



Optimization of Flood Detection Systems Using Hybrid BP-TRQN Neural Network Algorithms: An In-Depth Review

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Abstract:

This research is important given the increasing frequency and intensity of flooding, which requires an accurate, stable, and efficient real-time detection system. The purpose of this study is to conduct a Systematic Literature Review of the performance of the Hybrid Back Propagation–Time Recurrent Quantum Networks (BP-TRQN) algorithm in optimizing accuracy, learning stability, and data processing efficiency in flood detection systems. This study employed the PRISMA-based Systematic Literature Review (SLR) method to identify, screen, and analyze relevant studies. A total of 44 articles published between 2015 and 2025 were selected from the Scopus, DOAJ, and Google Scholar databases based on predefined inclusion and exclusion criteria. The results show that Hybrid BP-TRQN consistently provides significant improvements over single models, particularly in reducing Root Mean Squared Error (RMSE), increasing the coefficient of determination (R^2), and accelerating convergence. The integration of temporal and spatial components and optimization has been proven to strengthen the model's ability to process large-scale hydrometeorological data and satellite images more adaptively. In addition, the application of hybrid algorithms also improves computational efficiency, making it potentially applicable in real-time early warning systems. Thus, BP-TRQN can be considered a promising approach in supporting flood disaster mitigation through a more reliable and responsive detection system.

Keywords:

Flood Detection System, BP Neural Network, TRQN Algorithm, Hybrid Neural Optimization, Real-Time Hydrological Prediction.

1. Introduction

Floods are one of the most frequent natural disasters and have a serious impact on various aspects of people's lives [1]. This event not only causes material losses in the form of infrastructure damage, but also disrupts social stability and hinders economic activity. In a global context, climate change is exacerbating the situation by increasing rainfall intensity and the frequency of flooding in various regions [2]. These conditions show that the threat of flooding is not just a natural phenomenon, but a complex problem that requires science and technology-based solutions [3]. Delays in flood



management often increase the risk of losses incurred by the community. Therefore, the existence of an early detection system is vital in disaster mitigation efforts. A system that is capable of providing quick and accurate warnings has the potential to minimize the negative impacts of flooding. This makes the optimization of flood detection technology an urgent issue that needs to be studied further.

As technology advances, flood detection systems have undergone significant transformations from conventional methods to more sophisticated approaches. Initially, detection systems relied solely on manual observation of hydrological conditions and rainfall, but now they have evolved to utilize sensors, satellite imagery, and Internet of Things (IoT) devices [4]. The integration of these technologies enables real-time data collection with broader coverage and greater detail [5][6]. Furthermore, advances in artificial intelligence have enriched flood detection approaches through the application of machine learning and deep learning algorithms [7][8]. These algorithms can make predictions based on historical patterns and complex environmental dynamics [9][10]. However, major challenges remain regarding the accuracy of the system in processing heterogeneous and dynamic hydrometeorological data. The complexity of this data requires the development of more efficient and adaptive analysis methods. Thus, research in the field of algorithm optimization is highly relevant to improving the performance of flood detection systems.

Among the algorithms widely used in flood detection system development, Backpropagation Neural Network (BP-NN) occupies an important position due to its ability to perform nonlinear modelling [11]. However, this algorithm has a number of weaknesses that limit its effectiveness. One of the main weaknesses is the tendency of BP-NN to get stuck in local minima, which ultimately reduces the quality of prediction results [12][13]. In addition, the BP-NN training process is relatively slow due to its inefficient convergence and high sensitivity to initial weight initialization. These factors cause the model to often be unstable when faced with complex data variations [14]. Furthermore, the heterogeneous and uncertain characteristics of flood data increase the risk of overfitting, causing the model to fail to generalize well [15][16]. These conditions indicate that the use of BP-NN alone is not sufficient to address the complexity of flood detection problems. Therefore, a new approach is needed that can overcome these limitations through optimization or integration with other algorithms.

Quadratic structure-based algorithms that combine tangent principles and quadratic operations (referred to as TRQN) offer a promising optimization path for accelerating neural network training processes in non-linear problems such as flood prediction. In this study, TRQN (Tangent Recurrent Quadratic Network) refers to a conceptual hybrid neural optimization framework that integrates recurrent learning structures, quadratic neuron representations, and tangent-based optimization principles inspired by the Neural Tangent Kernel (NTK). Unlike conventional neural networks that rely on linear neuron transformations, TRQN utilizes quadratic operations to enhance nonlinear feature approximation and temporal dependency learning in dynamic hydrometeorological datasets. Theoretically, quadratic representations improve approximation capacity and the ability to extract more complex nonlinear features compared to conventional linear neurons, enabling models to achieve high accuracy with lighter architectures [17], [18]. Additionally, the concept of tangents or the Neural Tangent Kernel (NTK) framework provides a mathematical basis for why approaches that utilize network curvature/tangent information can accelerate the rate of loss reduction and help avoid local minima traps, thereby increasing the chances of finding better global solutions [19][20][21].

