation cover, and human interventions (Wheater, 2006). In natural settings, floods help rivers maintain their dynamic equilibrium by balancing erosion and deposition processes (Loë, 2000). However, in highly modified rivers with artificial levees, dams, or urban encroachments, flood energy may be redirected in ways that cause excessive erosion, infrastructure damage, or loss of floodplain function (Tingsanchali & Karim, 2010). Understanding these dynamics is essential for sustainable river management and flood risk mitigation (Plate, 2002).

Flood energy attenuation refers to the reduction in the intensity and energy of floodwater as they move downstream (Sholtes & Doyle, 2011). This phenomenon occurs due to various factors, including frictional resistance, changes in topography, and interactions with natural or artificial obstacles (Lininger & Latrubesse, 2016). Attenuation is important in flood risk management as it helps to mitigate damage to infrastructure, reduces erosion, and supports ecosystem stability (Turner-Gillespie et al., 2003). The attenuation of flood energy can be quantified using different approaches, including hydraulic modeling, empirical equations, and field measurements (Terêncio et al., 2020). Hydraulic models such as the Saint-Venant equations and the Manning equation are commonly used to describe the energy dissipation process (Magilligan et al., 2015). Empirical methods, on the other hand, rely on observed data to establish relationships between flow parameters and energy loss (Ahmed & Ghumman, 2019). Additionally, direct field measurements of velocity, depth, and turbulence provide valuable insights into energy dissipation mechanisms (Ren et al., 2021). In riverine environments, flood energy attenuation is influenced by channel morphology, roughness elements, and external boundary conditions (Montaldo et al., 2004). Vegetation plays a significant role in modifying the flow characteristics by increasing hydraulic resistance, enhancing sediment deposition, and dissipating kinetic energy (Wyżga et al., 2018). This makes vegetated rivers more effective in reducing flood impact compared to non-vegetated channels (Magilligan et al., 2015). Vegetation in rivers affects flood attenuation through several mechanisms (Turner-Gillespie et al., 2003). Firstly, plants increase surface roughness, which slows down the velocity of water flow (Ren et al., 2021). This increased resistance leads to a decrease in flood energy and reduces the risk of downstream flooding (Sholtes & Doyle, 2011). Secondly, vegetation promotes sediment trapping, altering the riverbed morphology in a way that influences flood wave propagation (Ren et al., 2021). Over time, these changes contribute to a more stable and resilient river system. The type, density, and structure of vegetation significantly influences its effectiveness in attenuating flood energy (Forysinski, 2019). Emergent macrophytes, submerged aquatic plants, and riparian forests each contribute differently to energy dissipation (Wyżga et al., 2018). For instance, dense riparian forests along riverbanks create a buffer zone that absorbs flood energy, whereas submerged vegetation affects the turbulence and resistance within the water column (Ren et al., 2021). Figure 1 provides the topical flood wave hydrograph with and without vegetation retention.

One of the key factors determining the effectiveness of vegetation in flood energy attenuation is its flexibility and mechanical properties (Yiping et al., 2015). Rigid vegetation, such as shrubs and trees, offers high resistance and substantial energy dissipation, while flexible plants, such as grasses and reeds, adapt to flow conditions, influencing turbulence dynamics in a different manner (Forysinski, 2019). Figure 2 illustrates the conceptual diagram of the effect of vegetation on discharge at different scales. Understanding these variations is essential for accurate modeling and management of vegetated rivers (SV et al., 2019). Floodplain vegetation also contributes to flood energy attenuation by storing excess water and reducing peak discharge (Oude, 2010). During high-flow events, floodplains act as natural reservoirs that temporarily hold floodwaters, slowing their progression and reducing their erosive potential (Forysinski, 2019).

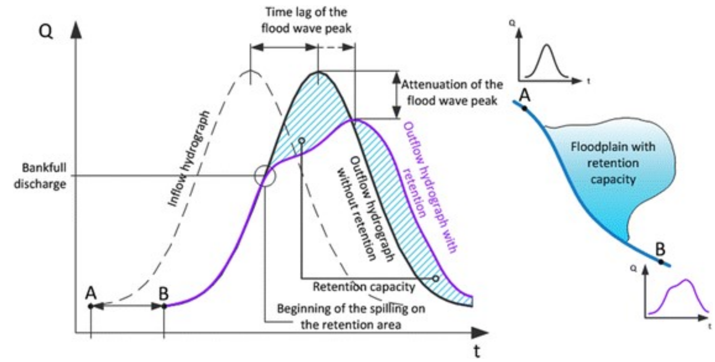

Fig. 1 Typical hydrograph changes caused by flood waves over rivers with and without vegetation (Rak et al., 2016)

