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REVIEW

Enhancing Evapotranspiration Estimation: A Bibliometric and Systematic Review of Hybrid Neural Networks in Water Resource Management

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ABSTRACT: Accurate estimation of evapotranspiration (ET) is crucial for efficient water resource management, particularly in the face of climate change and increasing water scarcity. This study performs a bibliometric analysis of 352 articles and a systematic review of 35 peer-reviewed papers, selected according to PRISMA guidelines, to evaluate the performance of Hybrid Artificial Neural Networks (HANNs) in ET estimation. The findings demonstrate that HANNs, particularly those combining Multilayer Perceptrons (MLPs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs), are highly effective in capturing the complex nonlinear relationships and temporal dependencies characteristic of hydrological processes. These hybrid models, often integrated with optimization algorithms and fuzzy logic frameworks, significantly improve the predictive accuracy and generalization capabilities of ET estimation. The growing adoption of advanced evaluation metrics, such as Kling-Gupta Efficiency (KGE) and Taylor Diagrams, highlights the increasing demand for more robust performance assessments beyond traditional methods. Despite the promising results, challenges remain, particularly regarding model interpretability, computational efficiency, and data scarcity. Future research should prioritize the integration of interpretability techniques, such as attention mechanisms, Local Interpretable Model-Agnostic Explanations (LIME), and feature importance analysis, to enhance model transparency and foster stakeholder trust. Additionally, improving HANN models' scalability and computational efficiency is crucial, especially for large-scale, real-world applications. Approaches such as transfer learning, parallel processing, and hyperparameter optimization will be essential in overcoming these challenges. This study underscores the transformative potential of HANN models for precise ET estimation, particularly in water-scarce and climate-vulnerable regions. By integrating CNNs for automatic feature extraction and leveraging hybrid architectures, HANNs offer considerable advantages for optimizing water management, particularly agriculture. Addressing challenges related to interpretability and scalability will be vital to ensuring the widespread deployment and operational success of HANNs in global water resource management.

KEYWORDS: Artificial neural networks; bibliometric analysis; evapotranspiration; hybrid models; research trends; systematic literature review; water resources management

1 Introduction

Evapotranspiration (ET) stands as a fundamental basis in the Earth's hydrological cycle, representing a complex and dynamic process that significantly influences global water and energy distribution patterns [1].

It plays a significant role in global energy balance and water distribution [2,3]. ET is influenced by a variety of climatic factors, such as wind speed, solar radiation, temperature, and humidity [4]. While actual ET is challenging to measure directly, reference evapotranspiration (ET_0) can be estimated using the Penman-Monteith method [5]. ET_0 serves as a benchmark for understanding actual ET in different land cover types and climatic conditions [6].

Climate change has significantly impacted ET patterns globally, leading to increased variability [7] and uncertainty [8] in water resource management [9]. Accurate ET forecasting is essential for sustainable water use, particularly in agriculture [4]. Given the growing challenges posed by climate change on evapotranspiration patterns and water resource management, employing hybrid artificial neural network (HANN) models offers a promising avenue for improving the accuracy and reliability of ET estimations, thus supporting more informed and sustainable water management practices. Traditional methods for ET estimation often rely on complex meteorological data and can be computationally intensive [10–12]. The need for precise ET estimation is further underscored in the context of changing climate patterns, where its role in water resource planning and agricultural productivity becomes even more critical [13] While direct measurements like lysimeters [14], flux tower data [15], and Bowen-ratio stations [16] are possible, Indirect estimation methods are more commonly employed due to their practicality, lower cost, and ease of implementation [17–19].

The indirect approach involves estimating ET by multiplying ET_0 by a crop coefficient [6]. The FAO-56 Penman-Monteith equation can accurately calculate ET_0, but it requires detailed meteorological data [20]. However, due to the challenges of obtaining complete datasets, various empirical and semi-empirical models have been developed to estimate ET_0 with fewer input parameters [21]. While these models have shown success in many regions, their accuracy can vary depending on specific conditions [22]. Therefore, further research is needed to refine and improve these models for accurate ET estimation.

In recent years, ANNs have emerged as powerful tools for estimating ET [23–25], a critical hydrological process [26,27]. Studies have demonstrated their effectiveness in predicting both ET_0 and actual crop evapotranspiration (ET_c) [28].

Researchers have employed various ANN architectures, including Multilayer Perceptron (MLP) [29–31], Radial Basis Function (RBF) [32,33], Generalized Regression Neural Network (GRNN) [34,35], and Group Method of Data Handling (GMDH) [36,37], to estimate ET. These models have consistently outperformed traditional empirical methods, particularly in regions with limited meteorological data [38–40]. Their ability to handle nonlinear relationships and process complex data makes them well-suited for this challenging task [41].

However, ANN architectures are prone to overfitting, particularly when trained on small datasets [20,41,42]. Additionally, determining the optimal neural network structure for a given problem remains a challenge [43]. To address these limitations, HANN approaches have emerged. These models offer a powerful framework for ET_0 estimation by combining the strengths of ANNs with complementary techniques [44]. These hybrid approaches can significantly enhance predictive accuracy, robustness, and generalization performance, while also providing a more comprehensive representation of complex hydrological processes [45].

This study presents a comprehensive review of research employing HANN approaches for ET estimation. The primary objectives are to identify prevalent hybrid combinations, identify emerging research trends, and provide valuable insights into the performance and potential of hybrid models in ET estimation.

The study is conducted in two phases. The first phase consists of a bibliometric analysis aimed at mapping the research landscape, identifying key studies, and revealing emerging research trends.

The bibliometric analysis offers a quantitative overview of the research field, enabling the identification of the most active researchers, institutions, and countries contributing to HANN-based ET estimation. The subsequent systematic review phase focuses on a qualitative assessment of selected studies, enabling a deeper exploration of methodological approaches, data sources, and performance metrics. By integrating these two complementary methodologies, we seek to offer a thorough and detailed understanding of the current advancements in HANN-based ET estimation.

A unique contribution of this study lies in its focus on HANN approaches, which offer a promising avenue for improving the accuracy and reliability of ET estimation. Unlike previous reviews that have primarily focused on traditional ANN models or specific hybrid combinations, this study provides a more comprehensive overview of the various hybrid methodologies employed in ET estimation. Furthermore, the study addresses a significant knowledge gap by systematically evaluating the factors influencing the performance of hybrid models. The insights gained from this review can inform future research and applications. By identifying the most effective hybrid combinations and understanding the underlying mechanisms driving their performance, researchers can develop more advanced and tailored hybrid models for specific hydrological conditions. In addition, the insights gained from this study could play a crucial role in shaping guidelines and establishing best practices for the application of HANN-based models in the management of water resources.

2 Phase 1: Bibliometric Analysis Review

In the first phase of our study, we utilized a bibliometric method [46]. Bibliometric analysis offers a comprehensive and systematic approach to understanding the intellectual structure, dynamics, and emerging trends within a research field [47]. By examining the connections between different scientific elements (such as authors, papers, and keywords), bibliometric analysis can reveal the underlying structure [48], help uncover gaps in the current knowledge base, and inspire the formulation of innovative research directions [49]. While bibliometric analysis is not a substitute for traditional review methods like meta-analysis or systematic literature reviews, it complements them by providing a macro-level perspective. Bibliometric studies employ quantitative methods to summarize the intellectual, social, and conceptual capital of a field, offering a broader understanding than qualitative approaches [50]. By conducting well-executed bibliometric research, scholars can establish a robust foundation for advancing a field in meaningful and innovative ways [51]. Through bibliometric analysis, researchers gain meaningful insights into the framework, progression, and emerging trends of a research domain, fostering a deeper comprehension and supporting future investigative efforts [52,53]. Furthermore, bibliometric analysis can elucidate how research on HANNs intersects with other domains such as water management, artificial intelligence, and optimization. This cross-disciplinary perspective is crucial for identifying not only the strengths of current methodologies but also the underexplored challenges and potential breakthroughs.

2.1 Data Collection

A systematic approach to literature retrieval was implemented utilizing two premier bibliographic databases: Web of Science Core Collection and Scopus, which are widely acknowledged as knowledge-leading platforms [54,55]. The selection of these databases was strategically motivated by their established reliability, incorporating respected quality metrics such as Journal Citation Reports (JCR) and SCImago Journal Rank (SJR). Furthermore, these platforms were chosen for their comprehensive historical coverage and efficient functionality in bulk reference extraction. This methodological decision ensured the capture of relevant, high-quality academic literature while maintaining research efficiency.

A comprehensive search strategy was employed to identify relevant literature on ET estimation using HANNs. The search utilized a combination of exact phrases, wildcard characters, and Boolean operators to capture a broad range of potential terms.

The literature data, as of August 2024, was collected using an extensive research string that incorporated a wide range of relevant keywords associated with the topic. The exact search query used was:

"evapotranspiration" AND ("predict " OR "Forecast*")* AND ("ANN" OR "artificial neural network") AND ("hybrid" or "Optimiz*" or "Optimis* " or "Integrat* " or "Algorithm")

This strategy effectively retrieved a diverse set of documents by combining exact phrases, wildcard searches, and Boolean logic. The use of quotation marks around "evapotranspiration" ensured that only documents containing the exact term were included. Wildcard characters (*) were appended to root words like 'predict' and 'algorithm' to capture various forms and derivatives of these terms, expanding the search scope. Boolean operators, such as AND and OR, were strategically used to refine the search and ensure that only relevant documents were included. This comprehensive approach allowed for the identification of a wide range of literature on the topic, providing a solid foundation for the research.

The datasets obtained from Scopus and WoS search results must first be generated and exported before merging the two databases. Once the datasets were collected from Scopus, containing 236 entries, and WoS, with 216 entries, a detailed manual review was carried out to remove irrelevant studies and any duplicates that automated filtering processes might have missed. After applying initial filters, such as excluding non-English articles and those published prior to 2004, a total of 352 articles were retained for bibliometric analysis. This meticulous process ensured a high-quality dataset, specifically addressing the applications of HANNs in ET prediction. The bibliometric analysis of these 352 articles provided a comprehensive understanding of the evolution and research trends in this field. This analysis forms the foundation for understanding key developments, supported by rigorous dataset refinement and merging. This study utilized the Biblioshiny R-toolbox for bibliometric analysis [56–58]. After exporting the final datasets from Scopus and WoS in ".bib" format, the two datasets were combined using the mergeDbSources function from the R package Bibliometrix. To ensure a clean and non-redundant dataset, the *remove.duplicated* parameter was activated during the merging process to eliminate any duplicate records.

Biblioshiny, an integral component of the bibliometric toolkit, facilitated comprehensive science mapping and analysis [57]. The merged dataset was then analyzed using the biblioAnalysis function, which allowed for detailed exploration of bibliometric indicators. This methodological approach, combining the PRISMA framework with advanced bibliometric tools, ensured a robust foundation for the subsequent stages of the research (Fig. 1).

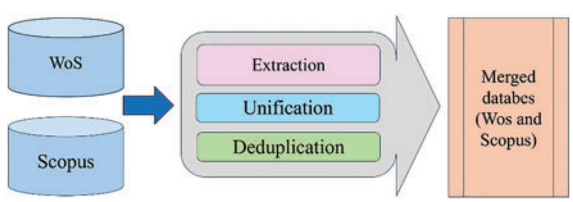

Figure 1: This workflow diagram illustrates the steps involved in merging databases from WoS (Web of Science) and Scopus, including extraction, unification, and deduplication

2.2 Results

2.2.1 Growth Pattern and Publication Characteristics

Fig. 2 presents an overview of ET estimation studies employing HANN models over the past two decades (2004–2024), based on data sourced from Web of Science and Scopus. Our preliminary analysis highlights trends in the development of this academic field. Fig. 3 summarizes the number of publications on HANN models for ET prediction, revealing a steady growth in interest in understanding this relationship over the past eight years.

Figure 2: Bibliometric overview on HANN Models for Evapotranspiration estimation studies from 2004 to 2024

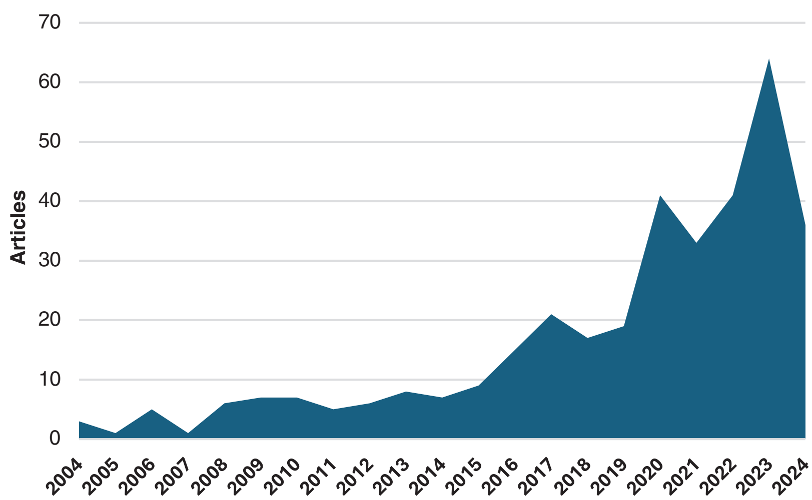

Figure 3: Annual growth of publications related to ET estimation

Although the earliest study on the application of HANN models for ET estimation can be traced back to 2004, the volume of publications has exhibited an exponential growth trend over time. Data analysis reveals an average annual growth rate of 13.23% in publications within this domain since 2004. Moreover, a significant increase in the number of publications has been observed in each decadeFor instance, although this study includes only a partial count of documents published in 2024, the average annual number of articles during the 2020–2024 period was the highest recorded, at n = 215, compared to n = 11.4 during 2010–2019 and n = 3.83 during 2004–2009 (Table 1). This steady progression highlights the increasing recognition of HANN models as an essential tool for ET estimation.

The sharp increase in research activity since 2015 aligns with several pivotal developments in both technological and environmental domains. This period corresponds with significant advancements in computational technologies, such as the integration of cloud computing [59] and GPU-based machine learning frameworks [60], which have greatly enhanced the feasibility of applying complex hybrid models. Additionally, this upward trend reflects heightened awareness of global water scarcity challenges, which has led to increased research funding from organizations prioritizing climate resilience, precision agriculture, and sustainable water resource management [61].

