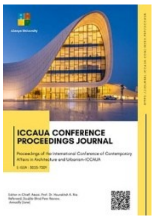

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Prediction of Fire-Induced Pollution Dispersion in Watersheds using ANN, A Case Study of Dareh-Moradbeyg River Watershed

* [1] Prof. **Babak Omidvar** , [2] Ph.D. Candidate **Ramin Samavati** and [3] Ph.D. Candidate **Mahsa Mohammad Reza Beyk**
[1] Department of disaster engineering, education and environment systems, Faculty of Environment, University of Tehran, Tehran, Iran
[2] Department of environmental engineering of water resources management, Kish International Campus of Tehran University, Kish, Iran
[3] Department of disaster engineering, education and environment systems, Faculty of Environment, University of Tehran, Tehran, Iran
E-mail [1]: bomidvar@ut.ac.ir, E-mail [2]: raminsamavati@ut.ac.ir , E-mail [3]: msbeyk@ut.ac.ir

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Abstract

Post-fire runoff, driven by the loss of vegetation cover and alterations in soil characteristics, represents a
significant source of pollutants in downstream ecosystems, residential, and urban areas.This study employs an artificial intelligence approach, optimized using the Artificial Bee Colony (ABC) algorithm, to predict water quality in a fire-affected watershed. pH variation data, collected following a prescribed burn in the study area, was utilized as input for developing an artificial neural network. The network's interlayer connection weights and threshold parameters were optimized using an enhanced version of the ABC algorithm. The results indicate that, compared to conventional models, the neural network trained using the ABC algorithm demonstrates approximately 25% greater predictive accuracy. These findings emphasize the critical role of machine learning techniques in forecasting pollutant dispersion in post-fire watershed environments.
Keywords: Prediction; Post-fire Pollution Dispersion; Watershed; Neural Network; Artificial Bee Colony (ABC).

1. Introduction

Forested watersheds are a vital source of high-quality water for billions of consumers worldwide. Forests mitigate the risk of flood events by absorbing and storing rain. The natural filtration processes occurring within watersheds provide significant economic benefits, with an estimated global annual saving of 4.1 trillion USD in water treatment costs. Wildfires are a natural disturbance processes that play a crucial role in supporting the long-term health of forest ecosystems; however, they can also degrade stream water quality and disrupt runoff generation mechanisms (Brucker et al., 2022).
In recent decades, the increasing frequency and intensity of wildfires have become major challenges for natural ecosystems and water resources (Nam et al., 2022). Wildfires alter the physical and chemical properties of the soil, leading to increased erosion, sediment delivery to water bodies, and the introduction of both nutrients and organic and inorganic pollutants into surface water resources. These impacts can significantly degrade water quality (McCullough et al., 2023).
Recent studies have shown that parameters such as pH, turbidity, electrical conductivity, and nutrient concentrations in surface waters undergo significant changes following wildfires. For example, a study conducted in Minnesota forests reported increases in nitrogen and phosphorus concentrations, reduced water transparency, and alterations in lake pH after wildfire events (McCullough et al., 2023). These effects (Figure 1) occur immediately after a fire but may persist for up to ten years (Brucker et al., 2022).

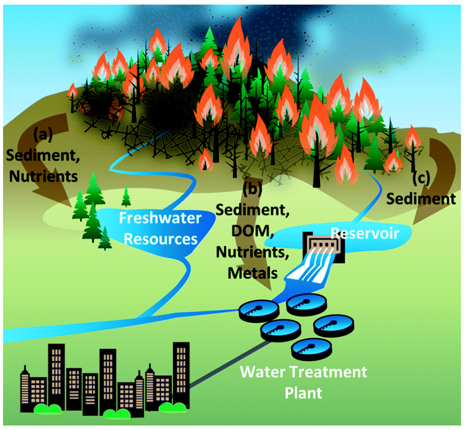

Figure 1. Conceptual image of the impacts of wildfires on water quality and supply (Brucker et al., 2022).

Given the complexity and non-linear nature of the interactions among various factors affecting water quality after wildfires, the use of accurate and intelligent predictive models is essential (Rammohan et al., 2024). In this context, artificial neural networks (ANNs) have been introduced as powerful tools for modeling and predicting water quality changes (Gholami et al., 2024). Integrating neural networks with optimization algorithms such as the Artificial Bee Colony (ABC) can further enhance prediction accuracy (Mahdavi Meymand et al., 2024).

The primary objective of this study is to develop a predictive model for assessing changes in river water pH following wildfire events using artificial neural networks trained by the Artificial Bee Colony (ABC) algorithm. To this end, a laboratory-scale pilot experiment was designed and implemented to generate the necessary data for model training and validation.

This research was conducted through an integrated approach combining field-based experiments, statistical analysis, and intelligent modeling. The main objective of the study was to investigate the effects of varying wildfire intensities on the chemical properties of surface runoff—particularly changes in pH—and to assess the likelihood of point-source pollution in nearby water resources, especially rivers. To achieve this, a controlled pilot-scale experiment (0.7 × 0.7 m) was designed, allowing for manipulation of key variables including fire intensity, vegetation type, and land slope. The runoff generated under natural conditions and after the application of controlled burns was collected and used as input for statistical analyses and predictive modeling.

The research methodology is based on the integration of an experimental approach for real data collection and an analytical-model-driven approach for interpreting the results and predicting system behavior. To analyze the impact of variables and their interactions, statistical tests (ANOVA) were employed. Subsequently, a multilayer perceptron (MLP) artificial neural network was used for modeling and predicting the changes in runoff pH. To optimize the model's performance, the Artificial Bee Colony (ABC) algorithm was utilized to adjust the weights and biases of the network. The combination of these methods provides a more precise understanding of the behavior of natural systems in response to wildfire and runoff and lays the foundation for the development of intelligent tools for environmental risk management.

2- Literature Review

Wildfires have significant environmental impacts, leading to increased levels of nutrients, heavy metals, organic carbon, and sediments in surface waters, which can result in substantial chemical and physical alterations in aquatic ecosystems. Forest fires, in particular, have a profound effect on surface water quality and pose a serious threat to the provision of drinking water for human populations (Paul et al., 2022). Numerous studies have demonstrated that wildfires lead to elevated concentrations of nitrogen and phosphorus in river systems. For instance, in a study conducted by Smith et al. (2011) in Australian forests, a significant post-fire increase in nitrogen and phosphorus concentrations was observed in river waters, which directly contributed to a decline in water quality. Similar impacts were reported by Zhao et al. (2025) in North America, where the combustion of organic matter resulted in increased turbidity and alterations in the pH of surface waters. Moreover, the study conducted by Chen and Chang (2025) revealed that following wildfires in the western United States, water turbidity increased up to 70 NTU in sub-watersheds affected by high-severity fires. In addition, wildfires can alter the chemical characteristics of water, such as alkalinity, posing not only a threat to drinking water quality (Hohner et al., 2019), but also adversely impacting aquatic ecosystem health through elevated concentrations of nitrogen, phosphorus, and heavy metals such as mercury and arsenic. These changes can lead to harmful phenomena such as algal blooms (Rhoades et al., 2019). The effects of such contamination may persist for years after the wildfire event, influencing both water quality and long-term water treatment costs (Bladon et al., 2014).