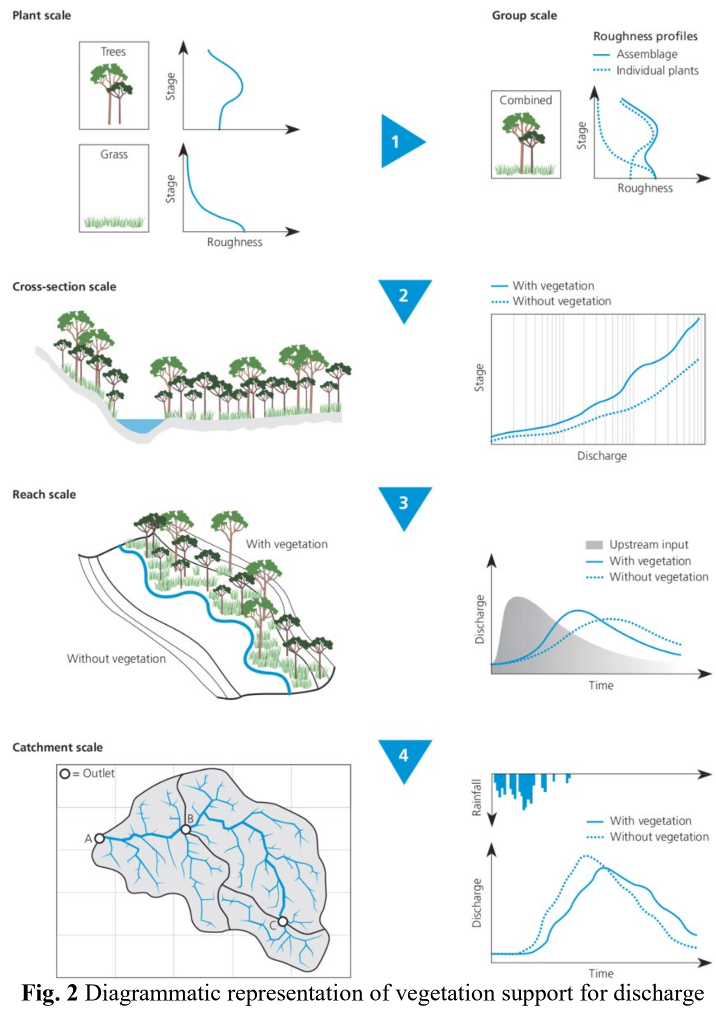

Fig. 2 Diagrammatic representation of vegetation support for discharge at the various scales (Rutherfurd et al., 2007)

The presence of dense vegetation enhances this effect by increasing the retention time and promoting infiltration (Oude, 2010). From an ecological perspective, vegetation not only aids in flood attenuation but also provides habitat for aquatic and terrestrial species (Forysinski, 2019). Healthy riparian vegetation supports biodiversity, stabilizes riverbanks, and improves water quality (Rak et al., 2016). Thus, maintaining and restoring vegetated river systems is a critical aspect of sustainable river management and flood mitigation strategies (Rutherfurd et al., 2007). Human interventions, such as deforestation, river channelization, and dam construction, can disrupt the natural flood attenuation process (Rak et al., 2016). The removal of vegetation reduces hydraulic roughness, leading to higher flow velocities and increased flood risk downstream (van Wesenbeeck et al., 2022). Therefore, incorporating vegetation-based solutions in flood management plans is essential for long-term resilience against extreme hydrological events (van Wesenbeeck et al., 2017).

Flood energy attenuation in vegetated rivers involves various natural and engineered mechanisms that reduce the intensity and velocity of floodwater (Sharpe & Kemp, 2021). One of the primary methods is increasing hydraulic roughness through vegetation (Quinn et al., 2022). Dense vegetation along riverbanks and within the channel creates resistance to flowing water, reducing flow velocity and dissipating kinetic energy (D'Ippolito e al., 2021). Different types of vegetation, including submerged, emergent, and riparian plants, contribute to this process by enhancing turbulence and promoting energy loss through friction (Lama et al., 2021). Another effective method is floodplain storage and infiltration, where floodwaters are allowed to spread across vegetated floodplains, reducing peak discharge and energy levels (Kalloe et al., 2022). Vegetated floodplains act as natural reservoirs, temporarily storing excess water and slowing down flood propagation (Zhao et al., 2023). The presence of vegetation further enhances this effect by increasing infiltration rates and reducing surface runoff, ultimately minimizing downstream flood risks (Forysinski, 2019). Restoring and maintaining healthy floodplains is a critical strategy in sustainable flood management (Oude, 2010).