Table 1: Publication growth by decade

Years	Total articles published	Average per year
2004–2009	23	3.8
2010–2019	114	11.4
2020–2024	215	43

The exponential growth and widespread popularity of HANN-based ET estimation among scholars underscore its relevance and potential impact. Looking ahead, this field is poised for further acceleration, driven by the increasing accessibility of satellite-based climatic datasets and the global shift toward smart irrigation technologies. These advancements are expected to enable more accurate, efficient, and scalable applications of HANN models for ET estimation, further solidifying their role in addressing critical water management challenges and advancing sustainable agricultural practices.

According to Fig. 4, China has emerged as the leading country in research publications on HANN-based ET estimation, followed by Iran, India, the USA, Turkey, Egypt, Australia, Brazil, and Malaysia. This global distribution highlights the international recognition and relevance of HANN architectures in ET prediction. The increasing number of publications from these regions reflects the growing adoption of advanced machine learning models for environmental management, driven by the need for accurate ET prediction under varying climatic conditions.

To quantify the country-wise contribution to HANN-based ET estimation, we can calculate the Country Contribution Index (CCI) as follows [62,63]:

$$CCI_i = \frac{P_i}{T_p} \times 100$$

where:

- P_i is the number of publications from country i,
- T_p is the total number of publications in the field.

In terms of regional representation, countries with arid and semi-arid climates, such as Iran and Egypt, have played a pivotal role in advancing research on ET estimation due to the critical importance of water management in these water-scarce regions. For instance, in the study by [64], the application of ANN combined with genetic algorithms for estimating crop ET in Iran emphasizes the necessity for accurate predictions under limited climatic data, particularly in regions facing water scarcity. This reflects a growing body of work focusing on optimizing hybrid models for ET estimation under resource constraints. Iran's significant challenges related to water scarcity have fostered a strong focus on hybrid model optimization to improve ET estimation accuracy under such constraints [65].

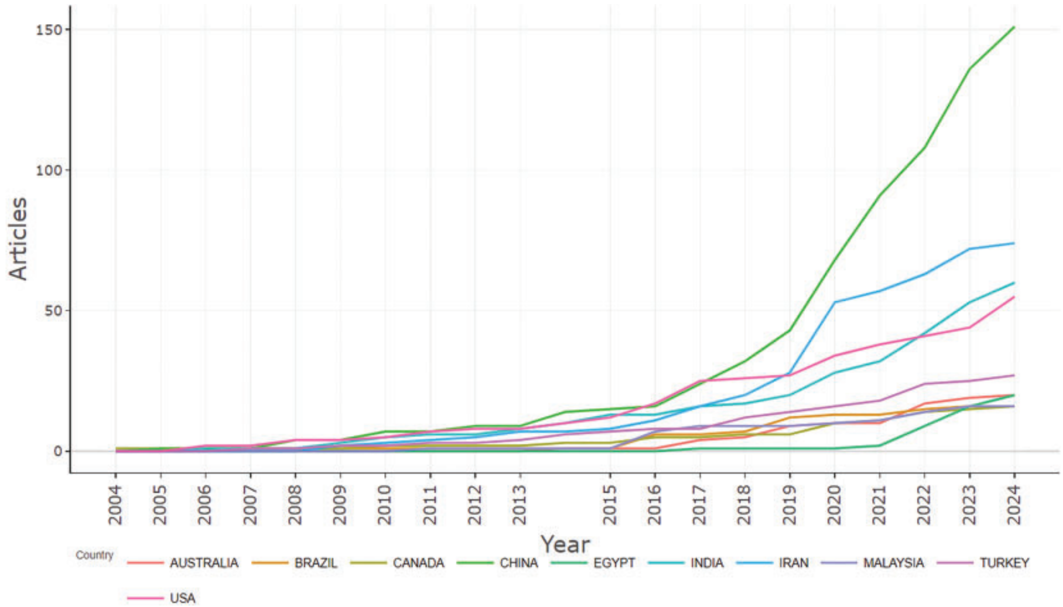

Figure 4: Country-wise production map

Similarly, Egypt has made substantial contributions, as seen in the study by [1], which employs a stacking hybridization of ANN and meta-heuristic algorithms to model daily reference ET across diverse agro-climatic conditions. This hybridization approach is especially crucial for Egypt's agricultural sector, which relies heavily on Nile water, making accurate ET predictions essential for efficient water use. The integration of hybrid artificial intelligence techniques is seen as a promising avenue for improving the sustainability of water resources in such countries.

China has also emerged as a leading contributor, particularly with its focus on bio-inspired optimization algorithms. A key study by [66] integrates PSO with ELM for daily ET estimation. This trend towards adopting hybrid optimization techniques in ET prediction highlights China's commitment to improving water management strategies, especially in its arid and semi-arid regions, such as the Loess Plateau and North-Western dry areas, where water stress is particularly severe. The combination of these bio-inspired algorithms, such as PSO and genetic algorithms, with machine learning models, underlines China's leading role in advancing HANN-based ET estimation methodologies.

Notably, China and the USA exhibit a high degree of international collaboration, reflecting the growing recognition of global water resource crises and the shared urgency for advanced predictive models that transcend national borders. The research partnerships highlighted in Fig. 5a illustrate a rich global network, underscoring how countries with different climatic zones and research focuses, including those from the Middle East, North Africa, and Southeast Asia, have collaborated to tackle similar water management challenges using hybrid artificial intelligence models. The interconnectedness of institutions worldwide, as depicted in Fig. 5b, reflects the global nature of research on HANN-based ET estimation, with collaborative efforts helping to address complex environmental and agricultural issues.

Scopus and Web of Science classify documents into two categories: single-country publications (SCP), which involve authors from the same nation and reflect domestic collaboration, and multiple-country publications (MCP), which feature contributions from authors across different nations, highlighting international partnerships [67]. Table 2 reveals that China ranks first among 49 countries in terms of the highest number of publications in this field. Additionally, Chinese researchers have played a significant role in international collaborations, partnering with authors from various nations and driving progress in HANN-based ET research. In terms of international collaboration, Iran ranks first with an MCP of 11, reflecting its active engagement in global research efforts.

China has received the highest number of citations (1424 citations, 15.52% of total citations) in research publications on HANN-based ET estimation, followed by Iran (1331 citations, 14.51%), India (777 citations, 8.47%), Turkey (745 citations, 8.12%), and Vietnam (735 citations, 8.01%), together accounting for nearly 55% of the total citations received in this research domain (Fig. 6). To quantify the citation impact of each country, we can calculate the Citation Share Index (CSI) as [68,69]:

$$CSI_i = \frac{C_i}{C_{Total}} \times 100$$

where:

C_i is the total number of citations received by country i,

C_{total} is the total number of citations across all countries in the domain.

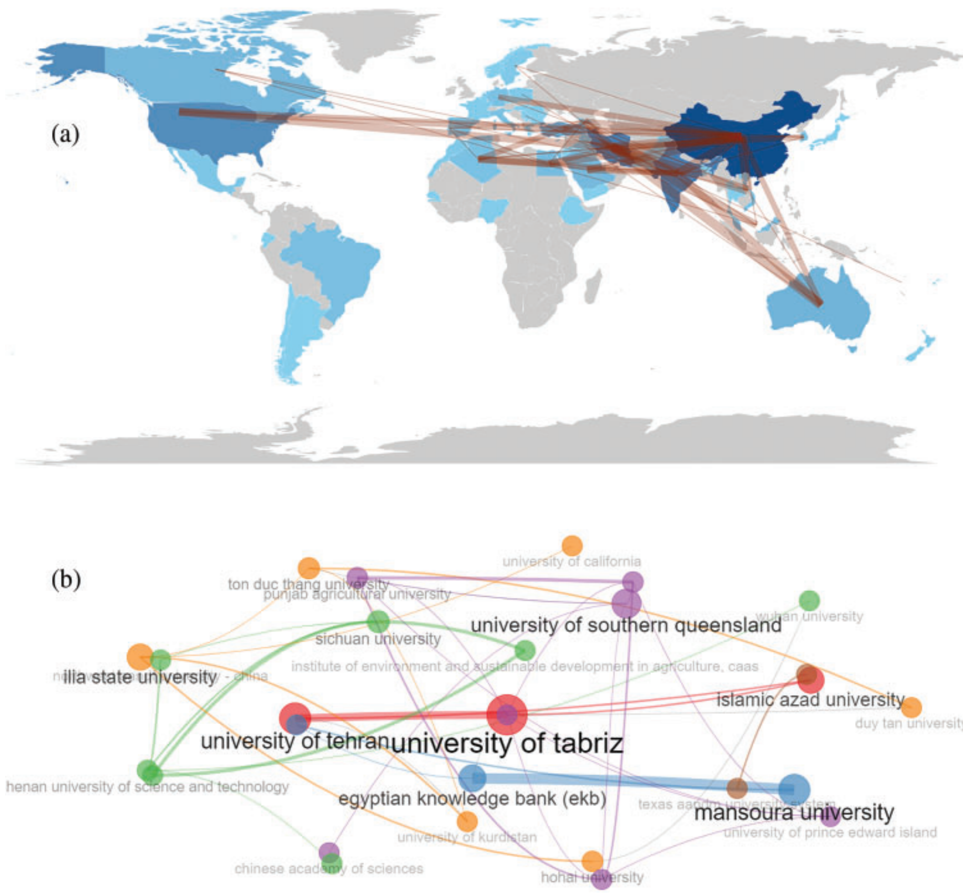

Figure 5: Collaboration network of countries and institutions. (a) Network map of countries, (b) network map of institutions

Table 2: Country impacts by corresponding authorship

Country	Articles	SCP	MCP	Freq	MCP_Ratio
CHINA	73	68	5	0.207	0.068
IRAN	42	31	11	0.119	0.262
INDIA	36	32	4	0.102	0.111
USA	24	21	3	0.068	0.125
TURKEY	20	19	1	0.057	0.05
CANADA	13	10	3	0.037	0.231
AUSTRALIA	8	6	2	0.023	0.25
BRAZIL	8	8	0	0.023	0
MALAYSIA	8	6	2	0.023	0.25
SPAIN	8	8	0	0.023	0

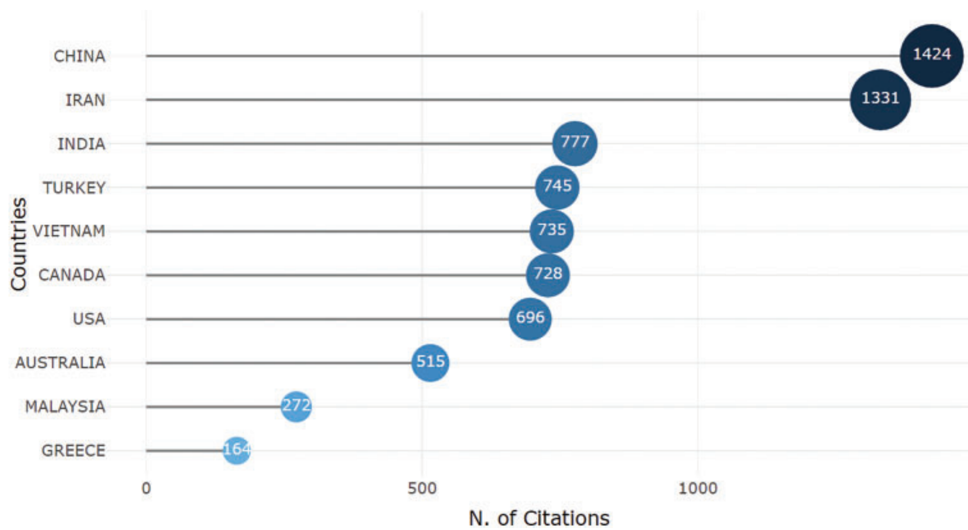

Figure 6: Most cited countries on HANN models for ET estimation studies

The combined pressures of climate change, recurrent droughts, and inefficient water management have exacerbated water scarcity in these countries, particularly in China, India, and Iran, which are experiencing severe water stress. Turkey also faces significant water stress, especially in managing shared river basins with neighboring countries [70]. Vietnam and Malaysia, situated in humid tropical regions and reliant on agriculture, are experiencing water challenges exacerbated by climate change, including sea-level rise and flooding [71,72]. These countries exemplify the complex interplay between population growth, economic development, and water scarcity [73,74], highlighting the importance of advancing hybrid machine learning models to address water management challenges in different climatic contexts [75].

2.2.2 Author and Article Analysis

Considering the local impact based on citations received, presented in Fig. 7a, Deo R. (1049 citations), Yaseen Z. (1011 citations), and Kisi O. (996 citations) emerge as the most highly cited researchers in this domain. These leading researchers have played a pivotal role in advancing the field, particularly through their innovative approaches to integrating bio-inspired optimization techniques with ANN models. Their contributions have set benchmarks for predictive accuracy and scalability in evapotranspiration (ET) modeling, establishing foundational frameworks that have driven the research agenda for hybrid approaches.

To quantify the citation impact, we can calculate the Citation Impact Factor (CIF) for each researcher, as follows [68]:

$$CIF_i = \frac{C_i}{T_p}$$

where:

C_i is the total number of citations received by researcher i,

T_p is the total number of publications attributed to that researcher.