A study conducted by Writer et al. (2012) demonstrated that following wildfires in the watersheds of Colorado, pH levels in surface water flows initially declined sharply and gradually returned to pre-fire levels over time. Similarly, Rhoades et al. (2019) reported that in burned forests of the western United States, a short-term decrease in pH occurred due to the influx of acidic ash and dissolved organic compounds, which had a direct impact on drinking water quality. McCullough et al. (2023), in a study on rivers in the western United States, found that wildfires can lead to substantial changes in both pH and turbidity levels, negatively affecting aquatic ecosystems. Similarly, Li et al. (2023) demonstrated that in burned forested areas, water pH can drop by up to 2 units, resulting in adverse impacts on aquatic life and overall water quality. In contrast, Emelko et al. (2016) reported that following severe wildfires, an increase in pH was observed in some cases due to elevated inputs of ash rich in carbonate compounds, with such fluctuations posing challenges to water treatment processes. Hohner et al. (2019) also stated that post-wildfire water pH can exhibit highly variable behavior depending on burn severity, vegetation type, and the timing of post-fire precipitation events; with some regions experiencing a pH decrease while others show an increase. Accordingly, the review of numerous studies reveals that fluctuations in pH are one of the primary effects of wildfires on water resources. These changes may stem from the influx of ash, organic matter, and soil sediments into surface waters. In a study published in 2024, Bruker et al. proposed an experimental design to simulate the effects of wildfires on water quality, in which the influence of parameters such as fire intensity, soil composition, and the chemical characteristics of water on pH was evaluated (Bruker et al., 2024). Zema et al. (2020) conducted a similar experiment aimed at modeling water pollution caused by wildfires, demonstrating that laboratory-scale pilot systems can accurately generate the necessary input variables for neural network models (Zema et al., 2020). Their study examined the concentrations of carbon and nitrogen in naturally burned residues, utilizing the combustion of deciduous litter under varying spatial fire intensities to simulate natural wildfire mechanisms. Similarly, the role of fire in promoting rill erosion—a plot-scale erosive process—was investigated using fire and rainfall simulation techniques at the plot scale (Bruker et al., 2022). In another study, Ferreira et al. (2008) analyzed sediment yield and runoff in post-wildfire plots at different spatial scales, including microplots (<1 m²), standard plots (16 m²), and small catchments (<1.5 km²), enabling comparison of results across scales (Ferreira et al., 2008). Laboratory and plot-scale simulation experiments, which replicate the combustion mechanisms in natural wildfires along with the kinetic energy of raindrops and leaching effects similar to post-fire rainfall, provide an alternative analytical technique for estimating the impacts of wildfires on water quality and supply. These studies primarily advance the understanding of the effects of burning on the physical and chemical properties of soil and water at small scales (Bruker et al., 2022), and require the consideration of various factors such as vegetation type, burn intensity, and slope (Shackelford & Duer, 2006). These parameters must be carefully adjusted in the pilot design, as they directly influence the amount of runoff, erosion, and pollutant transport (Serda, 1998). Rainfall intensity determines the volume and velocity of runoff, while slope controls the kinetic energy of surface flow, which directly affects the capacity for transporting suspended particles (Moody & Martin, 2009). Studies have shown that intense and short-duration rainfall events lead to a sudden increase in runoff discharge and rapid pollutant transport, while gentler, longer-duration rainfall typically results in greater infiltration and less runoff production (Moody & Martin, 2009). Steep slopes increase the kinetic energy of runoff, leading to higher soil erosion and greater pollutant transport. In experimental studies, increasing the slope from 10% to 30% resulted in a significant increase in sedimentation rates and changes in the chemical composition of runoff (Nyman et al., 2010). Vegetation also plays a crucial role in the intensity and extent of wildfires, as it determines the available fuel composition and heat distribution (Pereira et al., 2018). The reduction of vegetation after wildfires leads to increased runoff and the transport of sediments and nutrients to water sources. Plants play a key role in controlling pollution by stabilizing soil, reducing runoff velocity, and increasing water infiltration (Nearing et al., 2005). The intensity of a wildfire, measured by the applied temperature, can cause significant changes in pH, electrical conductivity (EC), and the release of elements such as nitrogen and heavy metals in runoff (De Bano, 2000). The duration of heat application is also important, as prolonged exposure can increase the depth of heat penetration into the soil, amplifying physical and chemical changes in the soil (Neary et al., 2005). The intensity of burning is a determining factor in the severity of hydrological changes after a wildfire. Areas subjected to high-intensity fires are typically faced with reduced soil permeability, increased runoff, and water contamination (Parsons et al., 2010).

Ferreira discusses the limitations of common methods and techniques for analyzing hydrological and erosional responses in post-fire environments, from laboratory scale to watershed level, and covers rainfall simulation methods (Ferreira et al., 2008). In 2014, Keesstra and colleagues designed an experiment in which soil samples were homogenized, reducing the uncertainty arising from variable soil structure and vegetation cover, but decreasing the resemblance of the samples to a natural environment (Keesstra et al., 2014).

Bhagowati et al. (2022) suggested the use of Artificial Neural Networks (ANNs) for predicting water quality in rivers and lakes (Bhagwati et al., 2022). In fact, Artificial Neural Networks (ANNs) are recognized as powerful modeling tools for simulating and predicting complex environmental processes, especially in situations where there are strong nonlinear relationships between variables (Maier et al., 2010).

Shiri et al. (2012) demonstrated that Artificial Neural Networks (ANNs) exhibit very high accuracy in predicting water quality parameters—such as pH, dissolved oxygen, and electrical conductivity—even under conditions with noisy and irregular datasets. The application of these models can notably reduce both time and cost compared to physically based models. Similarly, Perumal et al. (2023) highlighted the high precision of ANNs in simulating water quality variations in flood-prone areas. In another study, Gholami employed ANN models to predict water pollution and concluded that they are highly effective in forecasting pollution resulting from wildfires and in predicting changes in river pH.