Sediment trapping and morphological adjustments also play a significant role in flood energy attenuation (Sharpe & Kemp, 2021). Vegetation helps stabilize riverbanks and promotes sediment deposition, which gradually alters channel morphology to accommodate floodwater more effectively (Ren et al., 2021). Figure 3 provides an example of the impact of riverbank stabilization with vegetation. Natural levees, sandbars, and vegetated islands that form due to sediment accumulation create additional resistance to flow, further reducing flood energy (Oude, 2010). Over time, these morphological changes contribute to a more stable river system that can better withstand flooding events (Forysinski, 2019). The use of engineered nature-based solutions, such as vegetated buffer zones, reforestation of riparian areas, and constructed wetlands, enhances flood energy dissipation (Soler et al., 2024). These interventions mimic natural processes while improving flood mitigation capacity (van Wesenbeeck et al., 2022). For example, planting trees and shrubs along river corridors strengthens bank stability and increases roughness, while constructed wetlands act as flood retention basins that slow water movement and filter sediments (Croke et al., 2017). Integrating such solutions with traditional engineering structures improves the resilience of river systems (Baaij et a;/. 2021). Lastly, adaptive river management and land-use planning play a crucial role in enhancing flood energy attenuation (Forysinski, 2019). Policies that promote riparian zone conservation, restrict urbanization in flood-prone areas, and encourage ecological restoration ensure that vegetated rivers continue to function as effective flood mitigation systems (Zhao et al., 2023). Implementing controlled flooding strategies, where certain areas are designated to absorb excess water during extreme events, can also reduce pressure on main river channels and minimize flood damage (Ahilan et al., 2018). By combining natural processes with strategic management, the overall efficiency of flood attenuation in vegetated rivers can be significantly improved (Ahmed & Ghumman, 2019).