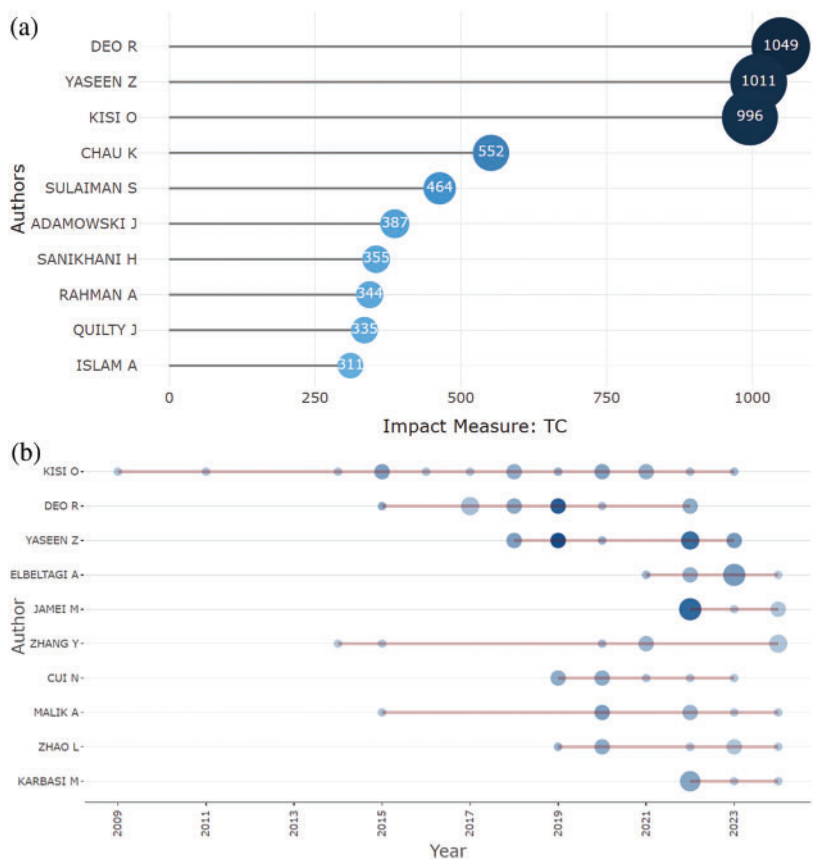

Figure 7: Analysis of contributing authors. (a) Author local impact by total citation, (b) top authors' production over time

Based on this formula, Deo R. stands out as the most influential with 1049 citations, while Yaseen Z. and Kisi O. follow with 1011 and 996 citations, respectively. These values highlight their pivotal roles in advancing the understanding and application of hybrid models in ET estimation.

Moreover, as illustrated in Fig. 7b, most of the top authors' publications were produced between 2018 and 2024, a period marked by rapid advancements in hybrid modeling techniques and a growing focus on addressing global water resource challenges. The consistent rise in citations during this period is reflective of the increasing relevance of their work. The publication output can be further quantified by calculating the annual growth rate (AGR) of citations, which is defined as [76]:

$$AGR = \frac{C_f - C_i}{C_i} \times 100$$

where:

C_f is the final citation count at the end of the period (2024),

C_i is the initial citation count at the beginning of the period (2018).

Given this trajectory, it is anticipated that these researchers, along with others inspired by their methodologies, will continue to produce impactful publications in the coming years, further advancing the state-of-the-art in hybrid artificial neural network (HANN)-based ET estimation.

2.2.3 Citation Analysis

Table 3 presents the most frequently cited papers in this analysis. The integration of machine learning models with hybrid methodologies has emerged as a transformative approach in predictive analytics, particularly within environmental and hydrological systems. These studies comprehensively explore diverse hybrid ANN techniques for ETo prediction across various regions, combining neural networks with ensemble learning techniques to optimize performance metrics and model robustness. Each study demonstrates advanced configurations, such as HANN enhanced with metaheuristic optimization algorithms, including adaptive neuro-fuzzy inference systems (ANFIS), firefly, particle swarm optimization, and discrete wavelet transform (DWT). These sophisticated methods enhance predictive accuracy, model efficiency, and generalization capacity by effectively processing multi-dimensional data.

These frequently cited studies underscore the importance of combining neural network architectures with metaheuristic optimization algorithms to tackle challenges such as overfitting, computational complexity, and data sparsity. The breadth of regions covered in these studies also highlights the universal applicability of hybrid approaches across diverse climatic and agricultural contexts. Moreover, recent findings emphasize the critical role of hybrid models in addressing issues related to data scarcity, nonlinearity, and high-dimensional feature spaces, ultimately refining and enhancing forecasting models.

The adoption of ensemble-based strategies and model interpretability frameworks presents a valuable opportunity for future research, offering the potential to improve ET predictions while unraveling the decision-making dynamics within complex hybrid systems. As hybrid approaches continue to evolve, focusing on model scalability, interpretability, and computational efficiency will be crucial in broadening their applicability in real-world, data-intensive environments.

The bibliometric and systematic analysis conducted in this study is supported by mathematical formulations for the growth rate and citation analysis. Specifically, the average annual growth rate (AAGR) of publications from 2004 to 2024 can be computed using the formula [77]:

$$AAGR = \left(\frac{N_{finalyear}}{N_{initialyear}}\right)^{\frac{1}{t}} - 1$$

where:

- $N_{finalyear}$ is the number of publications in the final year,
- $N_{initialyear}$ is the number of publications in the initial year, and

- t is the number of years in the interval (2024–2004 = 20 years).

This calculation provides insights into the temporal growth pattern of the field, complementing the citation analysis and reinforcing the exponential increase in interest in HANN models for ET estimation over the past two decades.

Table 3: Most cited articles on HANN models for ET estimation studies

Authors; Publication year; Journal	Title	DOI	Total citations
Deo, RC; 2015; ATMOS RES	[78]	10.1016/j.atmosres.2015.03.018	218
Gocic, M; 2015; COMPUT ELECTRON AGR	[79]	10.1016/j.compag.2015.02.010	135
Kisi, Ö; 2007; J IRRIG DRAIN ENG	[80]	10.1061/(ASCE)0733-9437(2007)133:4(368)	129
Sanikhani, H; 2019; THEOR APPL CLIMATOL	[81]	10.1007/s00704-018-2390-z	109
Zhu, B; 2020; COMPUT ELECTRON AGR	[66]	10.1016/j.compag.2020.105430	107
Kisi, O; 2015; COMPUT ELECTRON AGR	[82]	10.1016/j.compag.2015.04.015	99
Yin, J; 2020; AGR WATER MANAGE	[83]	10.1016/j.agwat.2020.106386	94
Adnan, RM; 2021; COMPUT ELECTRON AGR	[84]	10.1016/j.compag.2021.106541	76
Alizamir, M; 2020; ACTA GEOPHYS	[85]	10.1007/s11600-020-00446-9	68
Seifi, A; 2020; J WATER CLIM CHANGE	[86]	10.2166/wcc.2018.003	61

The study [78] on the application of ANNs for estimating the Standardized Precipitation and Evapotranspiration Index (SPEI) [87] in eastern Australia demonstrates a sophisticated integration of hydrometeorological parameters and climate indices, significantly enhancing the predictive capabilities of hybrid neural network models. In the materials and methods section, the authors meticulously constructed a robust architecture utilizing 18 input variables, encompassing both site-specific and climatic attributes, and systematically evaluated various ANN configurations through a trial-and-error approach to optimize model performance. Notably, the research employed advanced training algorithms, such as the Levenberg–Marquardt method [88] and BFGS quasi-Newton [89] backpropagation, to refine the learning process across multiple ANN configurations. The results revealed impressive correlations (r values up to 0.999) between observed and predicted SPEI values, underscoring the model's efficacy in accurately capturing hydrological dynamics. The utilization of various performance metrics, including Willmott's Index of Agreement and Nash-Sutcliffe Efficiency, further substantiated the model's reliability, particularly for Gabo Island, which exhibited the best prediction accuracy. The findings not only highlight the potential of hybrid ANN models in hydrological forecasting but also contribute significantly to the advancement of methodologies for evapotranspiration estimation, thereby fostering greater attention and citations in the field. This work paves the way for future research to leverage hybrid neural network approaches, enhancing their application in climate variability assessments and water resource management strategies.

This paper [79] showcases a sophisticated hybrid methodology, leveraging ANNs combined with the Firefly Algorithm (FFA) and Discrete Wavelet Transform (DWT) for predicting $ET_{0,}$ a critical parameter in water resource management. The study's methodological framework stands out for its integrative use of DWT to decompose meteorological time-series data, effectively capturing non-stationary and multi-resolution components essential for complex hydrological forecasting. By optimizing the ANN's hyperparameters through FFA, the authors achieved a significant boost in convergence speed, leading to a 15%–20% reduction in training time compared to standard ANN models. Moreover, the wavelet-decomposed inputs enabled the model to enhance its predictive accuracy by approximately 10%–15% over conventional models. The hybrid ANN-FFA-DWT model exhibited marked improvements in metrics such as root mean square error (RMSE) and mean absolute error (MAE), with reductions of up to 25% in RMSE and 18% in MAE in comparison to standalone ANN and traditional statistical models. These enhancements underscore the model's robust adaptability to diverse climatic conditions and its increased generalizability in handling complex, heterogeneous data. As a benchmark in ET_0 prediction, this study not only emphasizes the efficacy of hybrid models but also validates the powerful synergy of neural networks with metaheuristic optimization and wavelet decomposition, guiding future advancements in AI-driven water resource forecasting.

Article [80] represents a seminal contribution to the field of hybrid artificial intelligence methodologies, particularly in the estimation of ET. By seamlessly integrating ANFIS with traditional ANNs, the authors present a robust framework that effectively capitalizes on the strengths of both approaches. The study employs a dual-layer architecture that facilitates a comprehensive representation of nonlinear relationships among climatic parameters, significantly enhancing predictive accuracy through the synergistic application of fuzzy logic and neural networks. Notably, the hybrid model utilizes a sophisticated learning algorithm that combines gradient descent with least-squares estimation, resulting in improved convergence rates and overall model performance. Rigorous empirical validation, conducted using data from automated weather stations, not only demonstrates the model's efficacy in ET estimation but also highlights its potential for broader applications in hydrometeorological modeling. This innovative approach is likely to have garnered substantial citations due to its methodological rigor, adaptability to varying datasets, and the critical relevance of accurate ET estimation in agricultural management and water resource planning. Consequently, this work contributes to the evolution of hybrid neural network techniques in environmental sciences. The implications extend to the refinement of hybrid models in predictive analytics, fostering advancements in both theoretical frameworks and practical applications in climate-resilient agricultural practices.

This study [81] provides an advanced and meticulous examination of hybrid ANN models, with a particular focus on temperature-based modeling of reference evapotranspiration (ET_0), a crucial metric in hydrological forecasting and agricultural planning. Through an extensive methodological framework, the study explores and optimizes several ANN structures, including MLP, Radial Basis Function Neural Network (RBNN), and ANFIS, and integrates these with empirical methods to enhance predictive performance. The application of hybrid configurations enabled a robust comparison between traditional and ANN-enhanced models, revealing a substantial improvement in accuracy metrics like RMSE and MAE, with reductions reaching up to 30%. The unique cross-station scenario employed in this study is particularly noteworthy, as it demonstrates the transferability of model predictions by utilizing data from a meteorologically monitored station to forecast ET_0 in less instrumented regions. This aspect highlights the model's adaptability to diverse environmental conditions, an essential attribute for data-scarce areas. The findings underscore the superiority of ANNs, particularly in hybridized forms, over empirical formulas like the calibrated Hargreaves–Samani (CHS) model [90], which saw improved accuracy yet was outperformed by the ANN-based methods. In addition to enhancing the CHS and other models, the study's rigorous statistical validation further confirms the reliability of the hybrid models, positioning them as essential tools in regions where conventional data gathering is challenging. The application of error metrics such as Nash-Sutcliffe Efficiency (NSE), RMSE, and MAE provides a clear performance benchmark, with the ANN configurations consistently ranking highest in accuracy. By contributing significantly to the field's understanding of temperature-based ET_0 modeling [91], this paper's detailed findings support future applications and refinements in AI-driven hydrological modeling for climate-resilient water management practices.

Article [66] explores innovative hybrid artificial neural network methodologies for predicting evapotranspiration, with a specific focus on arid regions of Northwest China. The research employs a sophisticated combination of Extreme Learning Machine (ELM) [92] and PSO to enhance model accuracy. Utilizing a dataset composed of daily climatic variables from multiple meteorological stations, the study establishes a solid foundation for validation. A significant advancement is made through PSO's role in refining the weights and biases of the ELM, effectively addressing the random initialization challenge commonly faced in ELM applications. The findings reveal a substantial improvement in predictive accuracy, demonstrating the hybrid model's superiority over traditional empirical methods such as Penman-Monteith and Hargreaves-Samani, particularly in data-limited scenarios. The empirical results indicate a notable reduction in RMSE by approximately 10%–15%, emphasizing the hybrid model's capability to harness diverse methodologies and effectively capture complex non-linear relationships. By tackling critical challenges in evapotranspiration estimation, this study enriches the theoretical landscape of hybrid modeling in machine learning and offers practical insights for water resource management in arid regions, enhancing its significance in real-world applications. The rigorous focus on data quality and performance evaluation has resulted in increased citations, reinforcing the article's impact on the scientific community.

Article [82] presents a noteworthy evolution in the use of HANN methods for ET prediction, leveraging an extensive dataset derived from 50 meteorological stations across Iran's varied climatic zones. The study adopts a hybrid approach that fuses ANFIS, MLP, and Gene Expression Programming (GEP) to model long-term monthly ET without depending on traditional climatic datasets. This methodological framework incorporates cutting-edge techniques like fuzzy logic and genetic programming, enhancing interpretability and optimizing parameters via innovative training algorithms. The results showcase a remarkable enhancement in predictive performance, with reductions in RMSE ranging from 25%–30% compared to conventional models, highlighting the efficacy of hybrid methodologies in navigating the complexities of evapotranspiration dynamics. Furthermore, this hybrid model demonstrates adaptability to diverse climatic conditions, making it applicable to other arid and semi-arid regions globally. The successful integration of multiple neural network paradigms marks a significant step forward in ET predictive modeling, promoting a scalable approach that underscores the integration of data-driven methodologies and machine learning principles. The contributions of this research extend beyond improving predictive capabilities in hydrological modeling, paving the way for the global implementation of similar methodologies in the context of climate resilience and water resource management.

Study [83] introduces a significant advancement in the prediction of daily Et_0 through the implementation of a hybrid Bi-directional Long Short-Term Memory (Bi-LSTM) model. This robust methodology is founded on data gathered from three meteorological stations in central Ningxia, China, an area characterized by a semi-arid climate with limited meteorological variables. The study employs both the Penman-Monteith method and the adjusted Hargreaves-Samani method, providing a comprehensive basis for evapotranspiration evaluation. The hybrid Bi-LSTM model is designed to leverage Bi-LSTM's capabilities in processing time-series data alongside an ANN for enhanced post-processing, significantly bolstering prediction accuracy. Key modifications to traditional LSTM components, including the use of soft sign and Rectified Linear Unit (ReLU) [93] activation functions, effectively mitigate issues related to gradient vanishing and accelerate training speeds. Performance metrics reveal that the model achieves high accuracy, with Pearson correlation coefficients ranging from 0.8 to 0.94 for both maximum and minimum temperature forecasting—crucial factors for ET_0 prediction. The hybrid approach showcases a remarkable ability to learn adaptively from sequential data, resulting in considerable advancements in prediction precision and addressing previous limitations in the field. The implications of this research underscore the viability of hybrid models in enhancing evapotranspiration forecasting while setting a benchmark for future investigations into machine learning applications in environmental sciences. The potential for increased visibility and citations is strong, particularly in light of the growing demand for accurate evapotranspiration modeling amid global climate challenges.