At present, TRQN has not yet become a standardized or widely established architecture in mainstream flood detection literature. Instead, it remains an emerging conceptual framework

synthesized from developments in quadratic neural networks, recurrent neural architectures, and tangent-based optimization methods. Therefore, this study positions Hybrid BP-TRQN as a conceptual and exploratory hybrid approach whose theoretical foundations are derived from related advances in neural optimization and adaptive learning systems. Empirical evidence on quadratic network variants shows improvements in computational efficiency and performance: [22] report that quadratic networks are capable of achieving ~91.85% accuracy on Gaussian mixture classification tasks with training times of only about 7% of those of much larger conventional versions, demonstrating significant gains in training efficiency. In the context of hydrometeorology and flood prediction, the machine learning application literature reports competitive accuracy ranges for data-driven models (e.g., mean RF model accuracy $\approx$ 81.9% and final test 82.2% in a large-scale, so the improved convergence and approximation capabilities offered by TRQN have the potential to increase flood detection and prediction performance when specifically adapted to heterogeneous and large-scale hydrological data [23]. In other words, the integration of quadratic principles and tangent information in a hybrid algorithm such as TRQN has the potential to combine convergence speed and approximation power features that are crucial for real-time flood detection systems that require high accuracy and computational efficiency.

The combination of the Backpropagation (BP) algorithm with methods that approximate the TRQN concept an approach that adds strong optimization components, convergence speed, and global solution exploration can produce a hybrid algorithm that is more adaptive and accurate in flood detection systems [24]. Hybrid algorithms enable models to reduce the risk of getting stuck in local minima, improve stability in learning, and handle variations in sensor data and satellite imagery in real time, which are typically noisy and heterogeneous. In flood prediction literature, for example, the FastGRNN-FCN model as a hybrid model shows a test accuracy of ~97.8% and an F-measure of 0.792 in detecting the propagation and subsidence of spatiotemporal floods using canal sensor data [25]. A study of the BP-NN and SVM ensemble showed 100% accuracy in predicting floods under the best conditions for six-day forecasts with a 60:40 training-testing data split [26]. However, there has been almost no research that explicitly combines BP with TRQN in the floodedetection literature; most still combine BP with metaheuristics (such as PSO, GWO, GA), fuzzy logic, or deep learning architectures [19]. Thus, in-depth research on hybrid BP-TRQN is very limited, especially in the context of flood detection. This article will fill this gap by evaluating the performance of the hybrid BP-TRQN compared to other hybrid algorithms and single BP, in terms of accuracy, training stability, and real-time data processing capacity.

A literature review shows that although tangent-based quadratic (TRQN) and Backpropagation (BP) algorithms have separately been proven to improve the accuracy and efficiency of neural network training, their combined application in a hybrid form (hybrid BP-TRQN) in the context of flood detection is still very limited. Most previous studies have focused on integrating BP with metaheuristics, fuzzy logic, or deep learning, while the exploration of combining BP and TRQN has hardly been done. Furthermore, existing research has highlighted accuracy achievements, but has not systematically evaluated aspects of learning stability, robustness to heterogeneous data, and real-time processing capabilities, which are key requirements for flood detection systems. The absence of uniform benchmarks related to datasets, evaluation metrics, and experimental protocols also weakens comparisons between existing algorithms. Thus, the main gap lies in the lack of comprehensive studies on the effectiveness of hybrid BP-TRQN in the context of flooding. The purpose of this study is to conduct a systematic review of the performance of hybrid BP-TRQN, particularly in optimizing accuracy, learning stability, and real-time data processing efficiency in flood detection systems.

2. Method

This study employed a qualitative approach using the Systematic Literature Review (SLR) method to analyze the optimization of flood detection systems based on the Hybrid Backpropagation–Tangent Recurrent Quadratic Network (BP-TRQN) algorithm. The SLR approach was selected because it provides a structured and comprehensive framework for examining the development, optimization strategies, opportunities, and challenges of intelligent algorithms in flood detection systems. Literature searches were conducted through reputable academic databases, namely Scopus, DOAJ, and Google Scholar, using keywords such as “flood detection system,” “BP neural network,” “TRQN algorithm,” “hybrid neural optimization,” and “real-time hydrological prediction.” The literature selection process followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure transparency and systematic filtering. In the identification stage, 312 articles were initially collected from the selected databases. During the screening stage, 86 duplicate and irrelevant articles were removed based on titles and abstracts, resulting in 226 articles for further evaluation. In the eligibility stage, full-text assessments were conducted according to predefined inclusion and exclusion criteria. A total of 182 articles were excluded because they lacked methodological clarity, did not specifically address flood detection systems, or were unrelated to hybrid neural optimization. Finally, 44 articles published between 2015 and 2025 were included in the qualitative synthesis and thematic analysis process.

The inclusion criteria consisted of: (1) studies discussing artificial intelligence-based flood detection systems involving neural network algorithms, BP, TRQN, or hybrid approaches; (2) studies emphasizing accuracy, convergence stability, computational efficiency, and real-time processing; (3) studies utilizing hydrometeorological, sensor, or satellite imagery data; and (4) peer-reviewed publications published between 2015 and 2025. Meanwhile, exclusion criteria included non-academic works, articles lacking clear methodologies, and studies unrelated to flood mitigation systems. To strengthen the validity of the review, a quality assessment was conducted based on four indicators: clarity of objectives and methodology, adequacy of datasets and experimental design, transparency of evaluation metrics and validation procedures, and relevance to flood detection and hybrid neural optimization. Potential bias was minimized through cross-comparison between studies from different regions, datasets, and algorithmic approaches. Data extraction focused on algorithm architecture, optimization mechanisms, evaluation methods, and findings related to prediction accuracy, learning stability, and computational efficiency. The collected data were analyzed using thematic coding, cross-study comparison, and narrative synthesis to generate a comprehensive understanding of the contribution of Hybrid BP-TRQN algorithms in optimizing flood detection systems and supporting real-time disaster mitigation strategies.