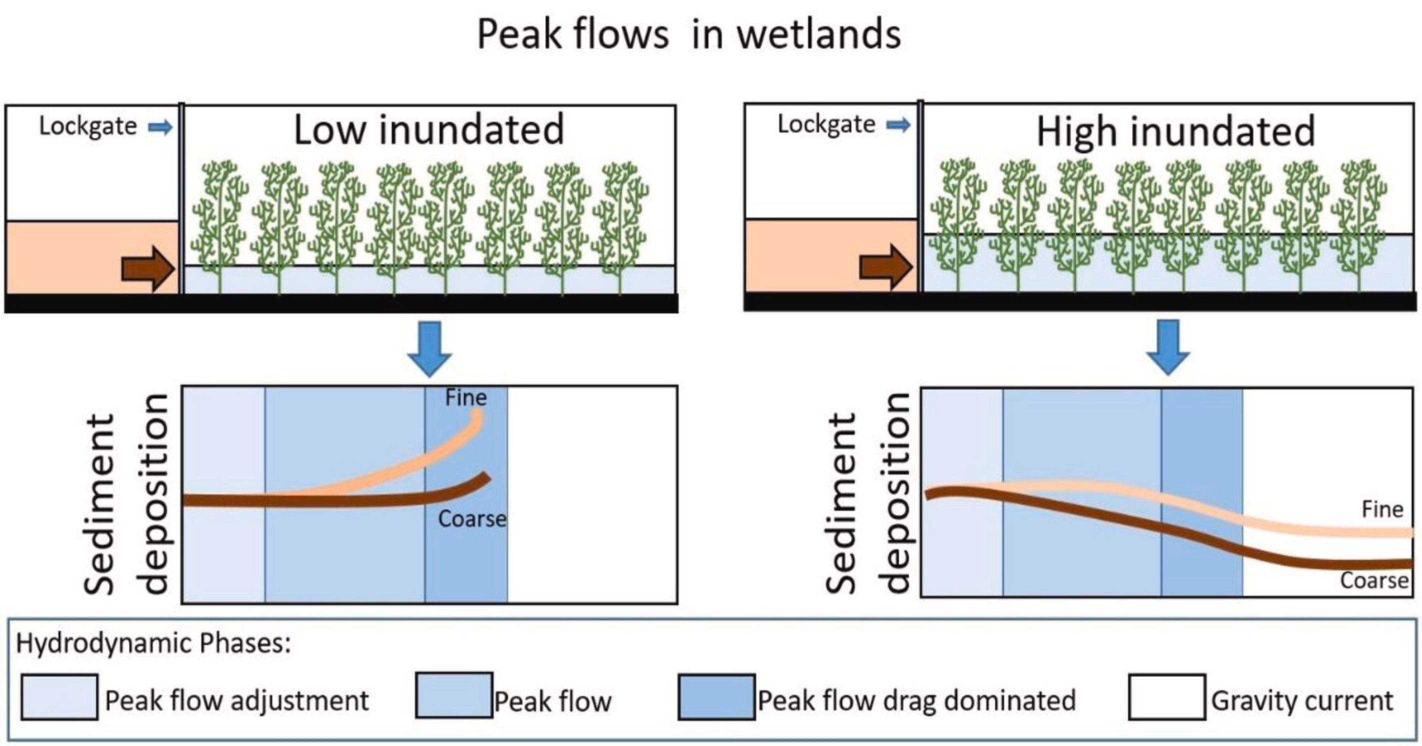

Fig. 3 Impact of vegetation on stabilization of riverbank by saving sediments (Soler et al., 2024)

The primary objective of this study is to establish a robust ANN model capable of predicting flood energy attenuation using key hydraulic and vegetation parameters. The implementation of a multi-layer perceptron (MLP) ANN in Python enables the extraction of complex nonlinear relationships, outperforming traditional empirical methods. Additionally, the research evaluates the model's accuracy using statistical metrics, ensuring its practical applicability for hydrologists and engineers in flood risk assessment and river management. The significance of this research lies in its potential to improve flood mitigation strategies by providing a more accurate and data-driven approach to predicting flood energy dissipation. The findings highlight the dominant role of vegetation characteristics, particularly vegetation density and backwater rise, in reducing flood energy. By demonstrating the superior predictive capability of ANN models, this study paves the way for integrating machine learning techniques into hydraulic modeling. The results can be instrumental in optimizing river restoration efforts, enhancing floodplain management, and developing nature-based solutions for flood risk reduction. Future research should focus on expanding the dataset and incorporating additional hydraulic parameters to further refine prediction accuracy and broaden the model's applicability across diverse riverine environments.

II. AI IN FLOOD ENERGY ATTENUATION

Artificial Intelligence (AI) is transforming the field of flood energy attenuation by enhancing predictive modeling, optimizing flood control measures, and improving decision-making processes (Lin et al., 2021). Flood energy attenuation refers to the reduction of the destructive power of floodwater through various natural and artificial means, such as wetlands, reservoirs, levees, and other hydraulic structures (Alamoudi et al., 2021). AI-driven technologies, including machine learning, deep learning, and data analytics, are playing an increasingly crucial role in developing more efficient flood mitigation strategies (Oladosu et al., 2024). By leveraging large datasets, AI can analyze patterns, predict flood behaviors, and recommend the best attenuation techniques to minimize damage (Sadoughi et al., 2019). One of the primary applications of AI in flood energy attenuation is predictive modeling (Oladosu et al., 2024). Traditional hydrological models require extensive manual calibration and are often limited in their ability to incorporate real-time data (Lin et al., 2021). AI-based models, on the other hand, can process vast amounts of historical and real-time hydrological data, meteorological records, and geographical information to provide highly accurate flood forecasts (Zhao et al., 2023). Machine learning algorithms can detect complex patterns in data, enabling early warning systems to anticipate flood events with greater precision and provide timely alerts to communities at risk (Yan et al., 2021).

AI also enhances flood attenuation through the optimization of hydraulic structures (Bui et al., 2020). Smart flood management systems equipped with AI can dynamically control the operation of reservoirs, dams, and floodgates based on real-time data (Goyal et al., 2021). For example, AI can analyze weather patterns and river flow rates to determine the optimal time for releasing water from reservoirs, reducing the risk of both upstream and downstream flooding (Zabihi et al., 2023). Such automated systems reduce human intervention and improve the efficiency of flood mitigation strategies (Hayder et al., 2023). Another key area where AI contributes to flood energy attenuation is the development of nature-based solutions (Koutsovili et al., 2023). AI can analyze satellite imagery and geographical data to assess the effectiveness of wetlands, forests, and other natural features in absorbing flood energy. By modeling different scenarios, AI helps urban planners and environmentalists design sustainable flood mitigation strategies that incorporate natural buffers to reduce flood intensity (Caloir et al., 2023). These AI-driven insights support the restoration and preservation of ecosystems that naturally mitigate flooding. AI-powered remote sensing and monitoring systems have also revolutionized flood management (Kumar et al., 2021). Using drones, satellites, and Internet of Things (IoT) sensors, AI can continuously monitor flood-prone areas and assess changes in water levels, soil moisture, and river flow (Oladosu et al., 2024). These technologies provide real-time information that improves flood response efforts, allowing authorities to take proactive measures such as reinforcing embankments or evacuating at-risk populations before disaster strikes (Lin et al., 2021). Additionally, AI can analyze social media data and crowdsourced information to enhance situational awareness during flood emergencies (Sadoughi et al., 2019).