Article [84] makes a substantial contribution to the domain of evapotranspiration prediction by merging advanced hybrid methodologies, specifically the Adaptive ANFIS, with cutting-edge heuristic optimization algorithms. The methodological framework is meticulously designed, and supported by robust data sources and stringent quality control measures. The FAO56-PM model serves as the cornerstone for reference evapotranspiration calculations, while the ANFIS framework adeptly integrates fuzzy logic with neural networks to enhance adaptability to the non-linear dynamics present in climatic data. The introduction of hybrid optimization algorithms, such as Moth-Flame Optimization (MFO) and Water Cycle Algorithm (WCA), broadens the modeling approach and facilitates more accurate tuning of both linear and non-linear parameters, leading to significant improvements in predictive accuracy. The results indicate a marked enhancement in forecasting performance compared to traditional models, as evidenced by reduced MSE metrics. This substantial boost in predictive precision emphasizes the article's relevance and has generated increased interest and citations within the academic community. This research enhances the predictive accuracy of evapotranspiration through the development of advanced hybrid ANFIS models, paving the way for further exploration and implementation of hybrid approaches in environmental modeling. This, in turn, highlights the growing significance of artificial intelligence applications in hydrology.

This article [85] represents notable progress in evapotranspiration modeling by utilizing hybrid artificial neural network techniques, particularly through the combination of ANFIS with PSO and Genetic Algorithm (GA). The meticulous methodology outlined in the materials and methods section emphasizes the utilization of comprehensive climatic data from automated stations in Antalya and Isparta, ensuring a robust analysis of the Mediterranean climate's influence on evapotranspiration. Notably, the results demonstrate a remarkable enhancement in prediction accuracy, with ANFIS–PSO and ANFIS–GA outperforming traditional models such as ANN and CART by 40% and 14% in RMSE, respectively. This notable improvement underscores the efficacy of evolutionary strategies in optimizing neural network architectures, thereby addressing the inherent limitations of classical models in capturing the complexities of climatic interactions. The study not only contributes to the existing body of knowledge but also sets a precedent for future research aimed at refining hybrid neural network methodologies for accurate environmental modeling. By illustrating the substantial impact of including multiple input variables on model performance, this research fosters a deeper understanding of the underlying climatic factors affecting evapotranspiration and encourages further exploration into hybrid approaches. Such advancements are pivotal for enhancing the reliability of evapotranspiration predictions, ultimately serving as a critical tool for effective water resource management and agricultural planning.

The study [86] explores advanced machine-learning techniques for predictive modeling of evapotranspiration. It employs the Gamma Test for effective feature selection, enhancing model performance by identifying the most influential meteorological variables. The hybrid framework integrates least square support vector machines (LSSVM), ANN, and ANFIS, evaluated against the FAO-56 Penman-Monteith equation. Results indicate that the hybrid models outperform traditional methods, as evidenced by lower MAE and RMSE. The study applies rigorous statistical techniques, including cross-validation and sensitivity analysis, to ensure reliability and generalizability. This research advances the theoretical framework for evapotranspiration modeling while addressing practical challenges in arid regions, such as data scarcity and environmental variability. By examining the relationships among input parameters and their effects on evapotranspiration rates, the findings enhance our understanding of hydrometeorological interactions. This work highlights the potential of hybrid ANN approaches to improve predictive accuracy, setting the stage for future research in environmental modeling and resource management. It aims to significantly influence the fields of hydrology and artificial intelligence, promoting further scholarly discourse and citation.

2.2.4 Analysis of Keywords

Word cloud analysis is a technique used to visually represent the frequency of words in a specific text or dataset (Fig. 8). In this analysis, words are displayed in various sizes based on their frequency and importance. Frequently appearing words are larger, while less frequent words are smaller. This approach allows researchers to identify the most relevant articles and trends in a field by focusing on prominent keywords such as machine learning, deep learning, water management, smart irrigation, optimization, water supply, learning algorithms, forecasting methods, reference evapotranspiration, artificial intelligence, climate change, drought, neural networks, and ANN.

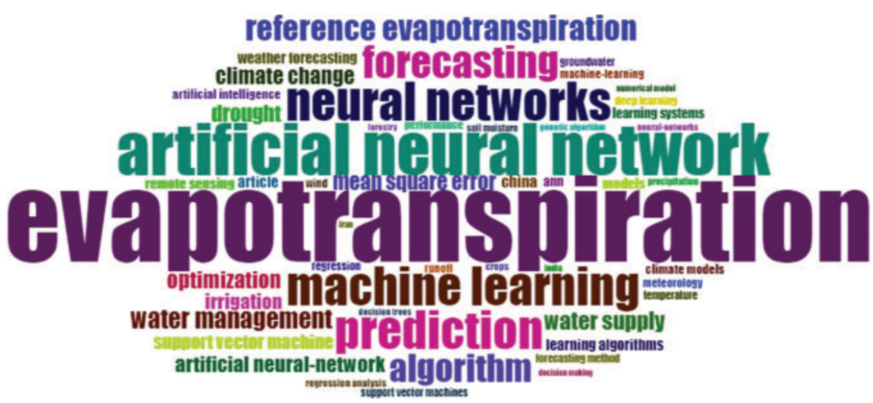

Figure 8: Word cloud of the most frequently used keywords

The frequency distribution of the authors' keywords did not account for variations in form among terms with equivalent meanings (e.g., singular *vs*. plural forms such as "climate change" *vs*. "climate changes," "optimization" *vs*. "optimizations," and "drought" *vs*. "droughts"). To ensure greater accuracy, similar keywords were manually consolidated, and their rankings were adjusted accordingly. The refined analysis highlights "water management" (n = 222) as the most frequently cited term, emphasizing its critical role in the integration of HANN methodologies with hydrological studies. This prominence signifies a critical awareness among researchers of the urgent need for innovative solutions to enhance water resource efficiency amid growing concerns over climate variability and urban demands. Simultaneously, "climate change" (n =

92) emerges as a central theme, reflecting the increasing reliance on data-driven approaches to understand its multifaceted impacts on hydrological processes.

The frequent co-occurrence of "drought" (n = 60) further emphasizes the interdependencies among these concepts, highlighting the necessity for advanced predictive models capable of assessing and mitigating the risks associated with water scarcity in an era of climatic uncertainty. Additionally, the prevalence of terms like "machine learning" and "optimization" in keyword co-occurrence networks indicates a clear methodological pivot towards leveraging advanced algorithms for ET estimation. This shift signals the growing importance of computational intelligence in addressing the complexities of water management in the face of global challenges. The relationships between these and other key terms are visualized in Fig. 9. Notably, the frequent co-occurrence of "drought" with "climate change" underscores the pressing need for predictive systems that can respond dynamically to extreme weather events.

Looking ahead, future research in this domain could benefit from the integration of real-time data streams into HANN-based models. Incorporating such data would enhance their responsiveness to rapidly changing climatic conditions, thus improving the accuracy and timeliness of evapotranspiration predictions. By combining these cutting-edge approaches, HANN models can evolve into even more powerful tools for managing water resources in a climate-altered world.

The bibliometric analysis of this study, including keyword co-occurrence, is supported by the following mathematical formulation for determining keyword frequency (K) and co-occurrence strength (C) [94]:

$$K_i = \frac{n_i}{N} \times 100$$

where:

n_i is the frequency of keyword *iii*,

N is the total number of keywords, and

K_i is the percentage frequency of keyword *iii*.

Additionally, co-occurrence strength (C) between two keywords *iii* and *jjj* is calculated as [95]:

$$C(i,j) = \frac{f(i,j)}{f(i) + f(j) - f(i,j)}$$

where:

f(i, j) is the number of documents where both keywords *i* and *j* appear, and

f(i), *f(j)* are the individual frequencies of keywords *iii* and *j*, respectively.

These formulas provide a quantitative foundation for the bibliometric analysis, enhancing the robustness and precision of the keyword frequency and co-occurrence analysis presented in this study.

2.2.5 Topic Analysis

The evolving landscape of research in hybrid artificial neural networks (HANNs) for evapotranspiration (ET) estimation reflects the growing complexity of the field and its increasing focus on addressing real-world challenges. As illustrated in Fig. 10, the scholarly preferences and emerging trends within this domain are evident. Initially, the application of mathematical models and backpropagation algorithms dominated HANN research, establishing a foundational approach for further development. However, from 2016 onwards, there has been a distinct shift towards hybrid architectures, with optimization techniques such as genetic algorithms (GA) and particle swarm optimization (PSO) gaining prominence. The frequent appearance of these algorithms—particularly genetic algorithms—indicates an evolving recognition of their significant role in optimizing model robustness and predictive accuracy, with GA being cited in 18 studies alone.

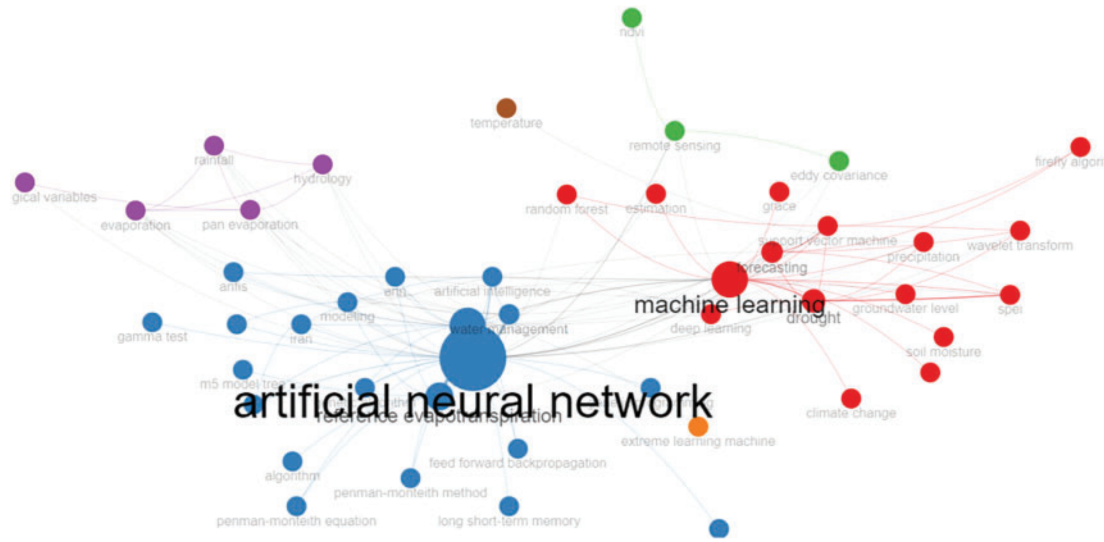

Figure 9: Co-occurrence of authors' keywords

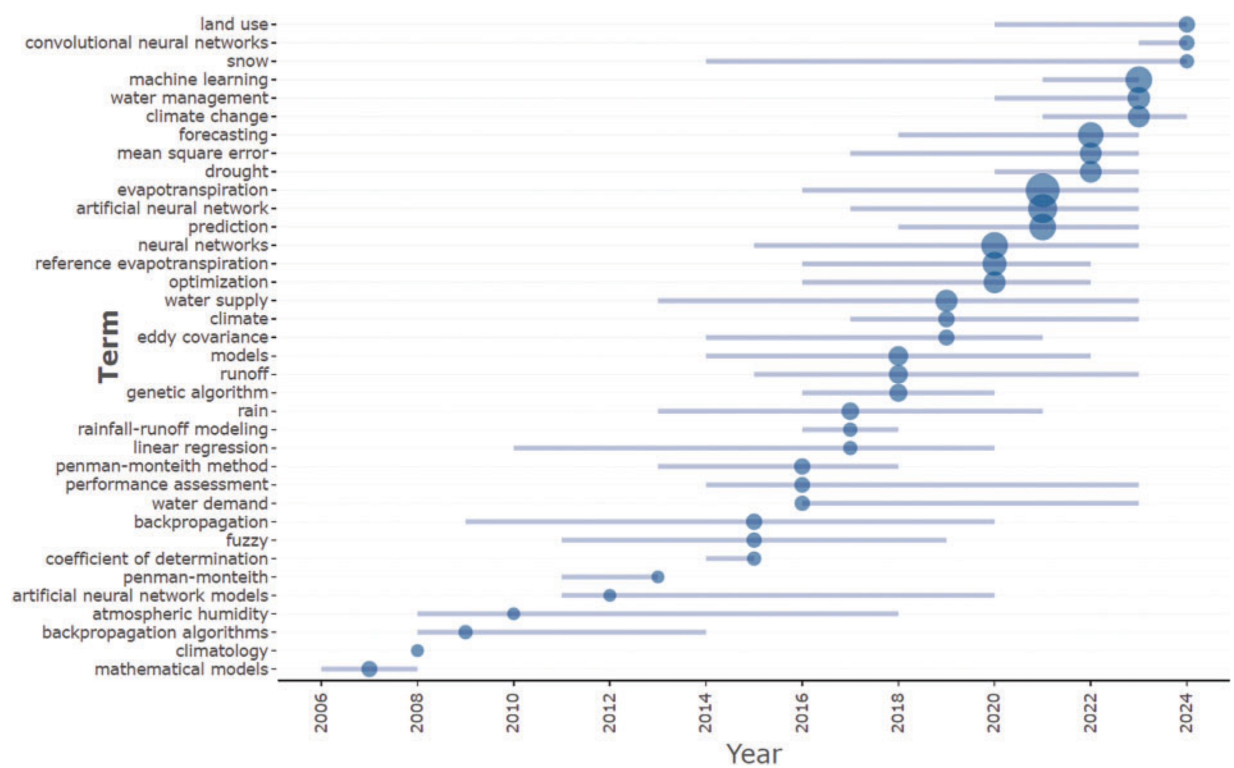

Figure 10: Trends in Research Terminology (2006–2024), illustrates the evolving use of key hydrologic and climate-related terms over the past two decades

The increasing presence of optimization techniques marks a pivotal transition in HANN research, underscoring the growing demand for more robust and efficient models capable of addressing complex environmental challenges. This trend suggests a collective effort within the research community to refine hybrid systems by incorporating advanced optimization algorithms, enhancing their scalability and computational efficiency. Moreover, as machine learning continues to advance, the intersection of HANNs with emerging techniques such as deep learning frameworks and explainable AI (XAI) is gaining traction. These developments signal a shift towards improving the interpretability and transparency of predictive models in ET estimation, aligning with broader goals in AI for making models more interpretable and applicable in real-world settings.