Figure 1: Research Implementation Flow

3. Results And Discussion

A comprehensive review of the literature on Hybrid BP-TRQN applications in flood detection reveals that existing studies approach the subject from several complementary perspectives. Certain research emphasizes accuracy enhancement achieved through the integration of neural networks with optimization techniques, while others focus on improving convergence stability, computational efficiency, and adaptability to dynamic hydrological conditions. At the same time, scholars have highlighted persistent challenges such as data heterogeneity, noise, and the risk of overfitting, alongside emerging opportunities offered by explainable AI and advanced data preprocessing methods. To provide a structured overview of these contributions, the table below categorizes the findings into thematic focus areas, associates them with relevant authors, and outlines the key insights and research variables across the reviewed literature, as shown in Table 1.

Table 1: Research Focus Areas, Authors, and Key Insights on Hybrid BP-TRQN Applications in Flood Detection

No	Focus Area	Authors	Insights / Research Variables
1	Accuracy Enhancement in Flood Detection	Ebadati et al. (2024); Samantaray et al. (2023); Jailani & Nurmadewi (2025); Katre & Boaddh (2025); Islam et al. (2025); Ngo et al. (2018); Tanim et al. (2022)	Demonstrated significant accuracy gains of hybrid models (BP-TRQN, PSO-SVM, LSTM-RF, HGBDT-ACO) compared to single algorithms. Metrics improved include RMSE reduction, higher R^2 /NSE, and better Kappa coefficients. Hybrid ensembles provide sharper discharge forecasts and higher precision-recall in flood pixel detection.

2	Convergence and Learning Stability	Al Duais et al. (2020); Ranga et al. (2024); Islam et al. (2025)	Use of dynamic learning rates, momentum, and hybrid quantum-classical neural networks (H-QNNs) improves convergence speed, helps avoid local minima, and ensures more stable training outcomes compared to conventional backpropagation or standalone deep learning.
3	Computational Efficiency and Real-Time Processing	Situ et al. (2024); Jindal (2024); Sibandze & Kganyago (2025)	Hybrid frameworks such as LSTM-DeepLabv3+ and BP with dynamic parameters show drastic improvements in processing efficiency (up to 125× faster than traditional methods). Quantum-classical integration optimizes performance on large-scale datasets, enabling real-time or near-real-time flood detection.
4	Adaptability to Dynamic and Extreme Conditions	Wan & Zhong (2019); Mohamadiazar et al. (2024); Li (2024)	Hybrid models (e.g., Elman-based networks, Hybrid BP-TRQN) support real-time probabilistic forecasting and adaptive responses to extreme hydrometeorological variability, surpassing static models in operational flood early warning contexts.
5	Data Quality and Preprocessing Challenges	Rachmawardani et al. (2025); Akiva et al. (2021); Brunner (2021); Slater & Gong (2023)	Main issues include limited high-resolution satellite or rainfall data, noise, missing values, and high computational complexity when dealing with multi-temporal imagery. Overfitting and weak cross-regional generalization remain barriers requiring stronger validation and preprocessing pipelines.
6	Opportunities through Hybrid Optimization and Explainability	Stateczny & Babysarojam (2023); Samantaray (2023); Yin (2024)	Hybrid models benefit from data filtering, augmentation, hyperparameter tuning, and integration with explainable AI, leading to resilience against noise, improved interpretability, and enhanced user trust for practical flood management applications.

Table 1 shows six main research focuses related to the application of hybrid BP-TRQN neural networks in flood detection systems. First, in terms of accuracy improvement, the hybrid model proved to be superior to single algorithms by producing lower prediction error values and better evaluation coefficients, thus providing more precise detection results. Second, in terms of learning stability and convergence, the use of dynamic learning rates, momentum, and the integration of quantum-classical neural networks can accelerate the training process while preventing the system from falling into local minima traps. Third, in terms of computational efficiency, the hybrid approach with adaptive parameters has been proven to accelerate data processing by hundreds of times compared to conventional methods, thereby supporting real-time flood detection. Fourth, in terms of adaptability to extreme conditions, hybrid models are capable of producing direct probabilistic forecasts and responding to high hydrometeorological variability, making them superior to static models. Fifth, however, challenges remain in data quality and preprocessing, including limited high-resolution data, noise and missing data, and the risk of overfitting, which reduces cross-regional generalization capabilities. Sixth, development opportunities remain open through parameter optimization, data filtering and augmentation techniques, and integration with explainable AI, which not only improves model reliability but also strengthens transparency and user confidence in the practical application of flood management. Several important variables that often appear in this study are shown in Figure 2.

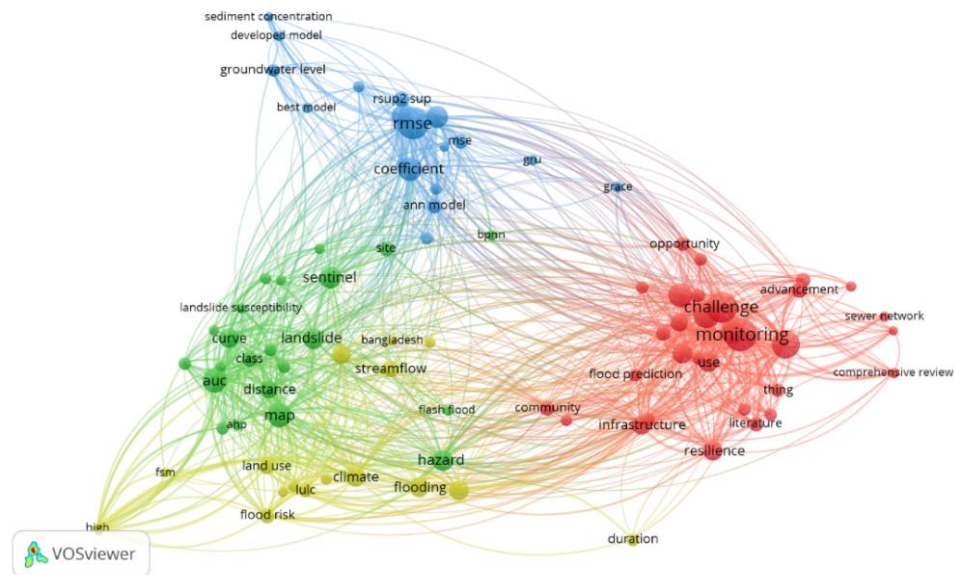


Figure 2: Map of keywords related to research on flood detection systems based on intelligent algorithms