Despite its numerous advantages, AI in flood energy attenuation has certain limitations. One major challenge is the requirement for vast amounts of high-quality data to train AI models (Zhao et al., 2023). In many regions, reliable and up-to-date hydrological and meteorological data are scarce, making it difficult to develop accurate AI-based flood prediction systems (Oladosu et al., 2024). Furthermore, AI models are highly dependent on computational power and infrastructure, which may not be readily available in developing countries or remote areas (Alamoudi et al., 2021). Another limitation is the complexity and interpretability of AI models. Many AI-driven flood prediction models function as "black boxes", meaning their decision-making processes are not easily understood by human operators (Koutsovili et al., 2023). This lack of transparency can lead to challenges in trust and adoption, especially among policymakers and emergency response teams who need clear justifications for implementing AI-driven recommendations. Addressing this issue requires the development of explainable AI (XAI) models that provide more interpretable insights while maintaining high accuracy (Kumar et al., 2021). Additionally, there are concerns regarding the cost and scalability of AI-driven flood attenuation systems (Lin et al., 2021).

Implementing AI-based solutions requires significant investment in infrastructure, data collection, and skilled personnel. Small communities or underdeveloped regions may struggle to afford these advanced technologies, creating a disparity in flood management capabilities between wealthier and less developed areas (Mosavi et al., 2018). Ensuring equitable access to AI-driven flood mitigation tools remains a significant challenge that needs to be addressed through policy and funding initiatives (Bentivoglio et al., 2022). Despite these challenges, the potential benefits of AI in flood energy attenuation far outweigh its limitations. AI offers innovative solutions to improve flood forecasting, optimize infrastructure management, and enhance emergency response efforts

(Alamoudi et al., 2021). By integrating AI with traditional flood management approaches, governments and organizations can develop more resilient and adaptive strategies to mitigate the impact of floods (Oladosu et al., 2024). As AI technology continues to evolve, its role in flood energy attenuation is expected to expand, offering new opportunities for sustainable and data-driven flood management solutions (Yan et al., 2021).

III. Materials and Methods

This study employs an ANN approach to predict flood energy attenuation in vegetated rivers across Iran. The methodology consists of several key stages, including data collection, preprocessing, model development, training and testing, performance evaluation, and sensitivity analysis. By integrating machine learning techniques with hydraulic and vegetation parameters, this research aims to enhance flood management strategies and improve riverine ecosystem stability.

Data collection and preprocessing: The dataset used in this study was compiled from hydrological records and field measurements of 760 rivers in Iran. Key parameters influencing flood energy dissipation were selected based on prior hydrodynamic studies and empirical research. The input variables included the Froude number (F_r), vegetation density and thickness (D_v), and relative backwater rise (Δr), while the output variable was energy reduction (ΔE). Prior to model development, the dataset was cleaned to remove inconsistencies, outliers, and missing values. Normalization techniques were applied to scale the data between 0 and 1, ensuring uniformity and improving the efficiency of the ANN model.

ANN model development: A Multi-Layer Perceptron (MLP) ANN was implemented in Python using the TensorFlow and Keras libraries. The model architecture (Figure 4) consisted of an input layer with three neurons corresponding to the input variables, multiple hidden layers with optimized neuron counts, and an output layer with a single neuron representing ΔE. Activation functions such as Rectified Linear Unit (ReLU) were used in hidden layers to introduce non-linearity, while a linear activation function was applied in the output layer. The Adam optimizer was chosen for weight optimization and mean squared error (MSE) and root mean square error (RMSE) were used as the loss function to minimize prediction errors.

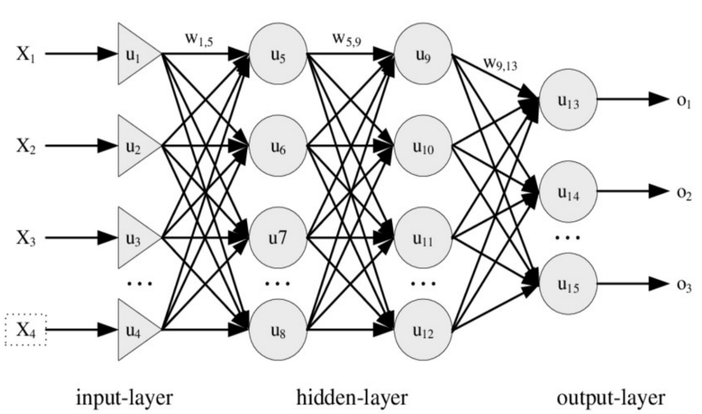

Fig. 4 A topical architecture for a MLP classifier (Wahyunggoro et al., 2013)