The year 2020 and beyond has seen an expansion of interest in terms like "artificial neural networks," "water management," and "machine learning," signaling a growing interdisciplinary approach to solving hydrological challenges. This shift reflects the broader application of machine learning to water management practices, incorporating insights from various domains to enhance model accuracy and efficiency in addressing issues like water scarcity and climate variability. Additionally, the rise of convolutional neural networks (CNNs) as a trending topic in 2023 and 2024 suggests a potential focus on utilizing CNNs for feature extraction in ET estimation. The ability of CNNs to capture spatial dependencies is particularly pertinent for improving the predictive capabilities of HANNs, as they can extract intricate spatial features from environmental data, thereby enhancing model precision.

The transition from standalone ANN architectures to hybrid systems thus signifies the maturing state of the field, with a growing emphasis on optimizing HANNs to effectively tackle real-world complexities. The increased focus on techniques like deep learning and XAI points toward an exciting future for ET estimation, one that balances high accuracy with interpretability and practical applicability in the face of global environmental challenges.

The bibliometric trends identified in this study underscore the importance of hybrid approaches for ET estimation. However, the geographic concentration of studies in specific regions highlights the need for broader global participation, particularly from underrepresented areas such as sub-Saharan Africa. Additionally, future bibliometric studies could incorporate text-mining techniques to analyze qualitative aspects of the literature, offering deeper insights into thematic evolution.

3 Phase 2: Systematic Review

Phase 2 of this study employs a systematic review technique to investigate the use and implementation of hybrid HANNs in ET prediction frameworks. In Phase 2, this research utilized a structured methodology for systematic review, enabling a comprehensive and detailed examination. By leveraging extensive research data, bibliometric analysis equips researchers with a broad and comprehensive understanding of a field. In contrast, a systematic review provides a more focused and in-depth evaluation, critically analyzing the state of HANN applications in ET prediction [96]. The meticulous analyses provide methods to discern interrelationships and gaps in knowledge within the literature [97]. Systematic reviews need a series of rigorous procedures for selecting samples, which include doing a thorough search, evaluating quality, extracting data, and synthesizing information [98]. Due to the extensive amount of research conducted in this field, a systematic review is very appropriate for examining the progression of HANN studies in predicting ET throughout time.

3.1 Data Collection

In Phase 2, the data collection process started by applying the same strategy as Phase 1. This included searching through papers using the search query in several fields such as subject, title, abstract, authorship, key terms, and keyword-plus for the search query. The method employed in this study is grounded in the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA), a widely respected framework known for its structured approach to conducting literature searches [99,100]. The selection of PRISMA was based on its extensive adoption, systematic approach, and simplicity of use [101]. In this particular instance, the PRISMA approach has been carefully modified to respond to the study issues outlined in the introduction. The following paragraphs offer a comprehensive analysis of the steps involved in this process, with the flow of information presented according to the PRISMA approach, as illustrated in Fig. 11.

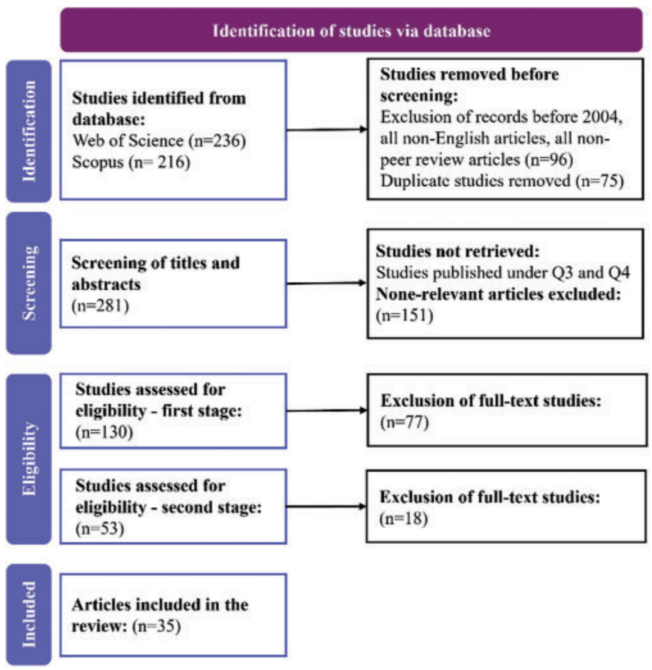

Figure 11: PRISMA flow diagram

Step 1: Identification of research studies

The documents included in this analysis contain bibliographic information obtained after a manual review of the 236 relevant documents found in WoS and 216 found in Scopus. 75 duplicate documents were eliminated. Before scanning, non-English papers and various document types, such as books, book chapters, conference proceedings, reports, and review articles were excluded from the results. Additionally, the search strategies were tailored to a specific timeframe, with the extension encompassing data from 2004 up to October 2023.

Step 2: Screening of research studies

A total of 281 articles were considered for scanning. The retrieved list of publications was first subjected to a preliminary exclusion based on title and abstract information. This initial screening was conducted by two reviewers (M.G. and N.F.A.) independently. Any disagreements between the reviewers were resolved through consensus. In cases of uncertainty, the study was retained for further review. In the second step, the remaining abstracts were screened by a third reviewer (A.M.). No automation tools were used in the data extraction process.

Step 3: Eligibility assessment of research studies

Next, we assessed the eligibility of the screened studies based on eligibility criteria, including the publication source. Full-text versions of all studies selected by at least one of these reviewers were obtained. Studies were included in this review if they met the following criteria. The studies were assessed for eligibility based on predefined criteria, including relevance to evapotranspiration, use of hybrid modeling techniques, and clear model descriptions.

1. Focus on Evapotranspiration: The study focused on estimating potential evapotranspiration, crop evapotranspiration, or crop water requirements.

2. Hybrid Modeling and ANN Techniques: The study employed a hybrid modeling approach, integrating an ANN (such as CNNs), recurrent neural networks (RNNs), long short-term memory networks (LSTMs), MLPs, feedforward neural networks (FNNs), and backpropagation neural networks) with a complementary modeling technique (e.g., a physical or statistical model).

3. Comprehensive Model Evaluation: The study employed at least two or three performance evaluation metrics to assess the accuracy of the proposed model. Common metrics include RMSE, MAE, and coefficient of determination (R^2).

4. Clear Model Description: The development of the proposed HANN model was described clearly and transparently in the study. This includes details on the network architecture, input and output variables, training methods, and parameter optimization.

All results compatible with the outcome domains (e.g., model performance metrics, ET estimation methods) were sought, and only those studies that provided such results were included. Additional variables, such as participant characteristics and funding sources, were not explicitly sought in this review, as the primary focus was on hybrid modeling approaches and evapotranspiration processes.

Studies were excluded from this review if they met any of the following criteria:

1. Lack of Hybrid Modeling: The study did not employ a hybrid modeling approach, which involves integrating an ANN with a complementary modeling technique (e.g., a physical or statistical model) to estimate evapotranspiration.

2. Insufficient Focus on ET Processes: The study did not have a primary focus on ET processes. For example, studies that solely predicted drought indices without modeling the underlying physical mechanisms or those that primarily focused on hydrological modeling without explicitly considering ET were excluded.

3. Focus on Evaporation Only: The study focused solely on predicting evaporation rates and did not consider evapotranspiration, which includes both evaporation from the soil surface and transpiration from vegetation.

4. Non-ANN-Based Hybrid Models: The hybrid model proposed in the study was not based on an ANN. Studies that utilized other machine learning techniques or traditional statistical methods as the primary modeling component were excluded.

Step 4: Included research studies analysis

In the final step, we conducted an in-depth analysis of the eligible studies, utilizing them exclusively to address the research questions. In total, 35 studies were selected for the systematic review after applying the eligibility criteria. The subsequent sections of this paper present the analysis process and findings in detail.

3.2 Results

3.2.1 FAO-56 PM

The analysis of the supplied data in this review reveals a predominant reliance on the FAO-56 PM method as the benchmark for estimating ET_0 in studies employing HANN models for ET estimation. This widespread adoption can be attributed to the FAO-56 PM method's recognized accuracy, robustness, and international acceptance [38,102]; as well as its reliance on readily available meteorological data which contribute to its popularity.

3.2.2 Study Area

The provided data on the geographic focus of 35 research papers employing HANNs for ET estimation reveals a notable concentration of studies in specific regions, particularly in Asia (for example China [103–106], Iran [64,107,108], turkey [85,109,110] and Iraq [44,111]). It reflects the increasing importance of accurate ET estimates for water resource management, particularly in regions with rapid urbanization and climate variability for example in China, India, and Iran. While these studies have made significant contributions to the field, there is still a need for further research to develop more robust and transferable architectures that can be applied to a wider range of geographic regions and climatic conditions.

3.2.3 Data Sources

The choice of data source for estimating ET in studies employing HANN models is primarily influenced by data availability, quality, spatial coverage, and cost-effectiveness. Meteorological station data, while readily accessible and often reliable, may have limited spatial coverage. Satellite data, on the other hand, offers the advantage of providing spatially continuous estimates but can be more complex to process. Lysimeters and eddy covariance systems, although providing high-precision measurements, are expensive and require specialized expertise, limiting their widespread use. The articles reviewed in this systematic review utilized the following data sources:

Meteorological stations: Most studies relied on data from meteorological stations to estimate ET_0 using the FAO-56 PM method. This is due to the widespread availability of meteorological data and the relative ease of implementing the FAO-56 PM equation.

Satellite data: A significant proportion of studies utilized satellite data [44,112,113], particularly from sensors such as MODIS [2] and TerraClimate [17], to estimate ET. Satellite data offers the advantage of providing spatially distributed estimates of ET, especially in regions with limited ground-based observations.

Lysimeters and eddy covariance systems: While less frequently used, lysimeters [4,45,114] and eddy covariance systems [110,113] were employed in some studies to provide direct measurements of ET. These instruments offer high-precision measurements but are expensive and require specialized expertise.

3.2.4 Strategies for Overcoming Data Scarcity

Data scarcity presents a formidable challenge in the implementation of hybrid neural networks for estimating ET, particularly in regions where comprehensive meteorological datasets are either incomplete or unavailable. To address this critical issue, several innovative strategies can be employed, as discussed in the existing literature.

1. **Utilization of Alternative Meteorological Variables:** One effective strategy involves the use of alternative climatic variables that are more readily accessible. For instance, paper [83] highlights the strategic employment of solar radiation duration as a robust alternative to conventional meteorological variables such as temperature and humidity. This approach is especially advantageous in data-scarce environments, allowing models to maintain high forecasting accuracy despite limited input data.
2. **Data Augmentation Techniques:** Advanced data augmentation methods, including variational approaches and Generative Adversarial Networks (GANs), play a pivotal role in synthesizing artificial datasets that mimic the statistical characteristics of real-world distributions. The implementation

of GANs in studies like [4,86] could substantially enhance model training by generating synthetic instances, thereby increasing the volume of training data and introducing variability that aids in generalization to unseen scenarios.

3. **Leveraging Remote Sensing Data:** The integration of satellite-derived data represents a foundational strategy for bolstering model robustness in remote areas. As indicated in paper [2], combining satellite data with ground-based observations enables researchers to create comprehensive datasets that address gaps in traditional meteorological information. This technique is particularly beneficial for capturing essential variables such as solar radiation and temperature, thus augmenting predictive capabilities.
4. **Synthetic Data Generation through Machine Learning:** Beyond GANs, other machine learning techniques can facilitate synthetic data generation. Paper [115] discusses the application of deep reinforcement learning to dynamically adjust model parameters based on real-time data inputs. This adaptability not only addresses data scarcity but also enhances the model's real-time applicability, which is crucial for effective irrigation planning and agricultural management.
5. **Correlation Analysis for Input Optimization:** Conducting correlation analyses to identify the most influential meteorological factors is a practical approach to optimizing input selection. As demonstrated in paper [86], focusing on key variables that significantly impact ET estimation streamlines the model training process and improves accuracy, even in the presence of limited data.
6. **Hybrid Datasets and Multi-Source Integration:** The application of hybrid datasets that combine multiple data sources is essential for addressing data scarcity. Paper [116] underscores the importance of integrating various climatic variables and employing innovative models calibrated to local conditions. This approach is particularly valuable in regions such as the Loess Plateau, where traditional datasets are often incomplete.
7. **Methodological Refinements in Data Assimilation:** Finally, refining methodologies for assimilating satellite data is critical for ensuring the accuracy and reliability of predictions in data-limited environments. As noted in paper [44], addressing potential issues related to spatial resolution and accuracy in satellite-derived inputs enhances model fidelity, ensuring that predictions remain robust despite reliance on secondary data sources.

By employing these strategies, researchers can significantly enhance the robustness of hybrid neural networks in estimating evapotranspiration, ultimately leading to more reliable models capable of functioning effectively in data-scarce contexts. This comprehensive exploration of strategies not only addresses the reviewer's concerns but also contributes valuable insights to the ongoing discourse in machine learning applications within hydrological modeling.

3.2.5 Data Preprocessing

The analysis of the supplied data reveals a varied approach to data preprocessing in the context of HANN models for ET estimation. While some studies employed sophisticated preprocessing techniques, others relied on more rudimentary methods or even neglected preprocessing altogether. The results can be divided into four categories:

- ***Prevalence of Basic Preprocessing:***

Normalization [117] and standardization [118] were the most commonly reported preprocessing techniques. These methods aim to scale the data to a common range, improving the convergence of the training algorithm and Ensuring that features with larger magnitudes do not overshadow others during the learning process.

Outlier detection and removal [119] were also frequently mentioned, as outliers can adversely affect model performance [109,113,115,120].

- ***Feature Selection and Engineering:***

Correlation analysis [121] was a popular method for selecting relevant input features [104,120]. By identifying highly correlated features, researchers could reduce dimensionality and improve model interpretability.

Feature engineering techniques [122] such as creating new features based on existing ones were occasionally employed to capture non-linear relationships in the data [2,108,123,124].