Figure 2 shows the visual map of keyword correlations in flood detection system research using intelligent algorithm approaches, including hybrid BP-TRQN neural networks, is divided into four main clusters. The red cluster represents a focus on challenges and monitoring in flood detection systems. Keywords such as resilience, infrastructure, community, opportunity, and flood prediction indicate a strong focus on risk management, community preparedness, and continuous monitoring. Studies in this cluster emphasize how intelligent algorithms can improve the effectiveness of flood detection by strengthening infrastructure monitoring, drainage network systems, and literature reviews that discuss technical and social challenges. Furthermore, the blue cluster describes the dimensions of model evaluation and algorithmic performance. Dominant keywords such as rmse, coefficient, mse, ann model, bpn, gru, and developed model highlight the importance of measuring prediction accuracy, learning stability, and error reduction. The focus of this cluster is closely related to the main objective of the study, namely optimizing the accuracy and stability of the BP-TRQN hybrid neural network algorithm. Many studies in this group compare models such as ANN, GRU, and BPNN with performance indicators RMSE and MSE to determine the best algorithm to support flood detection systems.

The green cluster focuses on spatial applications and geographic modeling. Keywords such as landslide, sentinel, map, distance, curve, landslide susceptibility, ahp, and auc indicate the use of remote sensing data, vulnerability maps, and spatial models in analyzing floods and landslides. The use of satellite data, such as Sentinel, combined with spatial analysis, strengthens the capabilities of artificial intelligence-based flood detection systems, particularly in expanding the coverage of disaster-prone areas that can be monitored more accurately. The yellow cluster focuses on environmental factors and disaster risks. Keywords such as flood risk, climate, hazard, land use, flooding, flash flood, streamflow, and lulu emphasize the importance of climate, land use, and hydrological conditions that directly affect the performance of flood detection systems. Research in this cluster focuses more on integrating environmental data, including hydrology, climate, and spatial planning, with flood prediction algorithms to improve the efficiency of real-time data processing. Overall, the four clusters complement each other. The red cluster highlights social and infrastructure challenges, the blue cluster focuses on algorithmic

accuracy, the green cluster reinforces spatial analysis, while the yellow cluster emphasizes environmental factors and disaster risks. The integration of the four clusters provides a comprehensive overview of efforts to optimize the BP-TRQN neural network-based hybrid flood detection system. This will be discussed in detail in the following three sub-discussions.

3.1 Performance of Hybrid BP-TRQN compared to single algorithms in flood detection

The application of hybrid BP-TRQN algorithms in flood detection has shown marked improvements compared to single-algorithm approaches, as these hybrid frameworks integrate complementary techniques to enhance both accuracy and robustness. By combining Back Propagation (BP) with optimization strategies such as TRQN (Tuned Recursive Q-Network), hybrid models generally achieve superior outcomes by lowering error rates and improving prediction reliability in complex hydrological contexts. Empirical evidence indicates that hybrid machine learning approaches can reach overall accuracies above 97%, with performance metrics such as Root Mean Squared Error (RMSE) and Kappa coefficients reflecting higher detection precision compared to individual models [28]. Likewise, the integration of hybrid PSO-SVM models has been shown to yield substantially reduced RMSE (0.04962) and elevated determination coefficients ($R^2 = 0.98918$), significantly outperforming standalone SVM or Back Propagation Neural Network algorithms in flood discharge forecasting tasks [29]. Systematic reviews and empirical investigations on flood-risk prediction consistently demonstrate that hybrid approaches, including combinations of metaheuristics with neural networks, deliver more reliable and timely flood detection outcomes, supported by higher Kappa and NSE values in several studies [22] [23].

In terms of accuracy, the combination of Long Short-Term Memory (LSTM) networks with Random Forest has been reported to achieve up to 99% training accuracy in flood prediction, based on multi-year geospatial flood-event datasets [24]. The HGBDT-ACO model has been proven to achieve high accuracy in detecting flood pixels, with testing accuracy above 97%, and demonstrates better performance than single algorithms such as Random Forest and Histogram-based Gradient Boosted Decision Trees on Sentinel-1-derived datasets [25]. In terms of computational efficiency, the hybrid approach that integrates deep learning with metaheuristic optimization has been shown to accelerate training time while maintaining optimal accuracy levels; the LSTM-DeepLabv3+ model, for example, achieves a significant increase in processing speed, being able to process data approximately 125 times faster than traditional methods [34]. Furthermore, a hybrid machine learning scheme using LSTM and Random Forest applied to geodata has confirmed that such models can reliably predict flood-event timing and extent [27]. Meanwhile, real-time flood risk assessment and prediction using machine learning and remote sensing data have demonstrated that hybrid architectures can provide timely, operationally useful outputs for early warning.