Tayebiyan et al. (2016) emphasized that ANNs are capable of estimating the behavior of aquatic systems by learning from historical data, making them suitable tools for managing water resources in situations with limited or incomplete field data—such as post-disaster scenarios. A comprehensive review by Yaseen et al. (2018) further supported the effectiveness of ANNs in water sciences, noting that these models reduce uncertainties in water quality modeling and play a crucial role in post-wildfire decision-making processes. Bilgili et al. (2022) introduced various environmental input variables for ANN modeling and showed that factors such as temperature, humidity, and soil type significantly influence model accuracy. In line with this, Basso et al. (2023) identified fire intensity, soil composition, and sediment levels as the most critical predictors for estimating post-wildfire pH changes in water bodies. Furthermore, Xu (2024) demonstrated through simulation that proper selection of ANN inputs can significantly enhance prediction accuracy for future water quality scenarios. He et al. (2021) also confirmed the superiority of ANNs over traditional models such as multiple regression, particularly in predicting chemical changes in water following natural disasters like floods and wildfires. Despite their effectiveness, ANNs face challenges such as getting trapped in local minima, slow convergence, and the requirement for large datasets to ensure generalization (Goodfellow et al., 2016). To address these limitations, the application of metaheuristic optimization algorithms for enhancing ANN training has become increasingly prevalent (Yang, 2010).

The Artificial Bee Colony (ABC) algorithm, introduced by Karaboga in 2005, is a population-based metaheuristic inspired by the foraging behavior of honeybees. Due to its strong global search capability, it has been proposed as a promising tool for optimizing neural network parameters (Karaboga & Basturk, 2007). Multiple studies have confirmed that incorporating the ABC algorithm into the ANN training process improves prediction accuracy, accelerates convergence, and reduces the risk of local minima entrapment. For example, Karaboga and Akay (2012) reported that using ABC to initialize ANN weights led to better performance than the traditional backpropagation algorithm.

Additionally, Tsai et al. (2012) demonstrated that training neural networks using the Artificial Bee Colony (ABC) algorithm significantly enhances the prediction accuracy of water quality parameters compared to traditional training methods. This finding supports the recognition of the ABC algorithm as an efficient and reliable tool for improving the performance of neural network-based models in environmental applications, including post-wildfire water quality prediction. In recent years, the integration of optimization algorithms with neural networks has garnered increasing attention for addressing complex environmental challenges such as modeling water quality dynamics following wildfire events. Owing to its balanced exploration and exploitation capabilities, the ABC algorithm is particularly well-suited to overcoming the issue of local optima entrapment and improving prediction accuracy in scenarios involving noisy and nonlinear data (Karaboga & Akay, 2009). Comparative analyses have consistently shown that neural networks trained with ABC outperform those trained using other optimization methods, such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), across a range of applications. Consequently, the application of metaheuristic algorithms like ABC has been widely recommended for enhancing the predictive performance of ANN models.

Recent studies reinforce these advantages. For instance, Chen et al. (2023) reported that integrating ANN with ABC increased prediction accuracy of wildfire-induced water pollution by up to 20%. Similarly, Wei and Yu (2023) found that ANN models optimized with ABC yielded more precise predictions of changes in water's physical parameters compared to conventional approaches. In another study, Mahdavi Mymaned et al. (2024) showed that combining ANN with ABC in fire-affected areas significantly reduced prediction errors and improved model robustness and accuracy. Beyond improving accuracy, another notable benefit of the ABC algorithm is the reduction in computational costs during the neural network training process. ABC reduces the number of iterations required to reach convergence, resulting in substantial savings in both computation time and processing power—a critical advantage in real-time environmental monitoring systems (Zhu & Kwong, 2010).

In conclusion, modeling water quality changes after wildfires necessitates high precision due to the inherent complexity and noise in field data. Neural networks optimized with the ABC algorithm offer a powerful solution for enhancing the reliability, efficiency, and applicability of predictive models in such sensitive environmental contexts.

3- Material and Methods

3-1. Case Study

This study investigates the Alusajerd River located in the Moradbig Valley, southwest of Hamedan, Iran, as the main focus area for assessing the changes in river water pH caused by post-wildfire runoff.

The Moradbig Valley, located approximately three kilometers southwest of Hamedan city center, lies at the southwestern foothills of the Alvand Mountains in Iran, with geographical coordinates of 48°29' E longitude and 34°43' N latitude. This region is geographically bounded by Hamedan city to the north, the villages of Abroo and Tafrijan to the east, Ganjnameh and Shahrestaneh to the west, and the Alvand Mountain range to the south, encompassing an area of approximately 800 hectares (Figure 2).

Vegetation varies according to elevation: alpine vegetation dominates the upper slopes, whereas orchards and diverse plant species cover the lower elevations. The region is characterized by steep slopes, which significantly influence runoff dynamics. The Alusajerd River—locally also called Alusgerd—originates from this valley, the largest in the Alvand range, historically known as Valeshgerd Valley, located south of Hamedan. The river is primarily fed by snowmelt and numerous springs, flowing from south to north with a relatively steep gradient.

As it courses through the valley and enters the urban area, the river passes along the southern and eastern flanks of Hegmataneh Hill and continues toward the northern outskirts of Hamedan. In the plains of Hamedan County, it eventually converges with other watercourses and discharges into the Qara Chay River (AAZAMI et al., 2024).

Figure 2. Geographical location of the Alusajerd River in Moradbig Valley, Hamedan (Source: Google Earth, 2025).

3.2. Design of a Pilot-Scale Experiment to Simulate the Impact of Wildfire on Water Quality

To investigate the effect of wildfire-affected soil on the chemical quality of river water—particularly pH changes induced by surface runoff—a pilot-scale field experiment was designed and implemented. The design of this experiment was informed by previous studies conducted by Marcos et al. (2000) and Santín (2013), aiming to realistically simulate wildfire conditions and the hydrological behavior of the environment.

Accordingly, wooden pilot plots measuring 70 × 70 × 10 cm^3 were constructed and filled with soil collected from the study area. A collection tank was installed beneath each pilot plot to capture the generated runoff (Figure 3-a).

The experiment was structured to evaluate the effects of three independent variables—vegetation type (grassy and dense), slope gradient (5° and 20°), and wildfire intensity (low and moderate)—on changes in water pH. Based on a factorial design framework, eight distinct treatments were defined, and each treatment was replicated three times, resulting in a total of 24 pilot plots (Figure 3-b).