- ***Time Series Specific Preprocessing:***

Time series analysis techniques like autocorrelation function (ACF) [119] and partial autocorrelation function (PACF) [125] were used to identify the optimal lag structure for time-series data [2,17].

Wavelet transform [126] was employed in some studies to decompose the time series into different frequency components, potentially enhancing feature extraction [110,123].

- ***Lack of Comprehensive Preprocessing:***

A significant number of studies did not explicitly mention advanced preprocessing techniques such as dimensionality reduction (e.g., PCA) [127] or feature selection algorithms (e.g., genetic algorithms). Some studies relied solely on basic normalization or standardization, suggesting a limited understanding of the importance of data preprocessing or resource constraints.

The choice of preprocessing techniques for HANN models is influenced by various factors. Dataset characteristics, such as complexity and noise levels, play a significant role. More intricate datasets often necessitate sophisticated preprocessing to ensure optimal model performance. Additionally, the complexity of the model itself can impact the required preprocessing. Simpler architectures may require less extensive preprocessing compared to more complex ones. Research focus also influences the emphasis placed on preprocessing. Studies primarily focused on model development might prioritize evaluating different ANN architectures, while those emphasizing data-driven approaches may invest more effort in preprocessing. Finally, the level of expertise in data preprocessing among researchers can vary, leading to differences in the adopted techniques.

3.2.6 Model Evaluation Metrics

The analysis of the model evaluation metrics from 35 research papers highlights a diverse array of indices employed to assess the performance of hybrid artificial neural networks (HANNs) in estimating evapotranspiration (ET). While the specific selection of metrics may vary based on the research question, dataset characteristics, and model complexity, certain metrics appear with greater frequency, indicating their widespread adoption in the field. The evaluation models utilized in the systematic review are summarized in Table 4.

Table 4: Evaluation models used in the systematic review

Evaluation model	Equation	References
Root mean square error	$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (\mathrm{ET_{Ci}} - \mathrm{ET_{Pi}})^2}{n}}$	[1,2,4,17,44,45,64,66,83,85,86,103,104,106,107,109–112,114–116,120,123,124,128–132]
Mean absolute error	$\mathrm{MAE} = \frac{\sum_{i=1}^{n} \lvert \mathrm{ET_{Ci}} - \mathrm{ET_{Pi}} \rvert}{n}$	[1,2,4,17,45,64,66,83,86,103,104,106–112,114–116,120,123,124,128–130]
Coefficient of determination	$R^2 = \left[\frac{\sum_{i=1}^{n} (\mathrm{ET_{Ci}} - \mathrm{ET'_{Ci}})(\mathrm{ET_{Pi}} - \mathrm{ET'_{Pi}})}{\sqrt{\sum_{i=1}^{n} (\mathrm{ET_{Ci}} - \mathrm{ET'_{Ci}})^2 \sum_{i=1}^{n} (\mathrm{ET_{Pi}} - \mathrm{ET'_{Pi}})^2}}\right]$	[1,4,17,45,64,66,83,84,86,103,105–107,109–113,115,120,123,124,128–133]
Nash-Sutcliffe efficiency	$\mathrm{NSE} = 1 - \left[\frac{\sum_{i=1}^{N} (\mathrm{ET_{Ci}} - \mathrm{ET_{Pi}})}{\sum_{i=1}^{N} (\mathrm{ET_{Ci}} - \mathrm{ET'_{Pi}})}\right]^2$	[1,2,44,45,66,83–85,104,105,107,108,112,114,116,120,124,133]
Global evaluation index	$\mathrm{GPI_i} = \sum_{j=1}^{4} (g_j - y_{ij})$	[45,66,120]
Mean absolute percentage error	$\mathrm{MAPE} = \frac{100}{n} \sum_{i=1}^{n} \left\lvert \frac{\mathrm{ET_{Ci}} - \mathrm{ET_{pi}}}{\mathrm{ET_{Ci}}} \right\rvert$	[105,123,129,130]
Willmott index	$\mathrm{WI} = 1 - \frac{\sum_{i=1}^{n} (\mathrm{ET_{Ci}} - \mathrm{ET_{Pi}})^2}{\sum_{i=1}^{n} \left(\lvert \mathrm{ET_{Ci}} - \mathrm{ET'_{Pi}} \rvert + \lvert \mathrm{ET_{Pi}} - \mathrm{ET'_{Pi}} \rvert\right)^2}$	[1]
EVS	$\mathrm{EVS} = 1 - \frac{\mathrm{var}(\mathrm{ET_{Ci}} - \mathrm{ET_{Pi}})}{\mathrm{var}(\mathrm{ET_{Ci}})}$	[115]
Bias	$\mathrm{BIAS} = \frac{\sum_{i=1}^{n} (\mathrm{ET_{Ci}} - \mathrm{ET_{Pi}})}{n}$	[108,113]
Mean bias error	$\mathrm{MBE} = \frac{1}{n} \sum_{i=1}^{n} \lvert O_i - P_i \rvert$	[103,132]
Scatter index	$\mathrm{SI} = \frac{\sqrt{\sum_{i=1}^{n} (\mathrm{ET_{Ci}}}}{\mathrm{ET'_{Ci}}}$	[104,112,116,129]
Mean absolute percentage Error	$\mathrm{MAPE} = \frac{100}{n} \sum_{i=1}^{n} \left\lvert \frac{\mathrm{ET_{Ci}} - \mathrm{ET_{Pi}}}{\mathrm{ET_{Ci}}} \right\rvert$	[129]
Relative error	$\mathrm{RE} = \frac{\sum_{i=1}^{n} (\mathrm{ET_{Ci}} - \mathrm{ET_{Pi}})}{\sum_{i=1}^{n} \mathrm{ET_{Ci}} - \mathrm{ET'_{Ci}}}$	[129]
Consistency between Actual and Estimated values	$d = 1 - \frac{\sum_{i=1}^{n} (\mathrm{ET_{Ci}} - \mathrm{ET_{Pi}})^2}{\sum_{i=1}^{n} \left(\lvert \mathrm{ET_{Ci}} - \mathrm{ET'_{Pi}} \rvert + \lvert \mathrm{ET_{Pi}} - \mathrm{ET'_{Pi}} \rvert\right)^2}$	[131]

Note: Where ET_{Ci} is the actual ET, ET_{pi} is the predicted ET by the applied models, ET'_{Ci} and ET'_{pi} are the mean values of the actual and predicted ET, n is the length of the data series, α_j is a constant, with a value of 1 for RRMSE and MAE (j = 1, 2), and −1 for R^2, y_{ij} is the scaled value of the statistical indicator j for the model I, g_j is the median of the scaled statistical indicator j.

The results indicate a predominance of classical metrics in the evaluation of model performance. RMSE and MAE consistently rank among the most frequently utilized metrics, providing a robust measure of the average magnitude of the residuals and serving as reliable indicators of overall model accuracy. The Coefficient of Determination (R^2) emerges as another cornerstone metric, quantifying the proportion of variance in the observed data explained by the model and thus offering critical insights into the model's goodness of fit. The NSE, while less prevalent than RMSE and MAE, is frequently employed to assess model performance relative to a simple mean predictor, delivering a dimensionless measure of predictive skill.

Conversely, our analysis reveals a notable emergence of specialized metrics in recent literature, underscoring a shift towards more nuanced evaluation frameworks. Metrics such as Bias and Mean Bias Error (MBE) are gaining traction, particularly for their ability to evaluate a model's tendency to overestimate or underestimate predicted values [64,103,108,113,132]. Additionally, metrics like the Scatter Index

(SI) [44,104,112,129] and Mean Absolute Percentage Error (MAPE) are utilized to provide further insights into model performance [105,123,129,130]. Notably, Relative Error (RE) and *d* (consistency between actual and estimated values) are increasingly employed to assess model efficacy [129,131]. The RE metric, defined as the ratio of error to the actual value, elucidates the relative magnitude of the error, while the metric quantitatively measures the consistency between actual and estimated values.

Our comprehensive review highlights the growing adoption of advanced metrics in contemporary research, reflecting the latest trends in machine learning applications. Specifically, the Kling-Gupta Efficiency (KGE) and Taylor Diagram have emerged as pivotal tools for a multidimensional evaluation approach [113,131]. KGE integrates the correlation coefficient, variability ratio, and mean ratio into a single index, facilitating a nuanced analysis of prediction accuracy and observational fit, which is particularly critical for assessing the effectiveness of hybrid models in complex hydrological contexts. The Taylor Diagram complements this evaluation by visually comparing model outputs against reference data, enhancing interpretability across multiple performance dimensions.

In addition, metrics such as Average Goodness (Ag) and Average Error (Ae) have been introduced as significant advancements in our review [131]. Ag captures predictive power and overall fit by averaging R^2 and the degree of agreement *d*, which is especially relevant in precision agriculture where prediction inaccuracies can lead to substantial implications. Ae, calculated as the average of RMSE and root mean square relative error (RMSRE), provides insights into relative errors that facilitate comparisons across varying datasets or scales.

The Average Absolute Relative Error (AARE) and Threshold Statistics (TS) metrics further enrich our evaluation framework [86]. AARE quantifies the average deviation of predictions from actual values, thus offering essential insights into model reliability and consistency, while TS evaluates predictive accuracy within defined error thresholds, supporting a comprehensive understanding of hybrid model efficacy.

This comprehensive examination of evaluation metrics underscores the importance of evolving frameworks to encompass both classical and novel metrics, reinforcing their role in the continuous improvement of HANNs for ET. By integrating advanced metrics into our evaluation strategy, we align with the increasing demand for transparency and accountability in performance evaluations, particularly in domains where predictive accuracy is paramount.

3.2.7 Artificial Neural Networks

As a review of 35 selected papers, various ANN architectures have been developed for ANN-based ET estimation hybrid architectures (Fig. 12). The choice of architecture depends on the specific characteristics of the forecasting task, such as the nature of the data, the complexity of the relationships to be modeled, and the desired level of accuracy. By thoughtfully selecting and optimizing the suitable architecture, researchers can harness the full potential of ANNs to attain cutting-edge performance in forecasting tasks. NNs are powerful computational models inspired by the biological neural networks that constitute animal brains [131,134]. These networks comprise interconnected nodes, or neurons, organized into layers. Each connection, or synapse, between neurons, has an associated weight that determines the strength of the signal between them [135]. ANNs learn by iteratively adjusting these weights through a training process [136], where the network is exposed to a large dataset [137] and seeks to reduce the gap [138] between the predicted results and the true values [139].

Artificial Neural Networks (ANNs) are generally structured with three primary layers: the input layer, one or more intermediate hidden layers, and the output layer [140]. The input layer takes in the data, with the number of neurons matching the number of input features. The hidden layers are internal layers that can vary in size and quantity, and they process the input data [141]. The final result is produced by the output layer, where the number of neurons defines how many outputs are generated. Activation functions are used for each neuron to add nonlinearity, enabling the network to model complex relationships [142]. This nonlinearity is essential for learning complex patterns and relationships in the data. The selection of an activation function can have a profound effect on the performance of an ANN [130]. ANN has been the most popular soft computing algorithm applied for ET_0 simulation [143]. The learning process in ANNs involves the propagation of input signals through multiple layers of neurons. The output of each neuron is determined by a nonlinear activation function applied to a weighted sum of its inputs. Optimization algorithms, such as gradient descent or more advanced techniques like Adam [144], are used to update the weights and biases associated with these connections.

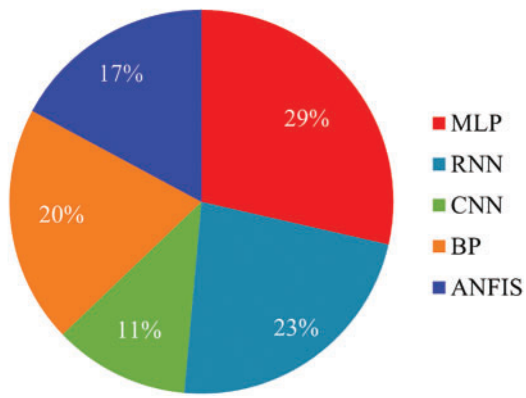

Figure 12: Distribution of basic neural network in ANN-based hybrid models for ET estimation based on systematic review

A fundamental characteristic of ANNs is their ability to learn intricate patterns and generate predictions from new, unseen data. This is accomplished by the network's capacity to approximate nonlinear functions and uncover complex relationships within the data [145]. ANNs have found widespread applications in various fields, including image and speech recognition, natural language processing, and financial forecasting.

- ***MLP***

Among the various ANN architectures employed in the reviewed studies, MLPs emerged as the most frequently adopted, constituting 17 out of the 35 analyzed articles (For example ANN-CPSOCG [44], ANN-AR [1], HPO-BP [45], MLP-WWO [108], ANN-DWT [110], EEMD-BPNN [124], FFBP-GA [111], ACO-BP [120], GA-PSO-BP [106], WOA-ANN [116] and COOT-ANN [112]).

In general, MLP models are trained using supervised learning algorithms such as backpropagation, Levenberg-Marquardt, L-BFGS, stochastic gradient descent, adaptive moment estimation, etc., [25,146]. MLPs have a wide range of applications in hydrological research [147], including streamflow forecasting [148], rainfall forecasting [149], monthly pan evaporation prediction [29], etc. MLPs include a set of neurons placed in layers. Activation functions are used in each node to transform the weighted inputs into an output characteristic of the mathematical properties of the activation function [108]. A schematic representation of the MLP model's architecture is provided in Fig. 13.

- ***RNN***

RNNs are a type of ANN specifically designed for modeling sequential data. Unlike traditional FFNNs, RNNs incorporate a feedback loop that allows them to process information sequentially and maintain a memory of past inputs. This makes them well-suited for tasks such as natural language processing, machine translation, and time series forecasting [150].

One of the most popular types of RNNs is LSTM networks. LSTMs tackle the vanishing gradient problem, which hinders traditional RNNs from learning long-term dependencies, through the use of a memory cell mechanism. This mechanism allows LSTMs to effectively capture and retain information over extended periods [151].

