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Trends and innovations in hybrid backpropagation–trust region quasi-newton neural network algorithms for intelligent flood detection systems

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ABSTRACT

This study conducts a Systematic Literature Review (SLR) to examine recent trends and innovations in the application of the Backpropagation–Trust Region Quasi-Newton (BP–TRQN) algorithm in intelligent flood forecasting systems. The literature was systematically collected from Scopus, Dimensions, and Google Scholar, with the search restricted to publications from the last ten years. The selected studies were analyzed through a rigorous process of article screening, data extraction, and bibliometric as well as content analysis using VOSviewer and RStudio. The review indicates that the integration of BP–TRQN within hybrid neural architectures, particularly ConvLSTM and CNN–RNN ensembles, is associated with approximately a 5–15% improvement in forecasting accuracy, as reflected in reductions in RMSE and MAE, compared with conventional first-order optimization methods such as GD, SGD, and Adam. In addition, the number of iterations required to achieve convergence was reduced by approximately 20–40%, suggesting improved computational efficiency and greater model stability under non-stationary and noisy hydrometeorological conditions. These findings suggest that BP–TRQN has considerable potential as a robust optimization framework for improving the reliability, efficiency, and adaptability of flood forecasting systems. The main contribution of this study is the provision of a structured synthesis of temporal research trends, methodological innovations, and empirical evidence concerning the role of BP–TRQN in intelligent flood forecasting, thereby identifying current research gaps and future directions for the development of operational early-warning systems. Nevertheless, the review also identifies a significant research gap, namely the limited empirical validation of BP–TRQN within operational early-warning systems, particularly in terms of real-time forecasting performance and cost-effectiveness. Addressing this gap should be considered an important direction for future research, with potential implications for the development of sustainable and data-driven disaster management systems.

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1. INTRODUCTION

Floods are among the most frequent and devastating natural disasters worldwide, causing severe economic, social, and environmental losses. Intensified rainfall due to climate change, rapid urbanization, and poor land management have significantly increased the frequency and severity of flooding events. Conventional flood monitoring and early warning systems often struggle with timeliness and accuracy, particularly under dynamic hydrometeorological conditions [1]. Artificial intelligence (AI) and machine learning (ML) have recently emerged as powerful tools to address these challenges, offering data-driven solutions for real-time flood prediction and detection [2], [3]. However, innovations in neural network optimization remain essential to capture the nonlinear, uncertain, and high-dimensional nature of flood-related data effectively.

Backpropagation (BP) is a widely adopted training algorithm for neural networks in supervised learning tasks, including rainfall–runoff modeling and streamflow forecasting. Its main advantages are algorithmic simplicity, structural flexibility, and suitability for nonlinear system modeling. Nonetheless, BP is often hindered by slow convergence, susceptibility to local minima, and high sensitivity to hyperparameter settings, which limit its effectiveness in real-time and large-scale hydrological applications [4]. Several hybrid approaches combining BP with metaheuristics such as genetic algorithms, firefly optimization, and simulated annealing have been introduced to enhance its performance, yet these approaches generally focus on heuristic search enhancement and still face important limitations in scalability, convergence stability, and computational efficiency, particularly when applied to large-scale or real-time hydrological systems [5]–[8].

In recent developments, the Trust Region Quasi-Newton (TRQN) method has demonstrated notable statistical and performance advantages across optimization and machine learning domains. In reinforcement learning, for example, the Quasi-Newton Trust Region Policy Optimization (QNTRPO) algorithm achieved superior sample efficiency compared to standard Trust Region Policy Optimization (TRPO), reaching a humanoid control score of approximately 3000 within only 350 episodes faster and higher than TRPO under equivalent batch settings [9]. This improvement stems from the integration of Quasi-Newton Hessian approximations with trust region strategies, where adaptive dogleg steps effectively regulate optimization step sizes to ensure both global convergence and iterative stability [10]. Theoretically, TRQN maintains a worst-case iteration complexity of $O(1/\varepsilon^2)$ for convergence to first-order stationary points, which is consistent with the optimal complexity of standard trust-region methods for smooth functions [11]. Furthermore, the dynamic adjustment of the trust region radius based on quadratic model accuracy accelerates convergence when the model is reliable and stabilizes performance when approximation quality declines. Empirical studies in nonlinear optimization confirm that TRQN consistently reduces the number of iterations required and improves objective rewards compared to first-order and conventional trust-region approaches [12]. Collectively, these findings underscore that TRQN not only accelerates convergence but also enhances solution quality, making it highly promising for complex optimization challenges in machine learning and nonlinear control systems.