In selected treatments, the soil surface was subjected to controlled burning using a flame torch. Under this method, the maximum recorded surface soil temperature reached up to 650°C (Figure 3-c).

(a) (b) (c)

Figure 3. (a) A sample of the treatments; (b) ignition of fire in primary samples; (c) runoff collection from treatment plots following local rainfall.

The rainfall required for the experiment occurred naturally over an eight-day period (April 29 to May 5, 2025) and consisted of scattered showers. According to the National Meteorological Service, a total long-term average of 287.3 mm was recorded at the Ekbatan Dam rain gauge station (Hamadan Regional Water Authority). After each rainfall event, runoff from each pilot plot was collected and stored in containers containing river water. To simulate the conditions of runoff entering a river, the runoff from each treatment was mixed with a specified proportion of river water and analyzed as the final sample (Figure 4-a).

In total, 24 samples were prepared for pH measurement. pH levels were determined using pH test strips (litmus paper) with a measurement range of 1 to 14 and an approximate precision of 1 unit. After contact with the sample, the color of the strips was compared with a reference scale according to the manufacturer's instructions (Figure 4-b).

(a) (b)

Figure 4. a) Runoff samples collected. b) pH test results from the samples.

3.3 Experimental Design in MATLAB Software

In the analysis of experimental data involving multiple independent variables, Analysis of Variance (ANOVA) serves as a fundamental statistical tool for assessing the main effects and interactions among those variables. In this study, a three-way ANOVA was conducted to evaluate the effects of fire intensity, vegetation type, and slope gradient on changes in river water pH. Such analyses are particularly useful for understanding the influence of

multiple environmental factors under complex experimental conditions, such as those present in forest ecosystems (Meng & Wu, 2024).
To analyze the effects of the selected variables, the data were first organized in tabular form and entered into MATLAB. Using the fitrm command, repeated measures models were fitted, and the ANOVA command was employed to perform the three-way ANOVA. This analysis assessed the main effects and interactions of fire intensity, vegetation type, and slope gradient on pH values. The results are presented graphically (Figure 5).

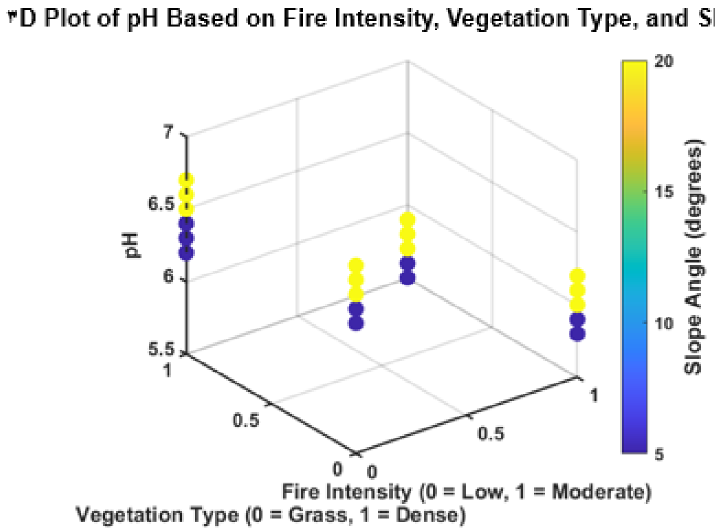

Figure 5. Experimental Design Diagram.

The ANOVA results indicated that fire intensity and vegetation type had statistically significant effects on pH variations. Specifically, both variables exerted a notable influence on river water pH. In contrast, the slope gradient exhibited a relatively smaller, yet still statistically significant effect. The analysis also revealed that the interactions among the variables did not have a significant impact on pH variations

3-4 Use of Artificial Neural Networks and Artificial Bee Colony Algorithm in Predicting pH Changes and River Water Contamination
Artificial Neural Networks (ANNs) are advanced machine learning tools, particularly effective in modeling complex and nonlinear systems. Inspired by the structure of the human brain, ANNs are capable of learning from data, identifying hidden patterns, and capturing nonlinear interactions between variables. These networks have been extensively applied in prediction and classification tasks across environmental sciences and engineering disciplines (Han & Wang, 2021).
In the present study, ANNs were employed to predict changes in pH and potential river water contamination resulting from runoff induced by wildfires. A key advantage of ANN utilization in this context lies in its ability to model the interdependent and nonlinear relationships between multiple input parameters—namely fire intensity, vegetation type, and slope gradient—and the resulting changes in pH. This approach enables the simulation of complex environmental interactions and facilitates more accurate forecasting. To enhance the predictive performance of the ANN and to optimize the network's weight parameters, the Artificial Bee Colony (ABC) algorithm was integrated into the modeling framework. The ABC algorithm is a bio-inspired optimization technique, mimicking the foraging behavior of honeybees as they search for the most efficient food sources. By systematically exploring the solution space, ABC helps identify the optimal configuration of network weights, thereby improving prediction accuracy (Kaya et al., 2022).
The integration of ABC with ANN is particularly important in this study due to the complex and high-dimensional nature of the weight space in neural networks. Through intelligent and adaptive search capabilities, the ABC algorithm enhances the network's ability to converge on a solution that minimizes prediction errors, leading to greater reliability and robustness in the modeling outcomes. The synergy of ANN and ABC offers a powerful hybrid approach for environmental prediction tasks, especially in the context of wildfire-induced water quality degradation.
To assess the performance of the ANN optimized via ABC, a comprehensive set of statistical and graphical indicators will be used:

- The Coefficient of Determination (R^2) and the regression plot between observed and predicted pH values will be examined to evaluate the overall fit of the model.
- The Mean Squared Error (MSE) and its trajectory during the training process will be analyzed to assess the model's convergence and the effectiveness of ABC optimization.
- To evaluate the classification capability and accuracy in identifying different levels of water contamination, the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) are computed.
- Additionally, a residual plot and an error histogram will be used to inspect the distribution and pattern of prediction errors.
- Finally, the Real vs. Predicted values chart will be applied to qualitatively assess the alignment of the network's output with the actual measured data.

These diagnostic tools collectively support a thorough evaluation of the ANN-ABC model's accuracy, reliability, and practical applicability, while also identifying potential shortcomings in the network architecture or training procedure.

4. Discussion and Conclusion

4-1. Hydrological Response Modeling Post-Wildfire

To evaluate the hydrological response following wildfire, particularly the effect of fire on runoff pH, several statistical analyses were performed based on experimental treatments that manipulated fire intensity, vegetation type, and slope gradient. Initially, data normality was assessed using the Kolmogorov-Smirnov test, confirming a normal distribution at the 95% confidence level. To ensure the homogeneity of variances across treatment groups, Levene's test was conducted, and the independence of observations was maintained through the random assignment of treatments and replications.