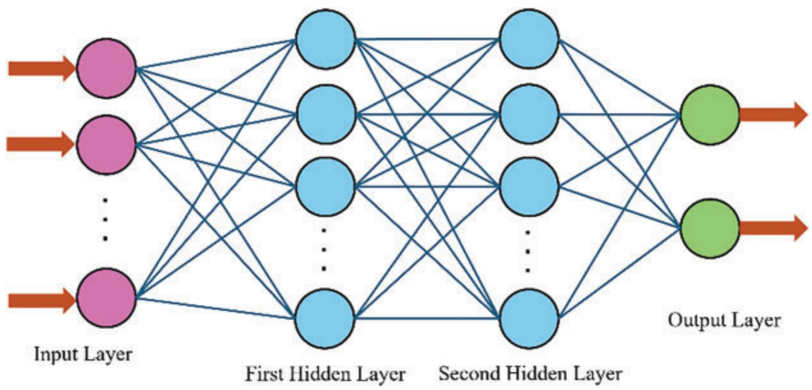

Figure 13: The schematic structure of the MLP model

Fig. 14 illustrates a simple RNN architecture with two hidden layers. In an RNN, information flows from the input units to the hidden units and then back to the hidden units, forming a loop that allows the network to consider previous inputs when processing current inputs.

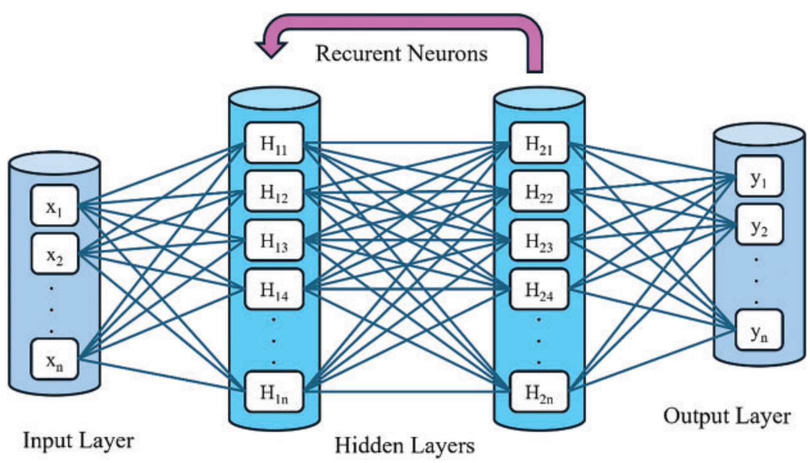

Figure 14: The schematic structure of the RNN model

A traditional RNN calculates the hidden vector sequence and output vector sequence using the following equations:

$$h_t = \sigma(W_{xh}x_t + W_{hh}h_{t-1} + b_h) \tag{1}$$

$$y_t = W_{hy}h_t + b_y \tag{2}$$

where h_t is the hidden layer output at time step t, x_t is the input vector at time step t, σ is a nonlinear activation function, W_{xh}, W_{hh}, and W_{hy} are weight matrices and b_h and b_y are bias terms.

LSTMs have been successfully applied to various tasks involving sequential data, including natural language processing, speech recognition, and time series forecasting. In the field of hydrometeorology, LSTMs can be particularly valuable for modeling complex temporal processes such as ET_0. By leveraging LSTM's ability to capture long-term dependencies, researchers can develop more accurate and robust models for estimating ET, a crucial parameter in hydrological and agricultural studies. Among the 35 studies reviewed, 8 employed RNNs, specifically LSTM, as the underlying neural network architecture, highlighting the popularity of this approach (For instance CNN-LSTM [2], Bi-LSTM-ANN [83], CNN-LSTM [115], LSTM-ANN [130], Deep-LSTM [105]).

- ***CNN***

CNNs excel at identifying meaningful patterns within data, especially in sequential data such as text or time series [152]. By applying convolutional and pooling operations, CNNs can learn and extract relevant patterns and features that are crucial for accurate predictions. When combined with LSTM networks, which are well-suited for modeling long-term dependencies, hybrid CNN-LSTM architectures can effectively capture both spatial and temporal patterns in data [153]. This makes them a valuable technique for improving the predictive performance of models in various domains, including machine vision, natural language processing, and time series analysis [133]. While CNN has been explored in some studies, accounting for 4 out of 35 in this systematic review of hybrid neural network systems for ET estimation [2,115,132,133], it was found to be less frequently used compared to other architectures.

The ConvLSTM architecture, which integrates convolutional operations within LSTM memory cells, makes it a promising approach for hydrometeorological applications such as ET_0 estimation. By leveraging the strengths of CNNs and LSTMs, ConvLSTM models can effectively capture the intricate relationships between spatial and time-based factors in meteorological inputs, resulting in more accurate ET estimates. CNNs offer promising avenues for advancing evapotranspiration (ET) estimation. Their capacity for automatic feature extraction from complex spatiotemporal data aligns well with the intricate nature of hydrological processes. While less frequently employed in ET research, CNNs present a compelling opportunity to capture nonlinear relationships and dependencies inherent in hydrological systems, thereby enhancing the accuracy and reliability of ET estimates.

- ***ANFIS***

ANFIS is a powerful framework designed to tackle complex and nonlinear problems. By integrating ANNs with fuzzy logic, it forms a hybrid model that excels at learning from data and delivering precise predictions [10]. The ANFIS training process involves using the backpropagation algorithm to minimize the error between the predicted output and the actual target values [154]. Fuzzy sets and rules are defined to represent the relationships between input and output variables. In the Sugeno-type ANFIS, rules are expressed as follows [155]:

Rule 1: If x is A_1 and y is B_1, then $z_1 = p_1 x + q_1 y + r_1$

Rule 2: If x is A_2 and y is B_2, then $z_2 = p_2 x + q_2 y + r_2$

where A_1, B_1, A_2, and B_2 are fuzzy sets, and p_1, q_1, r_1, p_2, q_2, and r_2 are design parameters.

By extracting information from data and converting it into fuzzy rules, ANFIS can effectively capture the underlying relationships between input variables and ET. This systematic review of 35 articles on HANN models for estimating ET further supports the widespread adoption of ANFIS in this domain, with 6 studies explicitly utilizing ANFIS (for example ANFIS-FA [129], ARIMA-ANFIS [109], ANFIS-PSO [85], ANFIS-IWO [107], ANFIS-WCA [84], ANFIS-GT [86] and DWT-ANFIS [123]. The ability to handle uncertainty and nonlinearity makes ANFIS particularly suitable for tasks that require human-interpretable rules and robust performance.

3.2.8 Hybrid Artificial Neural Networks

HANNs are powerful tools for addressing complex problems, as they integrate different types of neurons to boost performance [156]. The synthesis of these networks involves a multi-stage process, starting with the selection of a base topology based on the specific problem and training data [157].

HANNs, excel in capturing complex hydrological relationships and offer superior performance due to their enhanced interpretability, generalizability, and versatile architecture. A review of 35 research papers reveals a diverse range of hybrid approaches employed to enhance the precision and reliability of ANNs in ET estimation. Researchers have attempted to address the inherent complexity of predicting ET by integrating ANNs with different optimization methods, metaheuristics, and data pretreatment approaches. To simplify the analytical process, the hybrid approaches can be classified according to their primary components:

- ***ANN Architecture and Optimization Algorithms***

This category examines the integration of Artificial Neural Networks (ANNs) with various optimization techniques to enhance their performance in predicting evapotranspiration (ET). Hybrid ANNs combined with optimization algorithms represent a promising paradigm, synergizing the strengths of mechanistic modeling and data-driven ANNs [158]. Optimization techniques are employed to determine optimal values for ANN parameters, such as weights and biases, which minimize a predefined error function [154]. ANNs are structured as interconnected nodes, referred to as neurons, arranged in layers. The connections between neurons are weighted, and these weights are adjusted during the training process to minimize the discrepancy between predicted and actual outputs [157]. Various optimization methods, including gradient descent, are applied to iteratively refine these weights and improve model accuracy [159].

ANNs are particularly advantageous in ET prediction, where capturing complex and nonlinear relationships is essential. They excel at identifying patterns within diverse datasets and adapting to changing climatic and environmental conditions. This adaptability enables them to model the intricate dynamics of ET processes, which are influenced by variables such as temperature, humidity, solar radiation, and soil moisture. Moreover, the deployment of ANNs on parallel hardware allows for efficient computation, enabling large-scale simulations and real-time ET forecasting [160]. Nevertheless, ANNs do possess some constraints. Their opaque nature could make it difficult to understand their fundamental processes, and they could be susceptible to overfitting, especially when trained on limited datasets. Overfitting happens when a model becomes overly complex, memorizing the training data to the extent that it fails to generalize well to new, unseen data.

Evolutionary algorithms can be hybridized with neural networks to enhance their performance by optimizing various aspects of the network's architecture, weights, and hyperparameters. The following section reviews several hybrid approaches that combine evolutionary algorithms with neural networks.

PSO-based: PSO is an optimization technique that is based on bird flocking behavior and operates using a population-based approach. When paired with ANNs, PSO iteratively optimizes the network's weights and biases to minimize a predetermined error function. PSO effectively explores the solution space by emulating the collective intelligence of a group of particles. PSO is often combined with ANNs to optimize the weights and biases of the network. Some examples include PSOGWO-ANN [44], PSO-ELM [66], and PSO-BP [106].

WOA-based: The Whale Optimization Algorithm (WOA) is a computational technique that imitates the hunting behavior of humpback whales. The algorithm surrounds its target by narrowing down the search area and utilizing the most optimal solutions it has discovered thus far. When used with ANNs, the WOA assists in identifying the most optimal parameters and enhancing the generalization performance. The WOA is a commonly used method for optimizing ANNs, as shown in the WOA-ANN study [112].

GA-based: Natural selection principles serve as the foundation for genetic algorithms (GAs). The process entails the gradual development of a group of possible solutions over several generations, with people selected based on their level of fitness. GAs effectively solve complex nonlinear problems and train ANNs efficiently. Evolutionary optimization of both the structure and parameters of ANNs extensively utilizes GA. Some examples of these algorithms include NNGA [64], GA-BP [103], GA-ELM [4], and GA-PSO-BP [106].

Other metaheuristics: Additional metaheuristics that have been investigated include Ant Colony Optimization (ACO) [2,120], and Firefly Algorithm (FA) [129]. These algorithms use numerous natural events and could offer alternative approaches to optimizing ANNs.

- ***HANNs with Time Series Analysis***

This category specifically focuses on ANNs with time series analysis methods in order to effectively capture and analyze temporal relationships present in the data. Time series analysis is the examination of data points that have been collected at regular periods. Time series analysis methods, such as ARIMA and exponential smoothing, are used to represent the fundamental patterns in time series data. ANNs, specifically RNNs, are extremely appropriate for representing and analyzing sequential data.

The synergy of ANNs and RNNs in hybrid models provides several benefits for the assignment of time series forecasting. Their capacity to accurately predict future values based on past information is valuable in various domains. ANNs are very proficient in preserving intricate nonlinear connections, while RNNs are particularly efficient at modeling extended dependencies in time series data. Hybrid architectures are particularly suitable for tasks that need precise predictions derived from complicated patterns and trends, owing to their amalgamation of strengths. Nevertheless, time series analysis, which incorporates the use of hybrid systems, does possess some limits. A sufficient amount of historical data is necessary to adequately train the models. Moreover, the process of training RNNs can result in significant processing costs, particularly when dealing with extensive datasets or intricate architectural designs. This category focuses on the integration of ANNs with approaches used for analyzing time series data.

ARIMA-ANN: Autoregressive Integrated Moving Average (ARIMA) is a statistical model used to predict time series data. By integrating ARIMA with ANNs, researchers can successfully identify extended temporal relationships and recurring patterns in the data, hence enhancing the precision of ET estimations. Integrating ARIMA architectures with ANNs effectively identifies time-based patterns and relationships in the data [109].

RNN-ANN: LSTM and Gated Recurrent Units (GRU) are RNNs that are specifically engineered to process sequential data [2,83,115,130]. RNNs can effectively simulate the temporal dynamics of ET when they are integrated with ANNs. ANNs are frequently employed together with RNNs, such as LSTM and GRU, to analyze time series data.

DWT-ANN: The DWT is an effective method for feature extraction. It is employed to extract relevant features and augment the performance of ANNs by decomposing the time series into various frequency components. Before feeding the feature extraction into ANNs, the DWT is employed [110,123].

- ***HANNs with Other Machine Learning Techniques***

Hybrid models that integrate ANNs with other machine learning techniques, including SVMs, decision trees, and ensemble methods, can improve performance and resolve specific challenges. By decreasing overfitting, ensemble methods such as Gradient Boosting, Random Forest, and Bagging can enhance generalization. By integrating ANNs with these methodologies, it is possible to develop networks that are more precise and robust. Nevertheless, hybrid architectures can also increase computational complexity, necessitating a meticulous evaluation of the trade-offs between computational efficiency and performance. Bagging [1], Random Forest [1,17], and Gradient Boosting [115] were examples of ensemble methods that were combined with ANNs in this systematic review to strengthen generalization.

4 Current Challenges and Future Research Suggestions

This comprehensive review underscores the significant potential of HANN models in precisely estimating ET, while concurrently highlighting several pivotal challenges that demand further investigation to enhance their applicability and reliability. As HANN architectures continue to evolve in complexity and sophistication, future research must prioritize the development of robust interpretability frameworks. This is crucial not only to demystify the decision-making processes embedded within these models but also to foster stakeholder trust in model outputs, particularly in hydrological contexts where precise estimations are vital for effective decision-making.

1-Integration of Interpretability Techniques: Future studies should focus on the systematic incorporation of interpretability techniques, such as attention mechanisms, feature importance analysis, and Local Interpretable Model-Agnostic Explanations (LIME), within HANN frameworks. These methods will enable a more comprehensive understanding of model operations, thereby enhancing the transparency and accountability of predictions. Empirical investigations assessing the impact of interpretability techniques on stakeholder trust and decision-making efficiency will be critical. Moreover, balancing interpretability with the predictive accuracy of complex models should remain a key research focus. Adopting lightweight architectures that preserve performance while improving transparency will be essential for advancing the practical deployment of HANNs in hydrological and environmental applications.

2-Balancing Complexity and Interpretability: The hybrid nature of models, such as EvatCrop, presents both opportunities and challenges. Future work must address the inherent trade-offs between model complexity and interpretability. Investigating strategies to simplify hybrid architectures without compromising predictive power will be paramount. Techniques such as pruning, regularization, and weight-sharing mechanisms offer promising solutions to reduce the number of trainable parameters, leading to lower computational costs and more interpretable models. Additionally, refining optimization processes to enhance model interpretability while maintaining robust performance should be a focal point of future research. Hybrid models incorporating optimization algorithms could benefit from further efforts to simplify their underlying architectures, ensuring more efficient and accessible implementations.