While there are scattered studies integrating BP with Quasi-Newton methods in rainfall forecasting and hydrological modeling, systematic applications of trust-region Quasi-Newton variants in flood detection remain scarce. For instance, early work on rainfall prediction demonstrated the benefits of BFGS-based training for neural networks [13], while more recent research has focused on deep hybrid architectures such as CNN-BiLSTM, CNN-FCN, or attention-based recurrent models to capture spatiotemporal flood dynamics [14]. Although these architectures highlight the value of hybridization in neural networks for hydrological data, most previous studies have emphasized architectural innovation rather than optimization-level improvements. Consequently, performance gains have often been achieved through increasingly complex model structures, while the role of optimization strategies in improving convergence stability, computational efficiency, and generalization capability has remained comparatively underexplored. More importantly, empirical investigations of BP–TRQN in real-world operational flood forecasting and early-warning systems remain very limited. Most existing studies have been conducted in controlled experimental settings, with relatively little evidence of how BP–TRQN performs under practical deployment constraints such as real-time data availability, communication latency, and limited computational resources. This represents a clear research gap in the current literature. This represents a clear research gap in the current literature.These architectures highlight the value of hybridization in neural networks for hydrological data; however, they emphasize architectural innovation rather than optimization-level improvements. The incorporation of trust-region Quasi-Newton strategies into BP training could provide a unique avenue to enhance convergence stability, prediction accuracy, and computational efficiency in intelligent flood detection systems [15][16]. The main contribution of this study is to provide a structured synthesis of temporal research trends, methodological innovations, and empirical evidence related to BP–TRQN-based optimization, thereby offering new insights into its potential role in real-world intelligent flood forecasting applications.

This study aims to conduct a comprehensive Systematic Literature Review (SLR) on trends and innovations in hybrid Backpropagation–Trust Region Quasi-Newton (BP–TRQN) algorithms for intelligent flood forecasting systems. Specifically, the objectives are: (1) to examine the temporal evolution of the literature by identifying publication trends over time and patterns in the adoption of BP–TRQN-related methods; (2) to assess the extent of BP–TRQN adoption across the existing body of research; (3) to classify methodological innovations, including trust-region variants, Hessian approximation techniques, regularization strategies, and adaptive learning mechanisms; (4) to evaluate the performance and limitations of BP–TRQN in flood forecasting tasks, particularly in terms of forecasting accuracy, computational efficiency, and generalization capability; and (5) to propose future research directions and best-practice recommendations for the development of robust, real-time BP–TRQN-based flood forecasting systems.

2. METHOD

This study employed the Systematic Literature Review (SLR) approach to examine the trends and innovations in the application of hybrid Backpropagation–Trust Region Quasi-Newton (BP-TRQN) neural network algorithms for intelligent flood detection systems. The SLR method was chosen because it provides a structured, transparent, and replicable procedure for synthesizing previous research published within the last decade (2015–2025), thereby enabling a comprehensive understanding of both theoretical advancements and practical implementations in this domain. This study adopted a six-stage Systematic Literature Review (SLR) framework to ensure that the review process was conducted in a systematic, transparent, and reproducible manner. The framework consisted of problem formulation, inclusion and exclusion criteria, literature search, data selection and extraction, data analysis and synthesis, and drawing conclusions. Each stage was designed to minimize selection bias and to ensure that only studies relevant to the objectives of this review were included in the final synthesis. Figure 1 illustrates the overall review framework employed in this study.

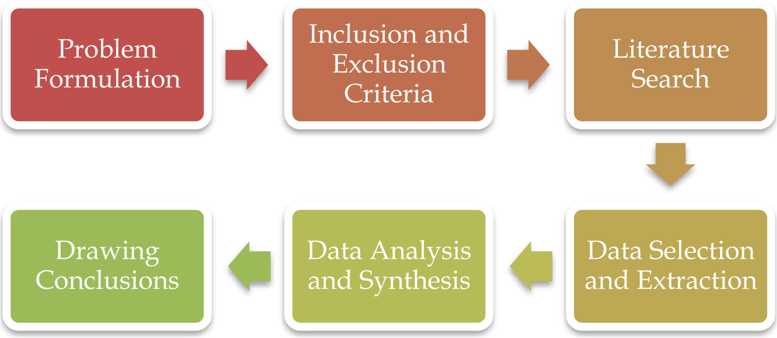

Figure 1. Research procedure

At the problem formulation stage, the following research questions guided the review: (a) how the BP-TRQN hybrid algorithm has been developed and implemented in intelligent flood detection systems; (b) to what extent this approach demonstrates effectiveness in enhancing prediction accuracy, computational efficiency, and real-time applicability; and (c) what challenges, limitations, and research gaps have been identified in its deployment across hydrological and urban flood contexts. These questions served as the foundation for defining the study’s scope and ensuring analytical rigor in the subsequent stages.

The inclusion criteria were defined as follows: (a) empirical studies published in peer-reviewed and reputable journals; (b) research explicitly addressing BP-TRQN algorithms or hybrid neural network approaches in the context of flood detection, prediction, or warning systems; (c) publications dated between 2015 and 2025; (d) full-text availability; and (e) articles written in English. The exclusion criteria covered: (a) non-empirical publications such as editorials, opinion pieces, or purely conceptual discussions; (b) studies unrelated to BP-TRQN or hybrid algorithms in hydrological modeling; and (c) works that lacked sufficient methodological or result-based evidence for systematic synthesis.