A three-way Analysis of Variance (ANOVA) was then used to determine the main effects and interaction effects of the independent variables (fire intensity, vegetation type, slope) on runoff pH. When significant effects were identified, Tukey's Honestly Significant Difference (HSD) test was applied for pairwise comparisons to evaluate which treatment groups significantly differed from one another.

Furthermore, correlation analysis was carried out to explore the linear relationships between the independent variables and pH. A multiple linear regression model was developed to quantify the predictive influence of these variables on pH changes. Model performance was evaluated using:

- Coefficient of Determination (R^2) – indicating the proportion of variance explained by the model.
- Root Mean Square Error (RMSE) – measuring the average prediction error.
- S-Statistic – assessing the standard error of regression.

Additionally, regression plots and R^2 plots were generated to visualize model accuracy and the goodness-of-fit between predicted and observed values.

The results from the three-way ANOVA test showed that fire intensity had a significant effect on runoff pH ($F = 145.71$, $p < 0.0001$), indicating its determinative role in the acidification of runoff. Additionally, vegetation type ($F = 13.11$, $p = 0.0021$) and slope ($F = 23.31$, $p < 0.001$) also had significant effects on pH. Among the interactive effects, only the interaction between fire intensity and vegetation type was significant ($F = 5.83$, $p = 0.0273$), suggesting that vegetation type could modulate the impact of fire intensity on runoff pH. Other interactions, such as between fire intensity and slope, as well as vegetation type and slope, were not statistically significant ($p > 0.05$) (Table 1).

The result of Levene's Test in MATLAB was calculated as ($p = 0.99998$). This indicates that there is no significant difference in variances between the groups, confirming the assumption of homogeneity of variances. Consequently, the ANOVA analyses can be conducted validly.

Subsequently, a correlation test was performed to examine the relationship between fire intensity and changes in runoff pH. The calculated correlation coefficient was -0.7773, indicating a strong negative correlation between these two variables. Additionally, the p-value obtained was (7.8769e-06), which is less than the significance level of 0.05. This result indicates that changes in runoff pH are significantly negatively correlated with fire intensity, such that as fire intensity increases, the runoff pH decreases.

Table 1. Results of Statistical Tests in MATLAB Software.

Analysis of Variance

Source	Sum Sq.	d.f.	Mean Sq.	F	Prob>F
Fire	1.5	1	1.5	145.71	0
Vegetation	0.135	1	0.135	13.11	0.0021
Slope	0.24	1	0.24	23.31	0.0002
Fire:Vegetation	0.06	1	0.06	5.83	0.0273
Fire:Slope	0.015	1	0.015	1.46	0.2439
Vegetation:Slope	0	1	0	0	1
Error	0.175	17	0.01029		
Total	2.125	23			

Constrained (Type III) sums of squares.

Next, to examine and predict the simultaneous effects of various factors on changes in runoff pH due to post-fire precipitation, multiple regression was employed. A regression model was designed with runoff pH changes as the dependent variable and fire intensity, vegetation type, and slope as independent variables. This model was implemented to assess the independent and combined effects of these factors on runoff pH and to predict its changes under different conditions. Metrics such as the coefficient of determination (R^2) and root mean square error (RMSE) were used to evaluate the accuracy of the model and the quality of the predictions.

$$pH = 6.45 - 0.675\,x_1 - 0.225x_2 + 0.015x_3$$

Where x_1 represents fire intensity (0 = low, 1 = moderate), x_2 represents vegetation type (0 = herbaceous, 1 = dense), and x_3 represents land slope (in degrees).
The resulting regression model indicates that fire intensity (x_1) and vegetation type (x_2) have a negative and significant effect on the river water pH, meaning that an increase in fire intensity and vegetation density leads to a decrease in water pH. These results are consistent with ecological assumptions, as the burning of vegetation and the release of acidic compounds during the fire process can result in a reduction in water pH. In contrast, land slope (x_3) has a slight positive effect on pH. This positive effect appears to stem from a reduction in the contact time between runoff and burned soil, which may reduce the concentration of acidic compounds in the runoff, thereby slightly increasing the water pH.

Table 2 - Summary of Results from Executing the Regression Model in MATLAB.

Variable	(Estimate)	Estimate Standard Error (SE)	t-Statistic (tStat)	p-Value (pValue)
Initial supply	6.45	0.049675	129.84	9.6144e-31
Fire intensity	-0.675	0.041332	-16.331	4.9676e-13
Vegetation type	-0.225	0.041332	-5.4437	2.5003e-05
Slope	0.015	0.0027555	5.4437	2.5003e-05

4- 2 Analysis of Statistical Indicators for the Linear Regression Model

After performing the multiple regression model with fire intensity, vegetation type, and slope as independent variables and river water pH as the dependent variable, the resulting statistical indicators demonstrate the high accuracy and explanatory capability of the model. The model was estimated with 24 observations and 20 degrees of freedom for error. The Root Mean Square Error (RMSE) value was 0.0924, and the model's Standard Error (S-statistic) was 0.1012, both of which indicate a very small error between the predicted and actual pH values. These results reflect the high accuracy and desirable stability of the model.
Additionally, the coefficient of determination (R-squared) was estimated to be 0.9422, and the adjusted R-squared was 0.9335. These values indicate that the model can explain approximately 93.3% of the variations in the pH variable based on the input variables of the model as the model adequacy, respectively. The high values of R^2 and Adjusted R^2 reflect the very strong predictive power of the model, even after accounting for the number of variables included in the model. Finally, the overall test of the model using the F-statistic also indicates the overall significance of the model ($F = 109$, p-value = 1.5×10^{-12}). This very low p-value suggests that at least one of the independent variables entered into the model has a statistically significant effect on the pH value.

4-3 Design of a Neural Network Trained with the Artificial Bee Colony Algorithm

In this study, a Feedforward Artificial Neural Network (ANN) was designed to predict changes in river water pH resulting from wildfire-induced runoff under varying environmental conditions. The network architecture comprises three layers: an input layer, a single hidden layer, and an output layer. The input layer receives three numerically encoded environmental variables—wildfire intensity, vegetation type, and slope gradient. These parameters reflect the main experimental conditions influencing runoff quality.
The output layer provides a continuous prediction of runoff pH, based on pilot-scale experimental results. The hidden layer contains five neurons equipped with a tangent sigmoid (tansig) activation function, allowing the network to capture the nonlinear interactions between the input variables and the output.
The output layer includes a single neuron with a linear (purelin) activation function, suitable for continuous value prediction beyond a restricted range. This minimalist architecture—featuring only one hidden layer—was deliberately selected to balance model complexity and generalization, particularly given the limited sample size of the pilot experiment. To further enhance prediction accuracy, the Artificial Bee Colony (ABC) algorithm was applied to optimize the network's weights, enabling better convergence and robustness. This ANN-ABC hybrid model effectively simulates the complex environmental dynamics associated with wildfire-driven water quality degradation (Figure 6).