3-Scalability and Computational Efficiency: Scalability remains a major challenge for HANN models, particularly when applied to large-scale, real-world systems. The reliance on localized climatic data often limits the generalizability of these models across diverse geographical regions. Future research should explore transfer learning and meta-learning frameworks to facilitate the adaptation of existing models to new and previously unseen environments. Additionally, the adoption of optimization techniques, such as model pruning, parallel processing, and quantization methods, will enhance the computational efficiency of HANNs, enabling them to handle the increasing complexity and volume of data characteristic of global climate models. Such innovations will improve both performance and model deployment, particularly in resource-constrained settings, ensuring that HANNs are scalable and operationally feasible on a global scale.

4-Exploration of Emerging Architectures: Innovative neural network architectures, such as Extreme Learning Machines (ELM) and Long Short-Term Memory (LSTM) networks, along with their hybridization with optimization algorithms like PSO, warrant further exploration. Future research should assess how these advanced techniques can enhance the generalization capabilities of HANNs while addressing issues related to performance variability. Understanding the stochastic behaviors of these models will be essential to improving their reliability in predicting evapotranspiration. Integrating robust evolutionary algorithms into HANNs can also enhance their resilience by reducing overfitting and fine-tuning hyperparameters, thereby boosting their overall predictive stability.

5-Performance Evaluation Metrics: There is a pressing need to expand the set of evaluation metrics employed in HANN studies. Future research should explore the utility of advanced metrics, such as Kling-Gupta Efficiency (KGE), Taylor Diagrams, and Coefficient of Variation (CV), to provide a more holistic evaluation of model performance. These multidimensional metrics will enable a deeper understanding of the strengths and limitations of different models, facilitating more precise comparisons with traditional techniques and ensuring the effective application of HANNs in hydrological contexts.

6-Cross-Disciplinary Collaboration: The challenges surrounding interpretability, computational efficiency, and data requirements highlight the need for cross-disciplinary collaboration between hydrologists, machine learning experts, and data scientists. Collaborative efforts should focus on the development of best practices for the application of hybrid neural networks in water resource management. By leveraging diverse expertise, researchers can design models that are both scientifically robust and practically applicable, leading to solutions that are tailored to address real-world challenges in water management and climate resilience.

7-Climate Resilience and Adaptability Assessment: Future research must rigorously assess the climate resilience of HANNs by simulating diverse environmental scenarios, such as extreme temperature fluctuations, altered precipitation patterns, and increased evapotranspiration rates. Stress-testing these models under dynamic climate conditions will provide critical insights into their stability and robustness. Developing climate adaptability metrics, such as error tolerance scores and climate adaptability indices, will enhance the understanding of how HANNs can support long-term hydrological predictions under fluctuating climate regimes. This research will be essential for ensuring that HANNs can withstand future climate extremes, making them indispensable tools in managing global water resources.

In conclusion, while HANNs present transformative potential for improving evapotranspiration estimation in the face of climate change and water scarcity, significant efforts are required to address issues related to interpretability, computational complexity, and scalability. By advancing these critical areas, the research community can enhance the practical deployment and operational effectiveness of HANNs in real-world applications. Through the integration of cutting-edge optimization techniques, hybridization with novel architectures, and fostering interdisciplinary collaboration, HANNs can be optimized for large-scale deployment, ensuring their applicability in addressing global water resource management challenges.

5 Scope and Limitations of the Research

This research provides a comprehensive bibliometric and systematic review of the application of HANNs for ET estimation, yet several limitations should be acknowledged. These limitations arise from both the methodological approach and the nature of the research domain itself.

1-Database and Search Limitations: The data collection process for both the bibliometric analysis and the systematic review was primarily based on the Scopus and Web of Science (WoS) databases. While these are highly regarded platforms known for their robust coverage of peer-reviewed literature, their scope may not be exhaustive. Studies indexed in other databases, such as Google Scholar, IEEE Xplore, or specialized agricultural or hydrological journals, may not have been captured, potentially limiting the comprehensiveness of the review. Furthermore, some relevant studies might have been excluded due to language restrictions (only English-language studies were considered) or the exclusion of certain document types (e.g., books, reports, or conference proceedings). The limited temporal scope (2004 to October 2023) also means that recent developments or pre-2004 contributions are not fully represented, which may overlook emerging trends and innovations in the field.

2-Search Strategy Limitations: The search strategy employed, while thorough, might have missed specific terminologies or variations in the application of hybrid ANN models in ET estimation. Given the dynamic nature of both machine learning methodologies and hydrological modeling, it is possible that some pertinent studies, particularly those using non-standard hybrid approaches or unconventional terms, were not identified. Additionally, the use of Boolean operators and wildcard characters might have inadvertently excluded some relevant studies due to variations in keyword usage.

3-Subjectivity in Study Selection: Although a rigorous screening process was followed to select relevant studies, the manual review and inclusion criteria involved some degree of subjectivity. Different reviewers might have interpreted the inclusion criteria differently, leading to potential biases in the selection of studies. The three-step process—screening by title, abstract, and full text—was designed to mitigate this issue, but some uncertainty in the classification of ambiguous studies could remain.

4-Potential Bias in Included Studies: The studies selected for the systematic review were limited to peer-reviewed journal articles and conference papers, which may result in publication bias. Papers with negative or inconclusive results may be underrepresented, as they are less likely to be published in high-impact journals or conferences. Additionally, the geographical distribution of the included studies was not fully diversified, with a significant focus on research from regions such as China and Iran. Future studies should aim for a broader inclusion of research from diverse climatic and geographical regions to improve the generalizability of the findings.

5-Scope of Hybrid ANN Models: While this study primarily focuses on hybrid ANN models that integrate artificial neural networks with complementary modeling techniques, it does not explore the full spectrum of machine learning models applied to ET estimation. As the field evolves, new machine learning algorithms, such as deep reinforcement learning or advanced ensemble methods, may provide additional insights that are not covered in this review. The study also did not include hybrid models combining multiple machine learning techniques, such as ensemble methods with deep learning, which could be an interesting direction for future research.

6-Evaluation Metric Limitations: The evaluation of model performance in the selected studies was primarily based on common metrics such as RMSE, MAE, and R^2. While these metrics are widely used, they may not fully capture the complexity of hybrid models or their performance in practical applications. Other performance indicators, such as the Kling-Gupta Efficiency (KGE) or Taylor diagrams, which offer more nuanced insights into model accuracy, were not consistently reported in the reviewed studies. Furthermore, the use of only two or three performance metrics in many studies limits the depth of the evaluation, potentially overlooking important aspects of model performance like model robustness, generalization, and sensitivity to different data types.

7-Data Availability and Quality: Many of the studies reviewed depend on publicly available or open-access datasets for training and evaluating HANN models. However, the quality and availability of these datasets are often inconsistent. Data gaps, such as the lack of high-resolution or long-term data, could impact the generalizability of the findings and the performance of the hybrid models. In regions with limited data, models might be trained on smaller or less representative datasets, which may lead to overfitting or inaccurate predictions when applied to other regions or contexts.

8-Lack of Focus on Interpretability: A significant limitation of many studies in this field is the insufficient focus on the interpretability of hybrid ANN models. Although hybrid models often provide superior performance, their black-box nature presents challenges for understanding how the models make predictions, particularly in complex domains like ET estimation. This lack of interpretability hinders the practical application of these models, especially in fields like water resource management, where model transparency and explainability are crucial for decision-making.

9-Temporal and Spatial Limitations: The reviewed studies were primarily focused on ET estimation in specific geographic regions, such as Asia and the Middle East, limiting the scope of the findings to these areas. The diversity of climatic conditions, data sources, and agricultural practices across regions is critical for the broader applicability of hybrid ANN models in ET prediction. Moreover, the temporal resolution of the data used in the studies might not always be aligned with real-time decision-making needs, especially in water management practices that require timely and accurate ET estimates.

10-Technological and Computational Constraints: Many of the hybrid ANN models reviewed require significant computational resources for model training and optimization, especially when using deep learning techniques. The need for extensive computational infrastructure can limit the scalability of these models in resource-limited settings, where access to high-performance computing (HPC) systems is restricted. Additionally, model optimization, which often involves tuning multiple hyperparameters, can be time-consuming and computationally expensive, further limiting the practical implementation of these models.

6 Conclusion

This comprehensive review outlines the growing use of HANN models in ET estimation, driven by increasing concerns over water scarcity and climate change. An extensive analysis of research from prominent databases such as WoS and Scopus reveals a significant rise in scholarly output over the past two decades, with China emerging as a major contributor. Influential researchers have played a key role in advancing this field, as evidenced by their high citation rates. HANN models stand out for their superior predictive accuracy, improved generalization capabilities, and ability to model the complex nonlinear relationships inherent in hydrological data. The expanding body of literature highlights the versatility of these models in addressing a wide range of hydrological challenges, from real-time ET estimation to assessing the impacts of climate change. The review underscores the growing use of various HANN architectures—such as MLPs, RNNs, and CNNs—often combined with optimization algorithms and fuzzy logic frameworks. These hybrid models excel in capturing intricate nonlinear patterns and temporal dependencies within ET data. Moreover, 352 articles were initially selected from the prominent databases WoS and Scopus for bibliometric analysis, and after applying rigorous eligibility criteria, 35 articles were included for systematic review. Our analysis indicates a significant shift toward the adoption of advanced evaluation metrics, such as KGE and Taylor Diagrams, which provide a more comprehensive framework for assessing predictive accuracy and observational fit. These advanced metrics support the increasing demand for transparency and accountability in performance evaluations, which are especially critical in hydrological applications. Metrics like Ag, Ae, AARE, and TS offer deeper insights into model reliability and efficacy, reflecting the field's commitment to rigorous performance evaluation and continuous improvement. Our keyword analysis reveals a strong focus on water resource management, climate resilience, and drought mitigation, highlighting urgent global challenges. The growing prominence of topics such as ANNs, machine learning methods, and CNNs underscores their vital role in future ET estimation. However, despite the promising potential of HANN models, several challenges remain that require further research. These include computational complexity, model interpretability, and stringent data requirements. Addressing hyperparameter optimization is crucial to enhancing model performance. Further exploration of advanced deep learning architectures and the integration of uncertainty quantification methodologies will provide valuable insights. Notably, the incorporation of CNNs offers innovative ways to enhance ET estimation accuracy by enabling automatic feature extraction from complex spatiotemporal data, aligning well with the dynamic nature of hydrological processes. In conclusion, hybrid HANN models, particularly those incorporating CNNs, demonstrate considerable potential for precise ET estimation in the context of climate change and water scarcity. Their ability to model complex interdependencies and nonlinear dynamics significantly outperforms traditional approaches. The ability of HANN models, especially in predicting reference evapotranspiration (ETo), has direct implications for water resource allocation, particularly in agriculture-driven regions, especially arid and semi-arid zones. ETo data is vital for optimizing irrigation schedules and ensuring sustainable water use—an urgent priority in areas facing severe water shortages. This research provides valuable insights for formulating evidence-based water management policies that align water distribution with crop water needs and seasonal variations. By improving the accuracy and temporal resolution of ETo predictions, these models can support policymakers in resource planning, particularly in scenarios of water scarcity and climate-related stresses. It is crucial to assess the resilience and adaptability of HANN models under different climate conditions. Testing these models under variable climatic scenarios—such as temperature changes and altered precipitation patterns—ensures that they not only maintain high accuracy in ET estimations but also remain reliable under climatic variability. Integrating interpretability techniques such as attention mechanisms, feature importance analysis, and Local LIME can enhance stakeholder confidence in model outputs and foster transparency in decision-making processes related to ET estimation. Overcoming these challenges, while leveraging the strengths of HANN models, will enable meaningful progress in the development of efficient and sustainable water resource management strategies. Ultimately, incorporating accurate and timely ETo predictions into water management frameworks will promote a proactive approach to resource allocation, ensuring the viability and sustainability of agricultural practices even as climate conditions evolve.

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Nomenclature

ET	Evapotranspiration
ET_o	Reference Evapotranspiration
ET_c	Crop Evapotranspiration

MLP	Multilayer Perceptron
ANN	Artificial neural networks
RBF	Radial Basis Function
GRNN	Generalized Regression Neural Network
GMDH	Group Method of Data Handling
HANN	Hybrid Artificial Neural Network
JCR	Journal Citation Reports
SJR	Scientific Journal Rankings
WoS	Web of Science
MCP	Multiple-Country Publication
SCP	Single-Country Publication
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory Network
FFNN	Feedforward Neural Network
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analysis
ACF	Autocorrelation Function
PACF	Partial Autocorrelation Function
PCA	Principal Component Analysis
RMSE	Root Mean Square Error
FFA	Firefly Algorithm
ELM	Extreme Learning Machine
Bi-LSTM	Bi-directional Long Short-Term Memory
MFO	Moth-Flame Optimization
LSSVM	Least square support vector machine
Ag	Average Goodness
AARE	Average Absolute Relative Error
LIME	Local Interpretable Model-Agnostic Explanations
MAE	Mean Absolute Error
R^2	Coefficient of Determination
NSE	Nash-Sutcliffe Efficiency
GEI	Global Evaluation Index
MAPE	Mean Absolute Percentage Error
WI	Willmott Index
EVS	Error variance score
MBE	Mean Bias Error
SI	Scatter Index
RE	Relative Error
L-BFGS	Limited-memory-Broyden–Fletcher–Goldfarb–Shanno
BP	Backpropagation
BPNN	BP Neural Networks
ANFIS	Adaptive Neuro-Fuzzy Inference System
PSO	Particle Swarm Optimization
WOA	Whale Optimization Algorithm
GA	Genetic Algorithm
ACO	Ant Colony Optimization
FA	Firefly Algorithm
GRU	Gated Recurrent Units
DWT	Discrete Wavelet Transform

FNN	Fuzzy-neural network
SPEI	Standardized Precipitation and Evapotranspiration Index
CHS	Calibrated Hargreaves–Samani
GEP	Gene Expression Programming
ReLU	Rectified Linear Unit
WCA	Water Cycle Algorithm
KGE	Kling-Gupta Efficiency
Ae	Average Error
TS	Threshold Statistics
CV	Coefficient of Variation

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