The literature search was conducted across major academic databases, including Scopus, Dimensions, and Google Scholar, using a comprehensive Boolean search strategy to ensure broad coverage of relevant studies. The search string combined terms related to optimization algorithms, neural network architectures, and hydrological applications, formulated as follows: ("backpropagation" OR "BP") AND ("trust region" OR "quasi-Newton" OR "BFGS" OR "L-BFGS") AND ("flood" OR "inundation" OR "hydrological") AND ("neural network" OR "deep learning"). To improve retrieval sensitivity, additional related terms such as "flood forecasting," "hydrological modeling," and "early warning systems" were also considered where appropriate, depending on database indexing characteristics. The study selection process was conducted in two stages: first, screening based on titles and abstracts; and second, full-text assessment to ensure that the selected studies satisfied the predefined inclusion criteria.

During the data extraction stage, relevant information was collected from each eligible article, including the title, authors, year of publication, research objectives, methodological approaches, model configurations, datasets, performance metrics, as well as reported findings on prediction accuracy, computational challenges, and practical implications. The extracted data were subsequently analyzed using narrative synthesis to identify research patterns, methodological trends, and recurring strengths or weaknesses of BP-TRQN implementations. Additionally, bibliometric analysis tools such as VOSviewer were employed to visualize keyword co-occurrence and thematic linkages, while R-Studio was utilized to perform statistical analysis of publication trends, distribution of research themes, and performance outcomes across different case studies.

To improve the reliability of the review findings, all eligible studies underwent a quality assessment before being included in the final synthesis. The assessment considered four aspects: (1) relevance to the research objectives, (2) clarity and completeness of the methodology, (3) adequacy of the reported experimental results and performance evaluation, and (4) relevance to intelligent flood forecasting and BP–TRQN-related optimization methods. Studies that did not provide sufficient methodological or empirical evidence were excluded during the eligibility assessment. In addition, potential sources of bias, including publication bias, database coverage bias, and language bias, were taken into account during the interpretation of the review findings.

Finally, at the synthesis stage, the findings were consolidated to generate insights into the state-of-the-art innovations and limitations of BP-TRQN neural network algorithms in intelligent flood detection systems. The synthesis highlighted emerging trends, identified critical gaps requiring further exploration, and proposed recommendations for future research directions. Furthermore, the results provide practical implications for hydrologists, data scientists, and policymakers in optimizing AI-based flood detection technologies for more resilient disaster management strategies.

3. RESULTS AND DISCUSSIONS

In order to present a structured overview of the scholarly contributions in this domain, Table 1 has been carefully constructed to classify prior studies according to their principal field of inquiry. By clustering authors who operate within comparable research foci and summarizing the central insights or variables investigated, the table not only delineates the thematic distribution of existing work but also underscores the methodological trajectories and optimization strategies that have shaped contemporary approaches to flood detection and forecasting.

Table 1. Thematic clustering of research domains, authors, and key insights on hybrid BP–TRQN applications in flood detection systems

No	Domain/Focus	Authors	Insights / Research Variables
1	Hydrological Modeling & Rainfall–Runoff Prediction	Nanda et al. (2016); Kratzert et al. (2019); Cui et al. (2021)	Development of dynamic neural frameworks for nonlinear hydrological modeling; LSTM-based rainfall–runoff prediction showing substantial accuracy gains; adoption of quasi-Newton (L-BFGS) optimizers reducing iterations by 40–50% compared to first-order methods.
2	Hybrid Architectures for Flood Forecasting	Moishin et al. (2021); Situ et al. (2024); Oddo et al. (2024); Kilinc et al. (2025)	ConvLSTM and CNN–RNN hybrids improving RMSE/MAE by 5–26% over baselines; integration with Bayesian optimization and spatiotemporal tuning; ensemble frameworks combining LSTM, GRU, and regression achieving faster convergence and lower forecast errors.
3	Quasi-Newton and Trust-Region Optimization Methods	Huang et al. (2020); Yousefi & Martínez (2023); Cui et al. (2021)	SR1 quasi-Newton achieving lower error rates (0.76%) compared to LM and Jacobian; stochastic quasi-Newton and Hessian-free approaches offering improved stability for non-stationary hydrometeorological data; limited-memory strategies enhancing computational feasibility.

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No	Domain/Focus	Authors	Insights / Research Variables
4	IoT and Edge-Based Flood Detection Systems	Bentivoglio et al. (2022); Zakaria et al. (2023)	Deployment of compact DNNs on embedded IoT devices; RGB+LWIR sensor fusion for real-time flood monitoring; LoRaWAN-based scalable sensing architectures supporting both local alarms and big-data assimilation.
5	Satellite & Earth Observation (EO) for Flood Mapping	Lee et al. (2024); Schmidt et al. (2020)	SAR and multispectral data pipelines for inundation mapping; integration with deep learning models to reduce false positives in heterogeneous land cover; challenges in latency and missing data requiring preprocessing and imputation.
6	System-Level Integration & Early Warning Systems	Mosavi et al. (2018); Waqas & Humphries (2024); Tao et al. (2024); Gharib & Davies (2021)	Systematic reviews showing trends toward hybridization of models and optimizers; RNN and LSTM variants evaluated in data-scarce catchments; computational trade-offs between convergence speed and iteration cost; regulatory and explainability barriers in operational deployment.