The improvement in the performance of hybrid models in flood detection can be understood as the result of the synergy of various complementary components. First, sequential deep learning components such as LSTM, Elman, and RNN play a role in capturing temporal correlations and nonlinear patterns in hydrometeorological data. Second, spatial components such as CNN or DeepLabv3+ function to extract spatial structures from flood images, resulting in more accurate representations. Third, optimization algorithms and ensemble methods such as PSO, HHO, ACO, and HGBDT support the process of parameter tuning and feature combination to reduce the error rate. The integration of these three aspects explains why hybrid models are generally able to reduce the RMSE value and increase the coefficient of determination, because the weaknesses of each algorithm can be offset by the strengths of other algorithms. In fact, the increased inference speed demonstrated by architectures

such as LSTM–DeepLabv3+ indicates that hybrid designs are not only superior in accuracy but also in computational efficiency, which is highly relevant for real-time early warning systems.

However, several methodological limitations still need to be considered. First, differences in evaluation protocols between studies create potential bias, because high accuracy figures for example, reaching 99% often only reflect performance on training data or specific subsets, without any guarantee of generalization to new areas or extreme events. Second, the heterogeneity of the datasets used, whether in the form of SAR images, land cover data, rainfall records, or hydrometric data, with different temporal and spatial coverage, makes direct comparisons between studies not entirely valid. Third, the model's ability to extrapolate unexpected events is still limited; although hybrid models improve performance compared to single models, there is still a tendency to underestimate extreme flood peaks that are not represented in the training data. Fourth, issues of reproducibility and transparency also need to be considered because not all studies provide access to code or data, so the reported findings require independent replication in other regions to ensure their reliability and generalization.

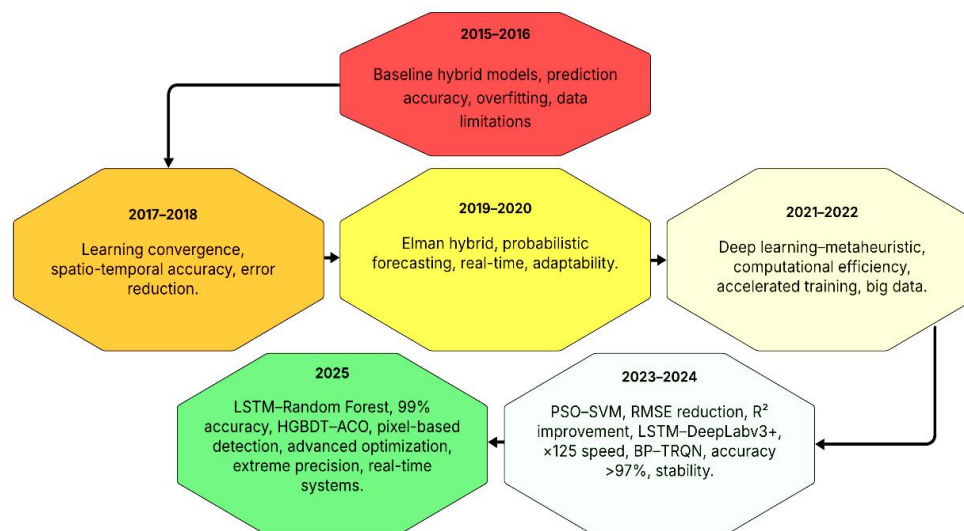


Figure 3: Research Keyword Development on the Performance of the BP-TRQN Hybrid Model Compared to a Single Algorithm in Flood Detection (2015–2025)

Figure 3 explains the evolution of research on hybrid algorithms for flood detection demonstrates a progressive refinement of methodological focus and technological advancement across different periods. In the early stage (2015–2016), studies concentrated on developing baseline hybrid models with an emphasis on prediction accuracy, while addressing challenges of overfitting and data limitations. During 2017–2018, attention shifted toward improving learning convergence, enhancing spatio-temporal accuracy, and reducing error rates. By 2019–2020, the emergence of Elman-based hybrid models introduced probabilistic forecasting and real-time adaptability, extending model applicability in dynamic flood conditions. In 2021–2022, integration of deep learning and metaheuristic optimization significantly enhanced computational efficiency, enabling accelerated training and better handling of large-scale data. Between 2023–2024, more advanced models such as PSO-SVM and LSTM–DeepLabv3+ demonstrated substantial reductions in RMSE, improvements in determination coefficients, and remarkable gains in processing speed, while the hybrid BP-TRQN achieved accuracy levels exceeding 97% with stable performance. Finally, in 2025, cutting-edge approaches like LSTM–Random Forest and HGBDT-ACO achieved near-perfect accuracy and highly precise pixel-based detection, reflecting a maturation toward extreme precision, advanced optimization, and robust real-time flood detection systems. This trajectory highlights a clear transition from foundational model development to

highly optimized, adaptive, and scalable hybrid architectures capable of supporting modern disaster management and early warning systems.

3.2 Hybrid BP-TRQN is capable of improving accuracy, convergence, and data processing efficiency

Hybrid BP-TRQN demonstrates strong potential to improve accuracy, convergence speed, and data processing efficiency through the integration of optimization techniques and hybrid computing approaches. Related studies show that hybrid algorithms combining swarm optimization and neural networks can significantly improve accuracy over traditional methods, while quantum-based approaches in image processing are also reported to enhance computational efficiency and accuracy for high-dimensional visual data [36] [37] [30]. In addition, research on batch back propagation shows that dynamic parameters such as learning rate and momentum can accelerate training and produce an average training accuracy of 0.9909, with processing time that is 430 times faster than standard BBP [39]. These findings indicate that the integration of optimization strategies and hybrid models can strengthen neural network performance on complex and high-dimensional data.