Training and testing process: The dataset was split into two subsets: 70% of the data was allocated for training and 30% for testing. During training, the model was exposed to input-output relationships, adjusting the weights and biases through backpropagation. Hyperparameter tuning, including learning rate adjustment, batch size selection, and the number of hidden layers, was performed using a grid search technique to achieve optimal model performance. A 10-fold cross-validation approach was employed to ensure robustness and prevent overfitting. The training process continued until convergence was reached, ensuring that the model generalizes well to unseen data.

Performance evaluation: The trained ANN model was assessed using various statistical performance metrics, including the coefficient of determination (R^2), MAE, RMSE as well as confusion matrix. A confusion matrix is a key tool used in machine learning to evaluate the performance of a model. It is a square matrix that compares the predicted labels with the actual labels of a dataset, providing insights into the model's accuracy and error distribution (Jordan & Mitchell, 2015). The matrix consists of four key components: True Positives (TP), where the model correctly predicts a positive class; True Negatives (TN), where the model correctly predicts a negative class; False Positives (FP), also known as Type I errors, where the model incorrectly classifies a negative instance as positive; and False Negatives (FN), or Type II errors, where the model incorrectly classifies a positive instance as negative (Müller & Guido, 2016). By analyzing the confusion matrix, various performance metrics such as accuracy, precision, recall, and F1-score can be derived, helping to assess the model's effectiveness, especially in imbalanced datasets (Kotsiantis et al., 2006). Figure 5 illustrates a topical confusion matrix structure that is generally used in machine learning based modeling.

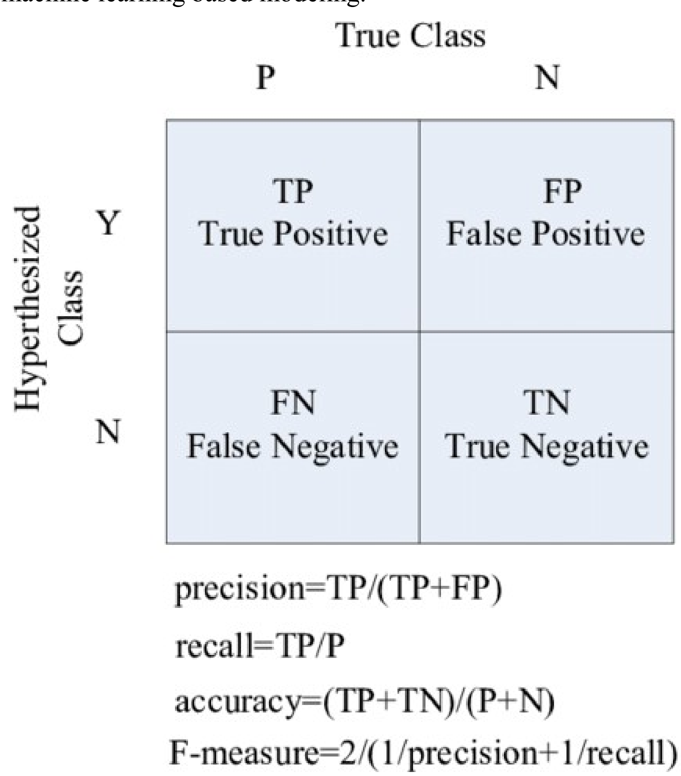

Fig. 5 A topical illustration of a confusion matrix (Cui and Pi, 2017)