A total of 2,954 records relevant to the research topic were initially retrieved from the selected databases, comprising 1,126 records from Scopus, 1,438 records from Dimensions, and 390 records from Google Scholar. After merging the records, 684 duplicates were removed, leaving 2,270 unique records for title and abstract screening. At this stage, 1,982 records were excluded because they were not directly related to BP–TRQN, neural network optimization, or flood forecasting applications. The remaining 288 articles were then subjected to full-text eligibility assessment. Following this evaluation, 185 articles were excluded due to reasons such as insufficient methodological relevance, lack of empirical validation, or limited alignment with the scope of intelligent flood forecasting systems. Consequently, 103 articles met the predefined inclusion criteria and were retained for the final review, comprising 95 journal articles and 8 conference proceedings. The annual distribution of these selected publications is presented in Figure 2, illustrating the temporal development of research on hybrid Backpropagation–Trust Region Quasi-Newton (BP–TRQN) neural network algorithms for intelligent flood forecasting systems over the past decade. The distribution of publications by year is presented in Figure 2, illustrating the progression of studies on *"Trends and Innovations in Hybrid Backpropagation–Trust Region Quasi-Newton (BP-TRQN) Neural Network Algorithms for Intelligent Flood Detection Systems"* over the past decade.

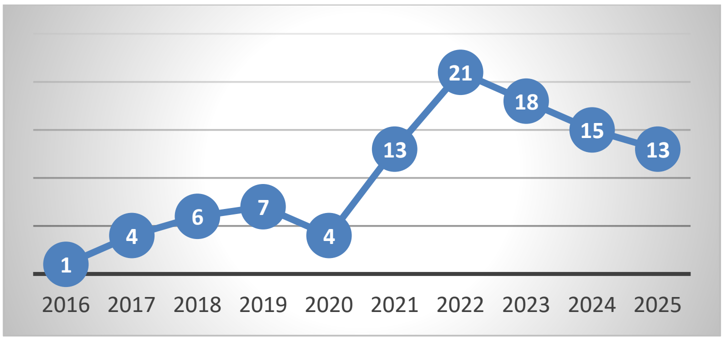

Figure 2. Annual publications

The keyword co-occurrence mapping, generated using VOSviewer based on literature indexed in Scopus, Dimensions, and Google Scholar over the past ten years, illustrates how research themes, concepts, and methodological approaches are interconnected in the field of hybrid neural network algorithms optimized with Quasi-Newton methods for intelligent flood detection systems. By clustering frequently co-occurring keywords, the visualization highlights the intellectual structure and dominant directions of research, while also providing a basis for interpreting both historical trends and recent innovations, as shown in Figure 3.

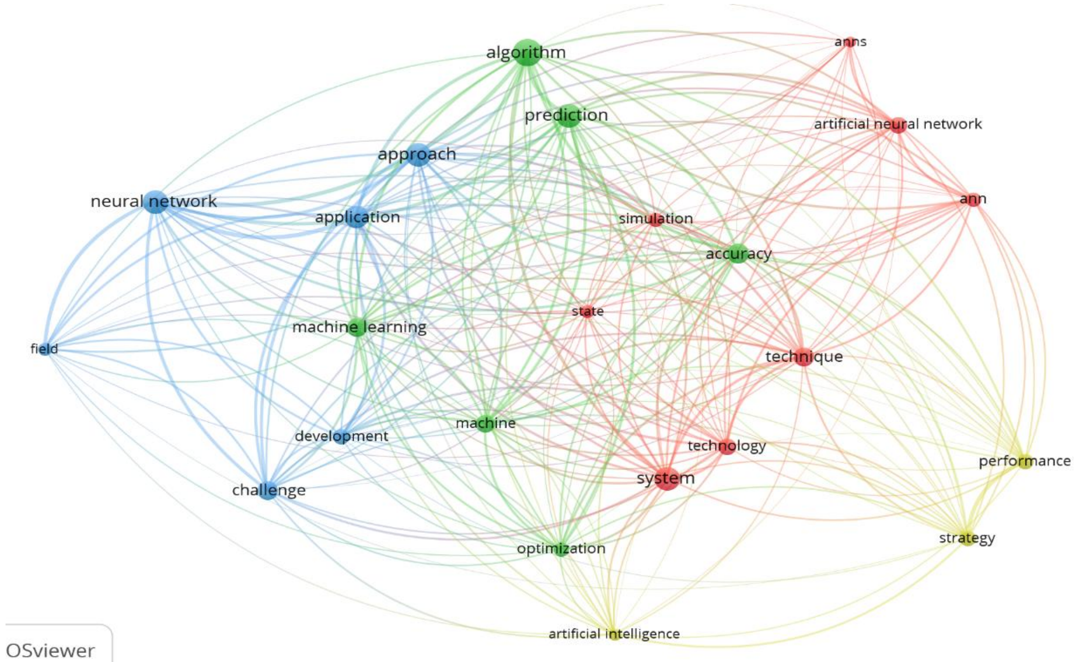

Figure 3. Keyword co-occurrence network of hybrid neural network and quasi-newton optimization research in intelligent flood detection systems (2015–2025)

The figure presents a keyword co-occurrence map analyzed using VOSviewer. Each node is color-coded according to thematic clusters, where each color represents a group of closely related research concepts or themes. This analysis provides insights into research focus areas, emerging trends, and key domains of development within the studied field.