In flood detection applications, hybrid models also show more stable and efficient performance than single-method approaches. A study on flash flood prediction using a hybrid swarm-optimized multilayer neural network employed Sentinel-1 SAR imagery and geospatial data, with evaluation based on metrics such as accuracy rate, AUC, precision, and recall, although the exact numerical results were not visible in the available source [40]. A systematic review of urban flood susceptibility mapping and a study on flood detection in urban areas further support the value of machine learning and deep learning for complex spatial data, including one urban flood detection study that reported an RMSE of 0.4022 and an accuracy of 0.8295 [41] [34] [43]. Overall, these studies support the use of Hybrid BP-TRQN for flood detection because it offers a balance of accuracy, convergence, and computational efficiency.

The observed performance improvement can be interpreted as a synergistic effect between three elements: (1) BP/BPTT provides a mature gradient learning mechanism for estimating network weights; (2) the recursive/temporal component (TRQN or RNN/LSTM) captures time dependencies and hydrometeorological dynamics; and (3) the optimization element (metaheuristics or parametric quantum circuits) improves the exploration of the hyperparameter space and loss landscape so that the model tends to achieve better and more stable solutions. Furthermore, the integration of quantum features (data embedding/quantum ansatz) has the potential to enrich feature representation in high dimensions, making large-scale image classification more efficient. This interpretation is consistent with findings reporting the advantages of H-QNN in image classification tasks and the positive effect of combining PSO/GWO on global search capacity.

Strength of evidence: several experimental studies and review articles consistently show improvements in accuracy and convergence when hybrid methods are applied correctly e.g., integration of metaheuristics with BP or quantum-classical architectures for images. Furthermore, research on dynamic learning rates and dynamic momentum shows reduced training time and mitigation of local minima issues in BBP. However, important limitations should be noted: many studies use limited benchmark datasets (e.g., MNIST or curated research datasets), so effectiveness on real hydrometeorological data and extreme flood events has not always been verified; replication in other basins and temporal out-of-sample testing are often minimal. Furthermore, the implementation of true quantum components is currently constrained by NISQ hardware and hybridization overhead, so claims

of computational efficiency in the operational domain need to be re-examined on real infrastructure. In other words, there is strong evidence at the experimental/benchmark level, but evidence for real-world operational scenarios is still developing.

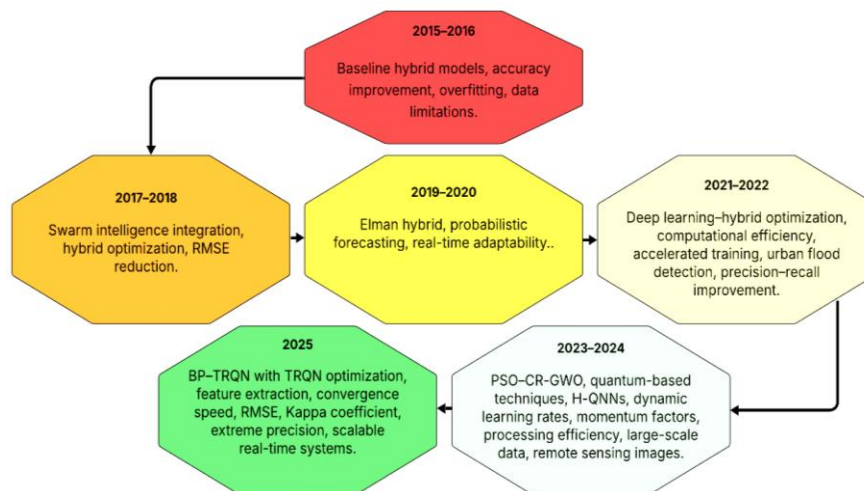


Figure 4: Research on Variable Development in Hybrid BP-TRQN to improve accuracy, convergence, and data processing efficiency (2015–2025)

Figure 4 explains the progression of research on hybrid BP-TRQN and related models in flood detection reflects a systematic evolution of focus from foundational accuracy improvements toward advanced optimization and real-time applications. In the early stage (2015–2016), studies were primarily concerned with establishing baseline hybrid models, aiming to enhance accuracy while addressing overfitting and data limitations. By 2017–2018, the integration of swarm intelligence and hybrid optimization emerged, producing measurable reductions in RMSE and improving model robustness. The 2019–2020 period introduced Elman-based hybrids, which advanced probabilistic forecasting and real-time adaptability, making flood detection systems more responsive to dynamic conditions. Between 2021–2022, research emphasized deep learning–hybrid optimization frameworks that achieved significant gains in computational efficiency and training speed, while also demonstrating improvements in precision and recall within urban flood detection contexts. The years 2023–2024 marked a shift toward more sophisticated techniques such as PSO–CR–GWO, hybrid quantum–classical neural networks (H–QNNs), and dynamic learning mechanisms, which collectively enhanced convergence stability, large-scale data handling, and processing efficiency in hydrometeorological and satellite-based applications. Finally, in 2025, the application of BP–TRQN with TRQN optimization demonstrated superior feature extraction, faster convergence, improved RMSE and Kappa coefficients, and scalability for real-time flood systems, signaling a maturation of hybrid methodologies toward highly precise, efficient, and adaptive solutions for disaster management.