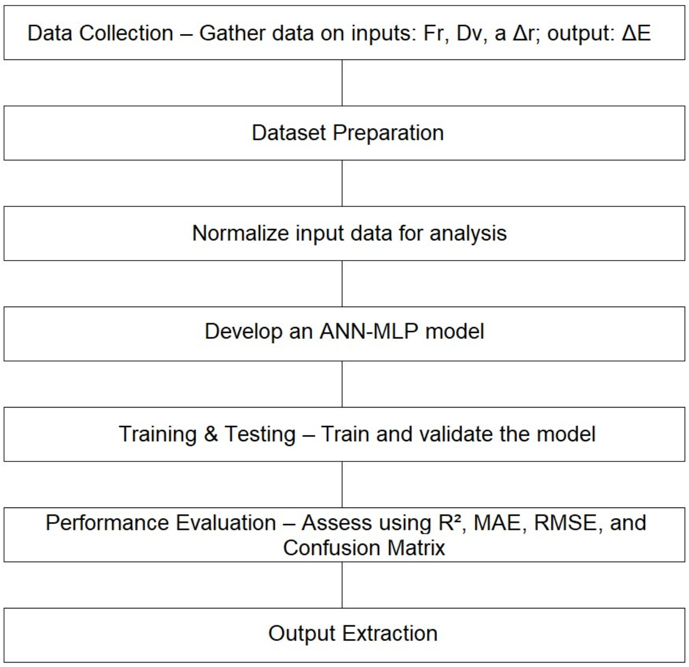

Fig. 6 The process flowchart used in this article

Sensitivity analysis: To evaluate the relative importance of each input variable, a sensitivity analysis was conducted. The analysis involved systematically altering one input variable while keeping others constant to measure its impact on the output (ΔE). Results revealed that the Δr had the most significant influence on energy dissipation, followed by D_v, and F_r. This finding underscores the importance of hydrodynamic interactions in vegetated rivers and suggests that flood management strategies should prioritize vegetation-related modifications for effective energy attenuation. Figure 6 provides an analysis flowchart for this article.

Limitations and future research directions: Despite its strong performance, the ANN model has some limitations. The model's accuracy depends on the quality and quantity of input data, meaning that regions with limited hydrological records may experience reduced prediction reliability. Additionally, while the study incorporated key hydraulic and vegetation parameters, other influential factors such as sediment transport, channel morphology, and climate variability were not included. Future research should focus on expanding the dataset to encompass a broader geographical range and integrating additional hydraulic parameters to further refine model predictions. The incorporation of hybrid AI models, such as combining ANNs with evolutionary algorithms or fuzzy logic systems, could further enhance prediction accuracy and generalizability.

IV. Results and Discussion

The results of the study demonstrate that the ANN model effectively predicts flood energy reduction in vegetated rivers. The statistical analysis of the dataset, comprising 760 rivers in Iran, reveals significant insights into the role of vegetation and hydraulic parameters in flood energy dissipation. As shown in Table 1, the input variables, including the F_r, D_v, and Δr, exhibited considerable variation. For instance, F_r ranged from 0.30 to 1.20, with a mean value of 0.75, reflecting the variation in river flow conditions. D_v varied between 0.10 and 0.85, with a mean of 0.45, showing the variability in vegetation characteristics. The Δr parameter, ranging from 0.05 to 0.50, has been shown to play a dominant role in energy dissipation, further confirmed by the sensitivity analysis. The model's predictive performance, evaluated through the confusion matrix and error metrics, indicates strong accuracy in both training and testing phases. As seen in Table 2, the MLP model achieved impressive classification results for both low, medium, and high energy dissipation categories. On the training set, the model correctly predicted 180 out of 220 low energy dissipation instances, 160 out of 220 medium, and 195 out of 220 high energy dissipation instances. Testing results were slightly lower but still showed reliable predictions, confirming that the model can generalize well to unseen data. The confusion matrix also revealed that while some misclassifications occurred between the low and medium categories, the overall performance remained satisfactory.

In terms of error metrics, the ANN model demonstrated strong performance, with a MAE of 0.025 for the training set and 0.032 for the testing set (Table 3). This small increase suggests the model's robustness and its ability to make accurate predictions even on new data. The RMSE for the training and testing sets were 0.012 and 0.023, respectively, indicating that the model's predictions closely align with actual values. The R^2 values of 0.92 for the training set and 0.88 for the testing set show that the model explains a significant portion of the variance in flood energy reduction, which highlights its predictive strength. The sensitivity analysis further revealed that Δr plays a dominant role in determining energy dissipation. This parameter, which represents the relative backwater rise in the river, has the greatest influence on the model's predictions, emphasizing the critical importance of river flow characteristics in flood energy attenuation. Vegetation parameters, particularly D_v, also showed significant influence, with denser and thicker vegetation leading to higher flood energy reduction. This insight supports the notion that vegetated areas can effectively mitigate flood risks by dissipating energy, which is vital for flood management strategies.