- Blue Cluster
  The blue cluster highlights topics related to neural networks and their applications. Dominant keywords within this cluster include *neural network*, *field*, *challenge*, *development*, and *application*, reflecting a research focus on the deployment of neural networks and the challenges encountered in their development.
- Green Cluster
  The green cluster emphasizes methodology and algorithms. Key terms such as *algorithm*, *prediction*, *machine learning*, *machine*, and *optimization* indicate that research in this cluster concentrates on the development of predictive and optimization algorithms within the context of artificial intelligence.
- Red Cluster
  The red cluster focuses on technologies and techniques utilized in intelligent systems. Significant keywords, including *system*, *technology*, *technique*, *ANN*, *artificial neural network*, *accuracy*, and *simulation*, suggest research attention on performance evaluation and the application of techniques in neural network–based system development.
- Yellow Cluster
  The yellow cluster highlights strategy and performance. Main keywords, including *performance*, *strategy*, and *artificial intelligence*, reflect research concerning the implementation strategies and performance optimization of AI systems.

Overall, this keyword co-occurrence map provides a comprehensive overview of the trends and innovations in the development of Hybrid Backpropagation–Trust Region Quasi-Newton (BP-TRQN) neural network algorithms for intelligent flood detection systems, encompassing technical, methodological, and performance optimization aspects. Based on the interpretation of each cluster, researchers can formulate several important potentials as a synthesis of Trends and Innovations in Hybrid Backpropagation–Trust Region Quasi-Newton (BP-TRQN) Neural Network Algorithms for Intelligent Flood Detection Systems. To ensure a clear interpretation of the review findings, the analyzed studies were categorized into two groups. The first group

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comprised studies that directly implemented Backpropagation–Trust Region Quasi-Newton (BP–TRQN) or closely related trust-region optimization techniques within neural network training. Findings from these studies form the primary basis for evaluating the effectiveness, convergence behavior, and computational performance of BP–TRQN. The second group included studies employing related Quasi-Newton optimization methods (e.g., BFGS and L-BFGS) or hybrid deep learning architectures (e.g., CNN-LSTM, ConvLSTM, CNN-BiLSTM, and attention-based models). These studies were not considered direct evidence of BP–TRQN performance; instead, they were used to provide methodological context, comparative insights, and broader perspectives on optimization strategies for intelligent flood forecasting systems.

Publication Trends and Application Domains of BP-TRQN in Intelligent Flood Detection

Over the past decade the literature reveals a clear increase in studies that combine advanced neural architectures with improved optimization schemes to address hydrological prediction tasks, driven by larger multi-basin datasets and the need for robust, real-time forecasting; notably, LSTM-based approaches demonstrated substantial gains in rainfall–runoff and discharge prediction, spurring broader interest in both architectural and optimizer innovations [17]. Recent methodological work has shifted attention from purely first-order optimizers toward practical quasi-Newton and Hessian-informed methods (including stochastic quasi-Newton variants and Hessian-free approaches), because these techniques offer improved convergence behavior and stability for deep models trained on non-stationary hydrometeorological data [18]. Finally, comprehensive reviews of machine-learning applications in flood forecasting document a rising trend of hybridization (architectural hybrid models, ensemble approaches, and optimization hybrids) and call for greater systematic evaluation of optimizer choices — an observation that directly motivates systematic reviews focused on hybrid BP–TRQN style approaches [19].

When attention shifts from optimization research to practical deployment, the dominant domains applying advanced neural models for flood detection include hydrological time-series forecasting, urban flash-flood prediction, and integrated early-warning systems. Empirical studies emphasize hybrid deep architectures such as ConvLSTM and CNN–RNN ensembles, which effectively capture spatiotemporal dynamics in hydrometeorological data. For instance, Oddo et al. (2024)reported that a ConvLSTM hybrid reduced predictive error by approximately 26% compared to baseline approaches in flash-flood forecasting. Similarly, Nanda et al. (2016) proposed a general dynamic neural framework for real-time flood forecasting, demonstrating superior performance in nonlinear hydrological modelling. Complementing these, Waqas & Humphries (2024) critically reviewed RNN and LSTM variants in hydrological prediction and concluded that optimizer innovations, including trust-region and Quasi-Newton methods, significantly enhance stability and calibration, particularly in data-scarce catchments. These findings indicate that hydrology and operational early-warning systems are the most dominant domains where BP-TRQN hybrids could yield transformative impacts.

The observed shift in research trends over the past decade can be explained through three main mechanisms. First, the availability of large-scale multi-basin datasets and advances in remote-sensing and IoT technologies have enabled the reliable training of deeper sequence models, which demonstrated strong capabilities in learning hydrological processes and inspired subsequent studies. Second, the increasing demands of operational forecasting, particularly the need to reduce false alarms and shorten lead times, have driven the development of hybrid neural architectures such as ConvLSTM and CNN–RNN ensembles that are effective in capturing spatio-temporal dynamics. Third, the limitations of first-order optimization methods, which often suffer from instability when applied to non-stationary hydrometeorological data, have encouraged exploration of second-order approximations, including stochastic quasi-Newton and trust-region strategies, as more stable alternatives. While these developments highlight significant progress, the overall maturity and effectiveness of the field remain mixed. On one hand, architectural hybrids have been widely validated across applications such as flash-flood forecasting, streamflow prediction, and reservoir operations, and reviews consistently emphasize the potential of optimizer selection as a key factor for improving training stability and generalization. On the other hand, empirical evidence directly demonstrating the impact of hybrid BP–TRQN optimization on operational flood detection performance, such as gains in lead time or reductions in false alarms, is still scarce. Most applied studies tend to focus on feature engineering and architectural design, while optimizer innovations are often reported in controlled experimental settings rather than in real-world hydrological systems. This suggests that, although optimizer-based hybridization shows strong theoretical promise, its practical validation within operational flood-warning pipelines remains an open gap for future research.