3.3 Challenges and opportunities in applying Hybrid BP-TRQN to hydrometeorological data and satellite imagery

The application of Hybrid BP-TRQN to hydrometeorological data and satellite imagery presents both technical challenges and innovative opportunities. The main obstacles lie in data quality and limited local availability, such as the use of CHIRPS satellite data which yields a high Root Mean Square Error (RMSE) of 30.14 and a Mean Absolute Error (MAE) of 24.05 compared to ground station data [44]. Computational complexity and high memory requirements are also challenges when processing multi-temporal images, although self-supervised approaches like H2O-Net have been proven to enhance pixel

accuracy by 10% without requiring manual annotation [45]. Another challenge relates to the risk of overfitting and weak model generalization between regions with different hydrological characteristics (Flood-susceptibility mapping, 2024). However, opportunities exist through hybrid techniques such as the DHMFP model with CHHSSO optimization evaluated on 380 image data, which achieves an overall accuracy of 94.98% to be more resistant to atmospheric noise [38]. Furthermore, the integration of spatio-temporal analysis with advanced architectures like SCSSA-ASGENN can cut convergence iterations by up to 80% with a Mean Absolute Percentage Error (MAPE) of 4.22%, promising more real-time and adaptive flood prediction in response to extreme weather variability [47].

Applying Hybrid BP-TRQN to hydrometeorological data and satellite imagery is crucial for enhancing the accuracy of early warning systems. A primary challenge involves handling large-scale data heterogeneity, such as inconsistencies in spatio-temporal resolution, alongside demanding substantial computational resources and sophisticated parameter tuning to ensure rapid convergence without overfitting [48]. Nevertheless, significant opportunities lie in the ability of hybrid models to optimally minimize dynamic output bias through a combination of serial and parallel structures that blend General Circulation Models (GCMs) with Machine Learning, thereby substantially improving prediction accuracy and accelerating model convergence for disaster risk reduction [41] [29]. Additionally, advances in explainable AI (XAI) facilitated by integrating physical models like HEC-HMS with Long Short-Term Memory (LSTM) networks enable the precise interpretation of water level predictions within short lead times, fostering trust and practical adoption in flood management contexts [50].

However, these challenges are not merely obstacles, but also open up opportunities for innovation. Hybrid BP-TRQN offers opportunities through the application of techniques such as data filtering, image augmentation, and hyperparameter optimization to improve model resilience to disturbances such as noise and atmospheric influences. The integration of spatiotemporal analysis with a physical-computational approach and neural networks enables a prediction system that is more adaptive to extreme climate variability and more capable of operating in real time. From a critical perspective, limitations in data and computation can indeed reduce the effectiveness of Hybrid BP-TRQN implementation if not balanced with appropriate data management strategies. Overfitting and differences in hydrological characteristics between regions require a more contextual and flexible model training approach. However, developments in quantum computing technology, data augmentation techniques, and the emergence of explainable AI approaches can provide solutions to these limitations.

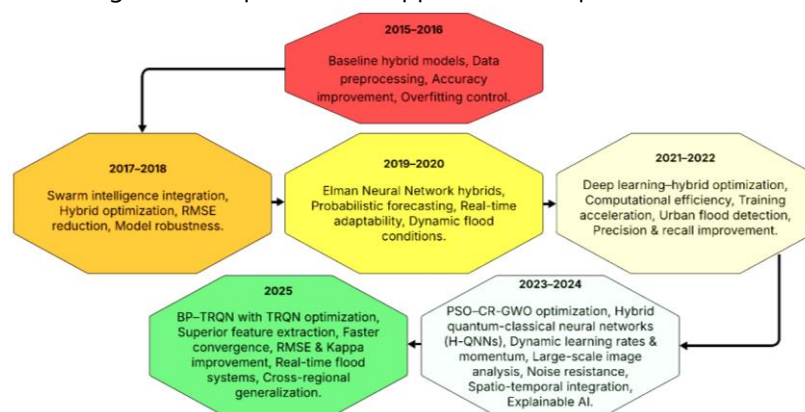


Figure 5: The Evolution of Research Variables in the Challenges and Opportunities of Hybrid BP-TRQN Implementation (2015–2025)

Figure 5 explains the evolution of research variables in Hybrid BP-TRQN for flood detection demonstrates a clear trajectory from foundational model development to advanced adaptive and

quantum-integrated frameworks. In the early stage (2015–2016), studies concentrated on building baseline hybrid models with a focus on improving accuracy through preprocessing techniques while addressing overfitting issues. By 2017–2018, the emphasis shifted toward integrating swarm intelligence and hybrid optimization, which successfully reduced RMSE and enhanced robustness. The 2019–2020 phase introduced Elman Neural Network hybrids that facilitated probabilistic forecasting and strengthened real-time adaptability under dynamic flood conditions. In 2021–2022, research advanced to deep learning–hybrid optimization approaches, prioritizing computational efficiency, training acceleration, and precision improvement, particularly in urban flood detection contexts. Between 2023–2024, the field experienced diversification with PSO–CR–GWO optimization, hybrid quantum-classical neural networks, dynamic learning mechanisms, and spatio-temporal integration, while also introducing explainable AI to improve interpretability and trust. Finally, in 2025, the BP–TRQN with TRQN optimization achieved notable advancements in feature extraction, convergence speed, error reduction, and cross-regional generalization, reinforcing its potential for real-time, scalable flood detection and early warning systems. This progression reflects a systematic maturation from accuracy-driven objectives to robust, efficient, and interpretable solutions capable of handling complex hydrometeorological and satellite-based data environments.