Table 1 Statistical analysis for input and output parameters

Parameter	Max	Min	Mean	St.Dv.	Variance
D_v	0.85	0.10	0.45	0.18	0.324
F_r	1.20	0.30	0.75	0.22	0.486
Δr	0.50	0.05	0.25	0.12	0.286
ΔE	0.80	0.15	0.50	0.22	0.432

Table 2 Results of the performance matrix for MLP model

Matrix	Predicted values / Training			
Actual values / Training		Low	Medium	High
	Low	180	30	10
	Medium	20	160	40
	High	10	25	195
Matrix	Predicted values / Testing			
Predicted values / Testing		Low	Medium	High
	Low	45	10	5
	Medium	5	40	15
	High	3	12	40

Table 3 Estimated error table for MLP model

Metrics	Training set	Testing set
MAE	0.025	0.032
RMSE	0.012	0.023
R^2	0.92	0.88

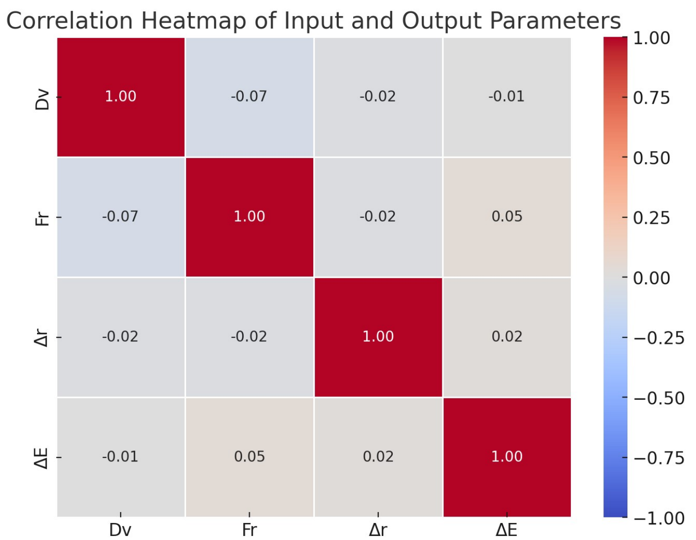

Fig. 7 Estimated correlation heatmap for this study

As result, the ANN model provides an advanced and accurate approach to predicting flood energy attenuation in rivers with vegetation. The model's strong performance, as demonstrated by its high R^2 values and low error metrics, shows that it outperforms traditional empirical methods. This makes the ANN model a valuable tool for hydrologists and engineers working on flood risk assessments and river management. Future studies should focus on expanding the dataset to include more diverse river types and integrating additional hydraulic parameters to further enhance the model's prediction capabilities. By doing so, the model's applicability to various river systems and flood scenarios can be improved, providing more comprehensive tools for flood mitigation planning.

V. Conclusion

This study successfully developed an ANN model to predict flood energy attenuation in vegetated rivers, demonstrating its strong predictive capability and superior accuracy compared to traditional empirical models. By utilizing a dataset of 760 rivers in Iran, the ANN effectively established relationships between key hydraulic parameters (i.e. F_r, D_v, Δr, and ΔE). The model achieved a high correlation ($R^2 = 0.92$) and low error rates (MAE = 0.025, RMSE = 0.012), confirming its reliability in flood risk assessment and river management applications. The findings highlight the significant role of vegetation in dissipating flood energy, with denser and thicker vegetation contributing to greater attenuation. Sensitivity analysis further revealed that Δr was the most influential factor, suggesting that hydrological interventions should prioritize vegetation management and water level control for effective flood mitigation. This underscores the importance of integrating nature-based solutions with advanced AI-driven approaches to enhance flood resilience and ecosystem stability. Comparing ANN predictions with traditional empirical models demonstrated that AI-based approaches outperform conventional methods, particularly in handling nonlinear and complex hydrodynamic processes. The ANN model's ability to learn from vast datasets and generate accurate predictions makes it a valuable tool for hydrologists and engineers working on flood risk mitigation and riverine ecosystem preservation. Despite its success, the study acknowledges certain limitations, including the dependence on data quality and the exclusion of additional hydrological factors such as sediment transport and climate variability. Future research should focus on expanding the dataset and incorporating hybrid AI models to improve prediction accuracy. Thus, this research confirms that ANN-based modeling is a powerful and reliable tool for optimizing flood energy attenuation strategies, paving the way for more effective and sustainable river management solutions.

Acknowledgment

We extend our thanks to the reviewers for their meticulous attention to detail and constructive suggestions that greatly improved the quality of this manuscript. Your contributions have been instrumental in shaping this work.

Authors' contributions

Narges Mohammadian, Mahdi Yeganeh and Shabnam Rad conducted the main data analysis, contributed to the data collection, preprocessing, and interpretation, and were responsible for drafting the initial manuscript. Chia-hao Fen and David Wang performed supervision, conceptual guidance. Mahdi Yeganeh conducted critical revision of the manuscript. David Wang provided overall project administration and final approval of the version to be published. All authors read and approved the final manuscript.

Conflict of interest

The authors have not disclosed any competing interests.

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