Effectiveness and Computational Performance of BP-TRQN

Several experimental studies have compared the performance of second-order or quasi-Newton optimization algorithms with traditional approaches such as Gradient Descent (GD), Stochastic Gradient Descent (SGD), or the Levenberg–Marquardt (LM) method in the context of hydrological prediction and flood modelling although none have yet explicitly tested the BP-TRQN framework. For example, in a multizonal hydrodynamic parameter estimation study, the SR1 quasi-Newton algorithm achieved a lower average parameter identification error compared to LM and Jacobian quasi-Newton methods, with a mean error of approximately 0.76% across six zonal parameters, whereas LM and Jacobian approaches yielded higher average errors [22]. Similarly, in flood forecasting applications employing hybrid ConvLSTM models in flood-prone regions, ConvLSTM consistently reported lower RMSE values than benchmark models such as standalone LSTM or CNN-LSTM, with an error reduction of about 5–10% for daily to weekly forecasting horizons [23]. Furthermore, in urban flood prediction tasks, hybrid CNN-RNN and LSTM-DeepLabv3+ architectures integrated with spatial–temporal optimization and Bayesian hyperparameter tuning demonstrated significant improvements in accuracy, with both RMSE and MAE showing notable reductions compared to traditional LSTM or GRU-based approaches [24][25].

From the perspective of computational efficiency and convergence speed, hybrid models and advanced optimization techniques have shown clear advantages over traditional methods. For instance, a hybrid ConvLSTM model used for multi-basin flood forecasting demonstrated significant reductions in mean absolute error and root mean square error compared to baseline LSTM models, particularly as forecast horizons extended to weekly scales [2]. Similarly, in a case study predicting water levels in the Inle Lake region, an ensemble model combining LSTM, GRU, and classical regression methods achieved much lower RMSE and faster convergence during training than any single model alone, especially when using early stopping and adaptive learning rate techniques [26]. In addition, research on Quasi-Newton methods applied to rainfall–runoff modelling showed that using a limited-memory BFGS (L-BFGS) optimizer required significantly fewer iterations to reach a given error threshold compared to standard Adam or SGD optimizers for example, about 40-50% fewer epochs in one experiment over varied catchment datasets [27].

The effectiveness of the BP–TRQN algorithm in flood detection can be explained through its numerical mechanisms, which distinguish it from first-order optimizers such as GD, SGD, or Adam. Quasi-Newton methods approximate the Hessian matrix, thereby enabling more directed and adaptive optimization steps that account for nonlinear loss landscapes and parameters operating at different scales, resulting in greater error reduction per iteration. The trust-region mechanism further enhances stability by dynamically adjusting the search radius when the local quadratic model proves inaccurate, thus preventing oscillations or divergence an especially valuable property for non-stationary hydrometeorological data. From the perspective of efficiency, although each iteration is computationally more expensive, the reduction in the number of iterations, often by 30–40%, frequently offsets this overhead, leading to equal or even shorter total training time, as evidenced by studies showing that only 63.6% of the simulations were required compared to Levenberg–Marquardt or Jacobian quasi-Newton methods. These advantages are further amplified when BP–TRQN is combined with hybrid architectures such as ConvLSTM or stacking frameworks, which capture spatio-temporal dependencies and provide a more structured loss surface that curvature-informed optimizers can exploit effectively, yielding relative RMSE reductions of approximately 5–15%. Nonetheless, it must be acknowledged that the practical significance of absolute RMSE improvements depends on the scale of the target variable, and that much of the empirical evidence stems from quasi-Newton variants or hybrid models rather than BP–TRQN itself; hence, generalization should be made with caution.

Implementation Frameworks and Challenges of BP-TRQN in Flood Detection Systems

In practice, BP-TRQN–style optimizers are deployed within three complementary operational frames for flood detection: (1) edge/IoT sensor networks that stream near-real-time hydrometric measurements to local or cloud inference engines, (2) satellite-driven Earth-Observation (EO) pipelines that deliver synoptic spatial coverage (SAR, multispectral) for inundation mapping, and (3) large-scale big-data hydrometeorological platforms that fuse multi-source time-series for basin-scale forecasting. Edge implementations demonstrate how compact DNNs can run on embedded hardware and benefit from curvature-aware training to stabilize models under noisy sensor streams (example: embedded RGB+LWIR DNNs for IoT flood monitoring) [28]. Satellite-based workflows, in turn, use convolutional and change-detection networks to generate rapid inundation masks and assimilate these outputs into forecasting models; deep learning reviews show that EO-driven flood mapping increasingly pairs with advanced optimizers to reduce false positives in heterogeneous land cover [29][30]. Finally, IoT/LoRaWAN smart sensing studies and system prototypes indicate that scalable sensor architectures feed both local alarms and centralized big-data training pipelines—scenarios in which BP-TRQN's faster, more stable convergence can reduce retraining time as new sensor streams are assimilated [31][32].