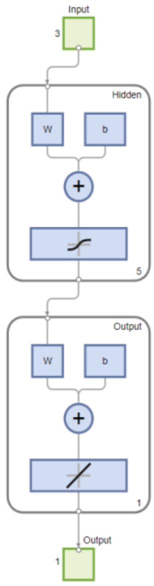

Figure 6. Network Diagram (Source: MATLAB output).

For training the designed neural network, the backpropagation learning algorithm with the Levenberg-Marquardt method was used, which is one of the fastest and most widely used methods for regression and prediction problems with small to medium datasets (MathWorks, 2023). The dataset consists of 24 experimental samples, which were divided into three categories: training (70%), validation (15%), and testing (15%). The purpose of validation was to prevent overfitting of the model and enhance its generalization ability to unknown data. The initial training of the network continued until the objective function (Mean Squared Error) reached its minimum value, or one of the stopping criteria, such as reaching the maximum number of iterations or experiencing three consecutive errors in the validation set, occurred (Hagan& Menhaj,1994).

In order to increase the model's accuracy and reduce learning error, after the initial training, the weights and biases of the network were optimized using the Artificial Bee Colony (ABC) algorithm. This algorithm, inspired by the foraging behavior of honeybees, is capable of finding optimal values for the weights and biases of the network within the continuous search space, guiding the model toward minimizing the output error. In this study, the combination of the neural network with ABC led to a significant reduction in the RMSE error from an initial value of 9.4655 (before optimization) to 0.1970 (after optimization) in the five-neuron structure. This remarkable improvement reflects the positive impact of the intelligent optimization of the weights on the model's performance and increased prediction accuracy (Figure 7).

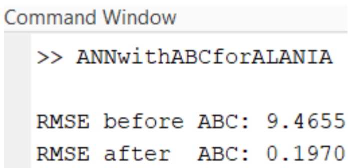

Figure 7. Results of the network optimization.

The results obtained from the training of the neural network indicated that the use of the Artificial Bee Colony (ABC) optimization algorithm played a significant role in improving the model's accuracy. Specifically, in the network structure with 5 neurons in the hidden layer, the Root Mean Square Error (RMSE) decreased from 9.46 before optimization to 0.197 after applying the ABC algorithm; this represents an almost 48-fold improvement in the accuracy of the runoff pH estimation. A similar comparison was made in the network structure with 10 neurons, but the RMSE value after optimization in this case (0.3908) was higher than that of the 5-neuron network. Therefore, the network with 5 neurons provided higher accuracy in predictions while maintaining a simpler structure.

Next, the optimization process of the Multi-Layer Perceptron (MLP) model using the Artificial Bee Colony (ABC) algorithm was examined. The chart "Trend of Optimizing MLP Using ABC," shown in Figure (7-b), illustrates the changes in the best value of RMSE during 100 optimization iterations. In this chart, the horizontal axis represents the number of iterations from 0 to 100, and the vertical axis shows the best value of RMSE within the range of 2.5 to 3.25.

As shown in the chart, with an increase in the number of iterations, the RMSE value gradually decreases, indicating an improvement in the model's performance and a reduction in prediction error. This trend demonstrates the positive impact of the ABC algorithm in optimizing the neural network's performance, leading to a decrease in prediction error and higher accuracy in simulating runoff pH changes. The chart shows that after the first 20 iterations, the optimization process significantly progresses toward optimal performance, with only minor changes in the RMSE value in subsequent iterations, indicating model stabilization and optimization (Figure 8).

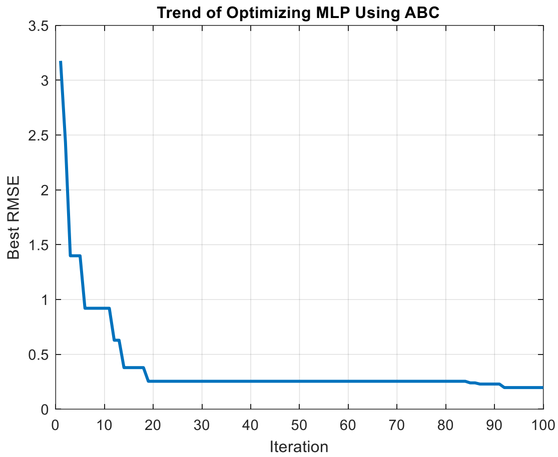

Figure 8. Network trained with ABC (Source: MATLAB software output).

The ROC curve for the training data using the ABC algorithm shows that the model performed with a false positive rate near zero and a true positive rate of one. With an AUC[1] of 1.00, this curve indicates the high accuracy of the model in correctly distinguishing between positive and negative data (Figure 9).

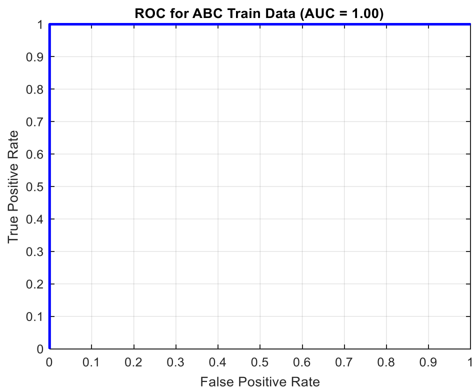

Figure 9. ROC curve(Source: MATLAB output).

In the MSE variation plot in Figure 10, it is observed that the model's error decreases rapidly over 8 epochs. The training curve (blue) started from a high MSE value and reached approximately 10^{-2} at epoch 1.

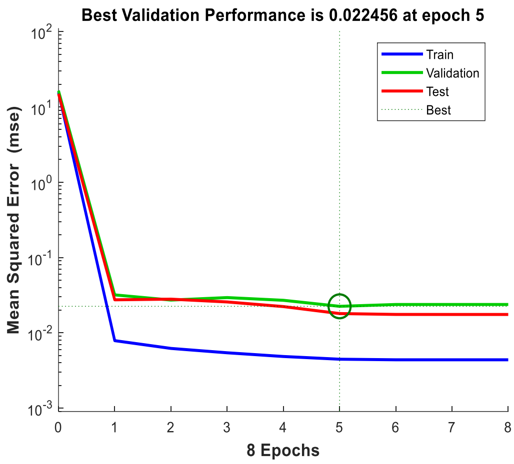

Figure 10. MSE diagram (Source: MATLAB output).