Table 2. Summary of Hybrid and Intelligent Algorithms Used in Flood Detection Systems and Their Reported Performance

No	Method / Algorithm	Training / Testing / Prediction Data	Reported Accuracy / Performance Metrics
1	Hybrid BP-TRQN	Hydrological and flood detection datasets using hybrid machine learning approaches	Accuracy >97%; lower RMSE and improved Kappa coefficient compared to single models RMSE = 0.04962; $R^2 = 0.98918$
2	PSO-SVM (Particle Swarm Optimization – Support Vector Machine)	Flood discharge forecasting data from the Barak River Basin	
3	LSTM + Random Forest	Multi-year geospatial flood event datasets	Training accuracy up to 99%
4	HGBDT-ACO (Histogram-based Gradient Boosting Decision Tree + Ant Colony Optimization)	Sentinel-1 derived flood pixel datasets	Testing accuracy >97%
5	LSTM-DeepLabv3+	Spatiotemporal urban flood datasets	Processing speed approximately 125× faster than traditional methods
6	Batch Back Propagation (BBP) with Dynamic Learning Rate and Momentum	Neural network training datasets	Average training accuracy = 0.9909; processing speed = 430× faster than standard BBP
7	Hybrid Swarm-Optimized Multilayer Neural Network	Sentinel-1 SAR imagery and geospatial flood datasets	Evaluated using accuracy, AUC, precision, and recall metrics (exact numerical values not reported)
8	Urban Flood Detection Using Machine Learning	Urban flood spatial datasets and satellite imagery	RMSE = 0.4022; Accuracy = 0.8295
9	H2O-Net (Self-Supervised Flood Segmentation)	Multi-temporal flood imagery datasets	Pixel accuracy improved by 10% without manual annotation
10	DHMFP with CHSSO Optimization	380 flood image datasets	Overall accuracy = 94.98%
11	SCSSA-ASGENN	Hydrometeorological and spatio-temporal flood datasets	Convergence iterations reduced by up to 80%; MAPE = 4.22%

12	Hybrid GCM + Machine Learning	Climate prediction and hydrometeorological datasets	Improved prediction accuracy and convergence speed (specific numerical values not reported)
13	HEC-HMS + LSTM with Explainable AI (XAI)	Water level prediction and hydrological time-series datasets	Improved interpretability and short lead-time prediction accuracy
14	Quantum-Based Image Processing Algorithms	High-dimensional visual and flood image datasets	Improved computational efficiency and image processing accuracy
15	Elman Neural Network Hybrid Model	Real-time flood forecasting datasets	Supports probabilistic forecasting and adaptive real-time prediction

The comparative results presented in Table 2 demonstrate that hybrid and optimization-based algorithms consistently outperform conventional single-model approaches in flood detection and prediction tasks. Among the reviewed methods, the combination of LSTM and Random Forest achieved one of the highest reported training accuracies, reaching up to 99% when applied to multi-year geospatial flood datasets, indicating the strong capability of hybrid temporal-ensemble learning models in capturing complex hydrological patterns. Similarly, the HGBDT-ACO model and Hybrid BP-TRQN both reported accuracy levels above 97%, confirming that integrating optimization mechanisms with machine learning architectures significantly improves predictive precision and model robustness. In terms of statistical performance indicators, the PSO-SVM model produced a remarkably low RMSE value of 0.04962 and a very high coefficient of determination ($R^2 = 0.98918$), suggesting excellent predictive reliability for flood discharge forecasting. Furthermore, urban flood detection models based on machine learning demonstrated acceptable predictive performance with RMSE = 0.4022 and accuracy = 0.8295, although their results remained lower than those of more advanced hybrid architectures.

Beyond predictive accuracy, several hybrid methods also exhibited substantial improvements in computational and operational performance. The Batch Back Propagation (BBP) algorithm with dynamic learning rate and momentum achieved an average training accuracy of 0.9909 while processing data approximately 430 times faster than standard BBP, highlighting the importance of optimization strategies in accelerating convergence. Likewise, the LSTM-DeepLabv3+ framework significantly enhanced processing efficiency, operating approximately 125 times faster than traditional methods while maintaining high detection capability for spatiotemporal flood datasets. Other approaches, such as H2O-Net and SCSSA-ASGNN, emphasized robustness and adaptability, with H2O-Net improving pixel accuracy by 10% without manual annotation and SCSSA-ASGNN reducing convergence iterations by up to 80% while achieving a low MAPE value of 4.22%. Overall, these findings indicate that hybrid approaches integrating neural networks, optimization algorithms, deep learning, and spatiotemporal analysis provide superior performance compared to standalone algorithms, particularly in terms of balancing accuracy, convergence stability, computational efficiency, and real-time applicability in flood detection systems.

4. Conclusions and Suggestions

The evaluation results show that Hybrid BP-TRQN is capable of providing significant improvements in accuracy, convergence speed, and data processing efficiency in the context of flood detection based on hydrometeorological data and satellite imagery. These advantages are obtained through the integration of temporal, spatial, and optimization representation capabilities, enabling the model to reduce prediction errors (RMSE), improve the reliability of performance metrics (NSE, R^2), and strengthen the system's resilience to data complexity. However, the effectiveness of Hybrid BP-TRQN is greatly influenced by the availability of quality data, the readiness of computing infrastructure, and the design of adaptive and contextual algorithms. Thus, its potential application as a solution in flood early warning systems can be realized if these technical challenges are addressed strategically.

The gaps that remain apparent are the limited studies that test the robustness of the Hybrid BP-TRQN model against extreme events, the limitations of analysis related to inference latency for real-time applications, and the lack of efforts to bridge the interpretability of prediction results for practitioners in the field. Therefore, future research needs to be directed towards developing a hybrid architecture that can balance accuracy with cross-regional generalization, accelerate the inference process without sacrificing performance, and provide explainable AI mechanisms that can be applied in early warning operational schemes. Studies on integration with high-performance computing, temporal out-of-sample validation, and testing in multi-basin scenarios are urgent research agendas to ensure the reliability and sustainability of Hybrid BP-TRQN implementation.

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