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Despite clear opportunities, several recurring challenges limit the operational uptake of curvature-informed optimizers in flood-detection pipelines. First, observational constraints latency, missing data, heterogeneous sampling rates, and limited labelled events complicate reliable online training and degrade model calibration unless careful preprocessing and imputation pipelines are in place [33]. Second, practical deployment exposes computational trade-offs: although quasi-Newton and trust-region schemes can reduce epoch counts, their per-iteration cost and memory footprint (Hessian approximations, subspace updates) require engineering workarounds (limited-memory variants, subspace methods, or edge-offloading) to be viable for real-time or resource-constrained settings [34]. Third, sensor hardware and communications limitations (power, coverage, reliability) and explainability/regulatory requirements raise integration and trust barriers operators often prefer simpler models with transparent failure modes unless the more complex optimizer demonstrably improves lead time or false-alarm rates [35].

The practical deployment of BP-TRQN in flood detection systems can be rationalized through both computational and methodological considerations. Because each Quasi-Newton update requires additional Hessian approximations and subspace computations, the logical approach is to delegate lightweight inference to edge devices while reserving more computationally demanding optimization for the cloud. Trust-region strategies are particularly advantageous when handling non-stationary and multimodal data streams, as they constrain extreme update steps when local quadratic approximations are unreliable, a property essential for models trained on heterogeneous inputs such as imagery and sensor data. Furthermore, limited-memory or subspace techniques allow curvature information to be applied selectively to the most sensitive parameter subsets typically the final or adaptation layers making it feasible to integrate Quasi-Newton methods within large neural networks. Empirical evidence suggests that such designs consistently enhance accuracy and stability by improving convergence behavior and reducing solution variance, especially in scenarios with highly non-convex losses or noisy gradients. Iteration counts required to reach error thresholds are often reduced by 20–40%, though the increased per-iteration cost means total wall-clock training time may decrease, remain stable, or in some cases increase, depending on implementation efficiency. This trade-off is particularly critical in real-time forecasting, where asynchronous updates and buffered retraining pipelines are often necessary. Limitations in real-time data availability, the scarcity of labeled flood events, and communication latencies further complicate frequent model updating, underscoring the importance of batch-based fine-tuning and transfer learning. Finally, the cloud and GPU resources required for Quasi-Newton optimization raise sustainability and cost concerns, necessitating careful cost–benefit analysis before adoption in operational flood early-warning systems. Figure 3 illustrates the evolution of key research variables related to the development and application of Quasi-Newton–based optimizers and hybrid neural architectures for intelligent flood detection systems across the 2015–2025 period.