The validation curve (green) and test curve (red) also showed a similar reduction, reaching values of $10^{-1.5}$ and higher at epoch 1. The best performance of the model was recorded at epoch 5 with MSE = 0.022456, and after that, the error changes were negligible (Figure 10)

The regression plot between the target values and the model's output in the test data indicates a strong correlation between the two variables. The correlation coefficient R = 0.97417 suggests a high correlation of over 97% between the target values and the model's output. This indicates that the model is capable of accurately predicting the target

[1] The Area Under the ROC Curve (AUC) is a performance metric that quantifies a model's ability to distinguish between classes; an AUC of 1.0 indicates perfect classification with no false positives or false negatives (Fawcett, (2006).

values and has been able to simulate almost all of the variations in the target, reflecting the high accuracy of the model's predictions (Figure 11).

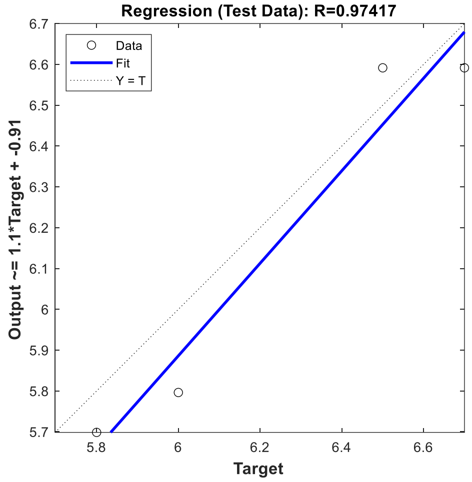

Figure 11. Regression plot between the target values (Source: Output from MATLAB software).

The residual plot after optimization using the ABC algorithm shows a uniform distribution of residuals, indicating that the model has been effectively tuned and that the predictions are both random and accurate (Figure 12).

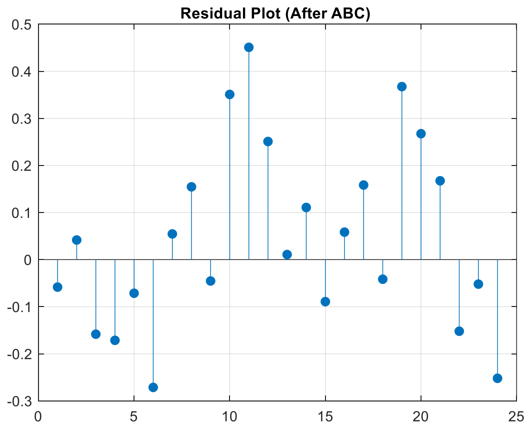

Figure 12. Residual plot (Source: Output from MATLAB software.

The Real vs. Predicted pH plot illustrates a direct comparison between the actual pH values obtained from the pilot experiments and the values predicted by the neural network model optimized with the ABC algorithm. In this plot, each point represents a test sample, with its coordinates determined by the actual pH value (horizontal axis) and the value predicted by the model (vertical axis).

The cluster of points close to the identity line (X = Y) indicates high accuracy and the predictive power of the model in reproducing actual values. Specifically, the small deviation of points from this line signifies that the model has successfully learned the system's behavior and is providing accurate estimates of runoff pH changes under various environmental conditions. This strong alignment between observed and predicted values confirms the successful performance of the model in simulating complex environmental phenomena, such as the impact of forest fires on the chemical quality of surface runoff.

Additionally, Figure 13 shows the actual pH versus. predicted pH, providing a comparative plot between the real pH values measured in experiments and the values predicted by the model.

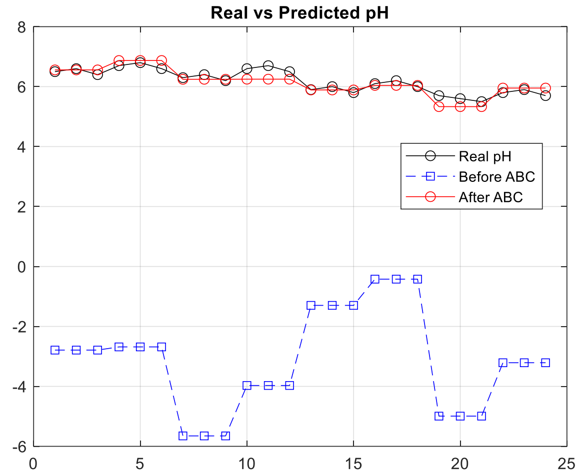

Figure 13. Prediction plot of pH changes in river water due to runoff after a wildfire, after optimization (Source: Output from MATLAB software).

The histogram of errors (error = target – output) also shows that the error distribution is concentrated within a narrow range of [-0.14, +0.19], with the majority of samples having errors close to zero. This indicates a proper distribution of prediction errors across the data and the absence of significant bias in the estimation (Figure 14).

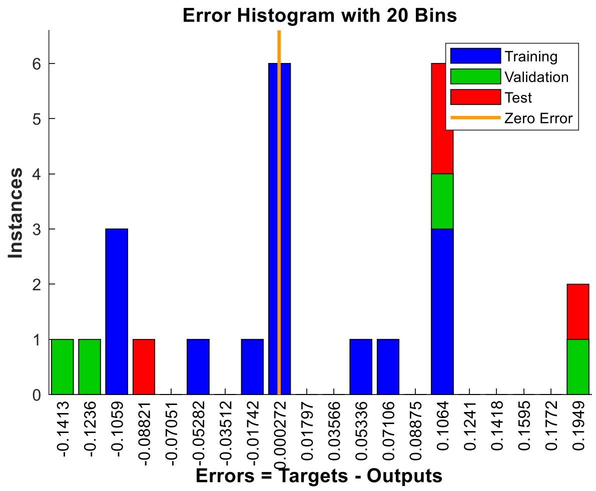

Figure 14. Histogram of Errors (Source: MATLAB Software Output).

In the regression analysis, the coefficient of determination (R^2) for the training, validation, and test data was 0.98719, 0.98877, and 0.97417, respectively. These high coefficients indicate a strong correlation between the predicted output of the network and the actual pH values. Additionally, the regression line equations in each section (e.g., Output ≈ 1.1 * Target - 0.91 in the test data) suggest an acceptable level of prediction accuracy, although a slight slope above 1 was observed in the validation data, which may indicate a slight overestimation in that section (Figure 15).