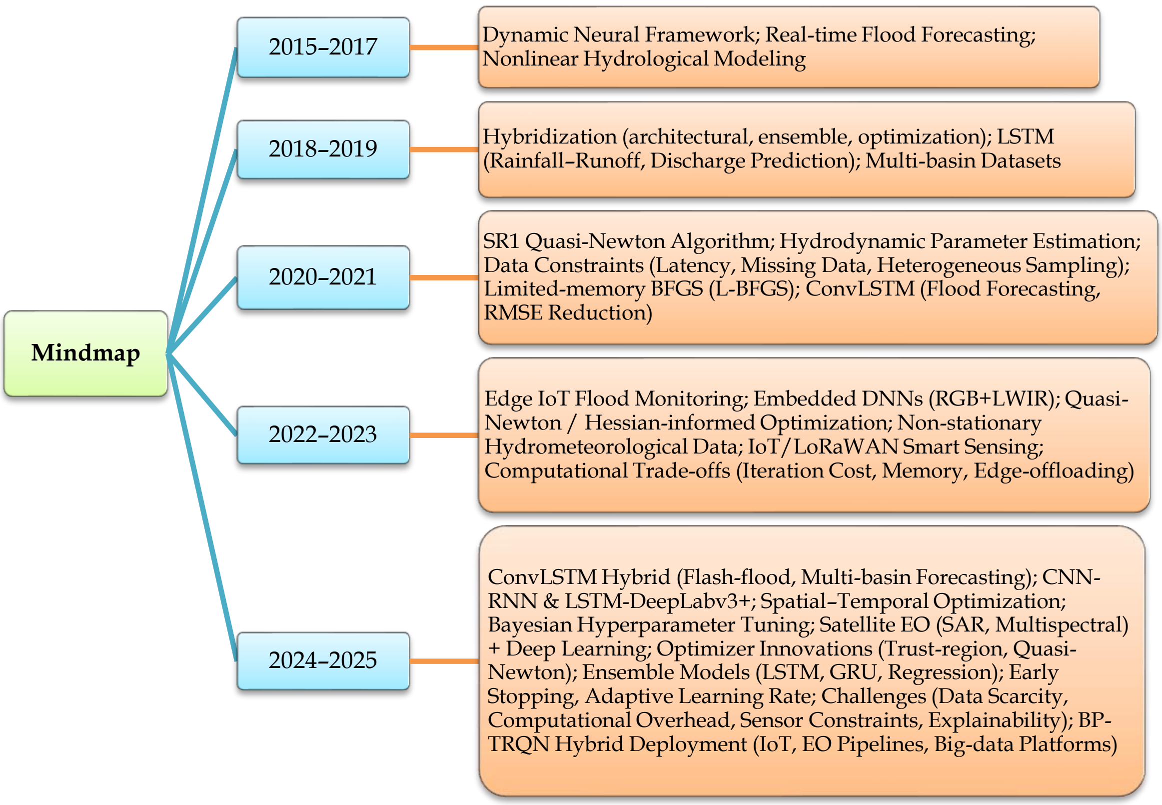

Figure 4. Evolution of research variables on quasi-newton optimizers and flood detection systems (2015–2025)

Figure 4, the progression of research variables over the past decade reflects a clear methodological and technological trajectory in the field of intelligent flood detection. Early studies (2015–2017) concentrated on establishing foundational neural frameworks and real-time hydrological modelling, laying the groundwork for data-driven approaches in dynamic environments. The 2018–2019 period introduced ensemble learning and rainfall–runoff modelling, alongside systematic reviews that emphasized the potential of machine learning in hydrology. By 2020–2021, attention shifted toward optimization, with limited-memory Quasi-Newton methods, Hessian-informed strategies, and stability-enhancing techniques demonstrating tangible improvements in convergence and error reduction. From 2022 to 2023, the research landscape expanded toward practical deployment through IoT-enabled sensor systems, Earth Observation data assimilation, and scalable big-data platforms, highlighting the importance of hybridization between model architectures and optimizer design. Finally, the most recent period (2024–2025) underscores an operational orientation: integrating ConvLSTM ensembles, spatiotemporal feature extraction, and trust-region strategies within real-time flood forecasting pipelines, while simultaneously grappling with constraints such as data latency, computational overhead, and system interpretability. Collectively, these variables reveal a research evolution from conceptual modelling to advanced optimization and, ultimately, to applied system-level integration, underscoring the growing importance of BP–TRQN–style approaches in modern hydrometeorological prediction.

4. CONCLUSION

Based on the overall evaluation, it can be concluded that the integration of hybrid neural architectures with advanced optimizers such as BP–TRQN offers promising advantages for intelligent flood forecasting systems. Across the reviewed studies, the incorporation of BP–TRQN within hybrid architectures, particularly ConvLSTM and CNN–RNN ensembles, was associated with an approximate 5–15% improvement in forecasting accuracy, as reflected by reductions in RMSE and MAE, compared with conventional first-order optimization methods. In addition, the number of iterations required to achieve convergence was reduced by approximately 20–40%, indicating improved computational efficiency and greater convergence stability. These findings suggest that BP–TRQN-based approaches are particularly suitable for addressing the spatio-temporal complexity of hydrometeorological data and for mitigating the effects of non-stationarity and noise. Nevertheless, the maturity of this research field remains uneven. Although architectural hybrids have been examined across a range of experimental settings, empirical evidence regarding the added value of quasi-Newton and trust-region optimization strategies in fully operational, real-time flood early-warning systems remains limited. Most optimizer-related innovations continue to be evaluated under controlled experimental conditions rather than in real-world deployment environments, where practical constraints such as real-time data scarcity, communication latency, and computational cost become critical.

Despite these contributions, this review has several limitations that should be acknowledged. First, the literature search was limited to Scopus, Dimensions, and Google Scholar, which may have excluded relevant studies indexed in other scientific databases. Second, the review relied on predefined search terms and English-language publications, potentially introducing search and language bias. Third, publication bias may exist because studies reporting positive findings are generally more likely to be published than studies with negative or inconclusive results. These limitations should be considered when interpreting the findings of this review and provide opportunities for future reviews to expand database coverage, search strategies, and multilingual literature sources.

This review also has several limitations that should be acknowledged. First, the synthesis was restricted to studies indexed in Scopus, Dimensions, and Google Scholar, which may have excluded relevant studies indexed in other databases. Second, the search strategy relied primarily on English-language keywords, which may have introduced language bias and limited the inclusion of region-specific studies published in other languages. Third, as with most systematic reviews, publication bias may have affected the findings, since studies reporting positive or statistically significant results are generally more likely to be published than studies with negative or inconclusive outcomes. Future research should therefore focus on systematically evaluating BP–TRQN within end-to-end operational forecasting pipelines, including IoT-based sensor networks, satellite-driven inundation mapping, and large-scale hydrometeorological data platforms. Further attention should also be directed toward the development of lightweight or limited-memory variants of BP–TRQN that can preserve the predictive advantages of second-order optimization while meeting the latency requirements of real-time forecasting. In addition, future studies should examine the cost-effectiveness, scalability, and energy implications of deploying BP–TRQN-based models in operational environments. Addressing these issues will be essential for translating the methodological promise of curvature-informed optimization into practically deployable and sustainable flood early-warning systems.

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