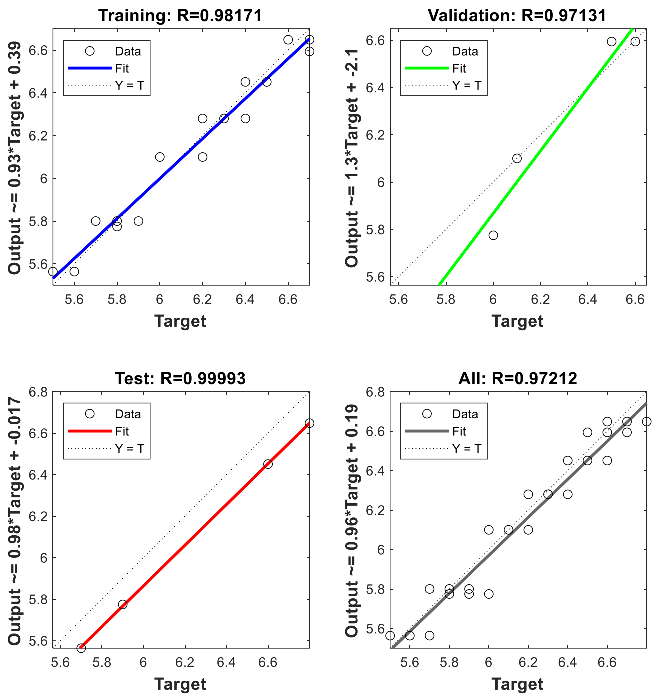

Figure 15. Validation plots (Source: MATLAB software output).

Finally, the chart related to the network training process also showed that the model reached its optimal point at epoch 8 (Epoch 8) with a very low gradient value (Gradient = 7.86e-12) and only 3 validation failures. This not only demonstrates the efficiency of the training algorithm but also indicates an appropriate balance between learning and preventing overfitting (Figure 16).

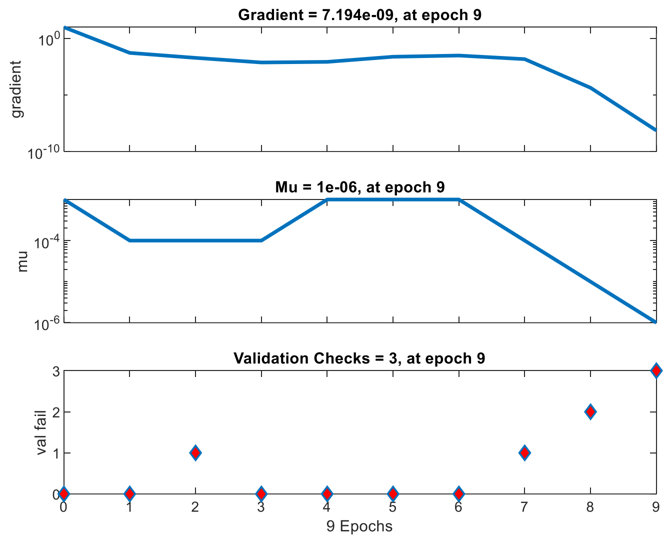

Figure 16. Chart related to the network training process (Source: MATLAB software output).

Conclusion

Large-scale wildfires in forested areas have become one of the most critical environmental challenges in recent decades, with significant direct and indirect impacts on the quality of surface water resources. To investigate the effects of wildfire intensity on runoff pH and the potential for point-source contamination of adjacent river waters, a pilot experiment was conducted outdoors under natural environmental conditions, using a soil-filled pallet measuring 70 cm × 70 cm in surface area with a soil depth of 10 cm. The experimental design included three independent variables: fire intensity (low and medium), vegetation type (herbaceous and dense), and slope gradient (5° and 20°).

After conducting controlled fires in each treatment, runoff resulting from both convective and natural rainfall was collected and analyzed. The pH of the runoff, serving as the dependent variable, was measured for each replicate and used as input for an artificial neural network (ANN) model to assess the relationships between environmental variables and runoff acidity.

Statistical analyses revealed that fire intensity had a significant effect on reducing runoff pH, leading to a marked increase in the acidity of post-fire inflows into the river. Moreover, vegetation type played a critical role; dense vegetation, due to its higher biomass, generated more acidic compounds during combustion, thereby further decreasing pH levels. Additionally, slope was found to influence the speed and volume of runoff, which in turn affected the leaching of surface residues and altered the chemical composition of the runoff. These findings highlight the complex interplay between fire dynamics and environmental characteristics in shaping water quality outcomes following wildfires.

The statistical analyses showed that fire intensity, vegetation type, and slope significantly influence changes in river water pH. Specifically, fire intensity had a strong and significant effect on water pH, with a p-value significantly less than 0.05. Vegetation type also had an independent effect on pH, with a p-value of 0.0021, confirming its role in the chemical changes of water. Additionally, slope significantly influenced runoff pH, underlining its importance in hydrological and chemical processes.

A key finding from the ANOVA analysis was the significant interaction between fire intensity and vegetation type (p-value = 0.0273). This suggests that vegetation type can either amplify or reduce the effect of fire intensity on runoff pH. However, no significant interaction was found between fire intensity and slope, or between vegetation type and slope.

To more accurately predict pH changes based on the combination of input variables, a multilayer perceptron (MLP) artificial neural network was employed. The feedforward neural network, with one hidden layer and five neurons, provided stable performance in estimating pH values due to its simple and flexible structure. By optimizing the network weights and biases using the Artificial Bee Colony (ABC) algorithm, the model's prediction accuracy was significantly enhanced. The reduction in RMSE from 9.46 to 0.197 after optimization—an approximately 48-fold decrease in error—demonstrates the effectiveness of this method in reducing error and improving the model's ability to generalize to new data.

Furthermore, the strong correlation between the target values and the model's output ($R^2 = 0.974$), as well as the results from ROC curves, MSE, residuals, and the comparison of actual and predicted data, highlight the model's high capability to simulate the system's response to changes induced by fire intensity, vegetation type, and land slope. Additionally, a comparative analysis of different network structures showed that the network with the simpler structure (five neurons) not only prevented overfitting but also achieved higher accuracy compared to more complex networks.

In conclusion, the findings of this study demonstrate that forest fires contribute to point-source pollution of nearby water resources by altering runoff pH. The research also illustrates that artificial neural network-based intelligent models, when properly trained and optimized, can serve as effective tools for predicting and managing environmental risks in post-fire conditions.

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Conflict of Interests
The Author(s) declare(s) that there is no conflict of interest.

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