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Artificial Intelligence and Hybrid Optimization Approaches for Potential Evapotranspiration Modeling: A Narrative Review and Future Perspectives

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Abstract

Accurate prediction of potential evapotranspiration (PET) is an important factor in irrigation planning, drought monitoring, and sustainable water resource management. This study presents a Narrative Review of the latest PET modeling studies, focusing on experimental models, artificial intelligence models, and optimized hybrid models. Sixteen studies were analyzed and classified into three main categories: optimized experimental models, standalone AI models, and optimized hybrid AI models. The results show that models such as ANN, RF, XGBoost, LSTM and DNN are able to represent non-linear relationships between climate variables and PET very efficiently. The integration of Meta-heuristic optimization algorithms with AI models also contributes to improving accuracy and fine-tuning of transactions. The study recommends focusing in the future on hybrid models, explainable artificial intelligence (XAI), and verification in multiple climates.

1. Introduction

"Blue gold" is the new name given to water in our modern era, a title that reflects its great value as the most important and sought-after resource on Earth. Water is the most important and essential element for all living organisms as three-quarters of our world is covered in water and the human body is mostly composed of it. However, water availability has become a matter of concern because only about 0.3% of the world's total water resources are suitable for human consumption [1]. Because of this limited availability and the doubling of water use between 1940 and 1980, more than a billion people today lack sufficient drinking water. This crisis is becoming worse due to an annual net increase in the human population of approximately 81,000,000, which drive the global freshwater demand to unprecedented levels [2]. In addition, nearly 70% of water consumption is for the agricultural sector, making it the largest consumer of water and a major contributor to its scarcity worldwide[2]. Today, the world face a true threat where more than 25% of the global population heavily rely on unsustainable groundwater extraction, creating a central point of global conflict and a serious challenge for future sustainability.

To address the global water scarcity crisis, it is first necessary to understand how water is consumed and to know which sectors are putting the greatest pressure on freshwater resources. Potential Evapotranspiration (PET) has become one of the most important hydro-climatic variables used in Water Resources Assessment and agricultural planning [3]. This variable expresses the atmospheric demand for water vapor when water is freely available. Since the agricultural sector consumes almost 70% of the total freshwater withdrawals globally, PET is directly related to estimating agricultural water needs and supporting more efficient irrigation management [3]. PET provides a theoretical indicator of the ability of the atmosphere to evaporate. It is influenced by several climatic factors, among which are air temperature, solar radiation, wind speed, relative humidity. PET therefore plays an important role in irrigation scheduling, drought monitoring, hydrological analysis, and Climate Impact Assessment. Accurate estimation of it also helps planners and water resource managers to understand the relationship between climatic conditions and water demand, which supports more rational water distribution and more efficient agricultural decisions.
Accurate prediction of PET values is becoming more and more important under the acceleration of climate changes, since a change in atmospheric elements may lead to a change in the water needs of crops and an increase in water stress in fragile areas [4]. An inaccurate estimate of PET may also negatively affect the design of irrigation systems, increase water loss, and reduce the effectiveness of adaptation strategies in the agricultural and environmental sectors. Therefore, the development of robust and reliable methods for estimating PET is no longer just a scientific issue, but has become an applied necessity to support the sustainability of water resources, enhance resilience to climate change, and improve management strategies, especially in data-limited environments.

PET research in recent years has seen a clear shift towards data-driven modeling methods [5]. This transformation has been accompanied by the rapid expansion of the use of Machine Learning models (ML) and hybrid frameworks combining Artificial Intelligence (AI) technologies and advanced optimization algorithms [6]. The volume of scientific literature has also increased significantly, in particular during the period from 2020 to 2025, which reflects the growing research interest in PET modelling using AI techniques [7].

The main goal of this study is to make a detailed narrative review of PET estimation techniques. This review includes compilation and evaluation of 3 different modeling approaches: OEM, SAI and OH-AI using Meta-heuristic algorithms. By having a rigorous screening process for input variables and performance metrics, this research manifests the intent of identifying modeling structures that actually have the highest precision for water resource management. In addition, through the identification of research analysis of the collaborating networks, common keywords and themes are outlined, the study reveals important information to the relevant designers and security practitioners and thus aids future developments and innovation in the critical area. To overcome gaps that have been found in the literature, this study provides the following main contributions:

1- It serves as a coherent integration of the traditional OEM approaches, the emerging SAI models and the advanced OH-AI methods, and creates a clear classification that fills the gap between the traditional and data-driven modeling.
2- In contrast to other reviews, this study examines research with multi-source data, such as ground station and satellite imagery data and field measurements, which covered a strong evaluation when they were under data constraint conditions.
3- We follow a strict process to analyses input variables and evaluation metrics to find the best modelling strategies.
4- The study highlights new prospects for future research in the field of predicting PET, including the integration of explainable Artificial Intelligence (XAI) and the incorporation of novel Meta-heuristic Optimization algorithms not previously used.

2. Literature Review

While past reviews have helped push the analysis forward, they tend to focus on isolated points across the modeling landscape. As summarized in Table 1, current reviews have certain limitations in terms of scope and methodology. Amani et al. [8] explored only the remote sensing and ML limitations with no integration of physical formulations and optimized hybrids. Wanniarachchi & Sarukkalige [3] made a review on agricultural management with no systematic evaluation of AI based Meta-heuristic. Similarly, the sources of uncertainty took precedence with Ezenne et al. [9] over a structured synthesis of modeling patterns. While Taheri et al. [10] and Tosan et al. [11] treated AI interpretability and hybrid ANN frameworks, respectively, their scope was still limited to a certain AI architecture. Notably, Khairan et al. [12] set their sights on meta-heuristic optimization, whereby they had their way strictly to ETo without considering the full PET spectrum. This review establishes a clear and integrated classification to bridge the gap between traditional formula and advanced data-driven modeling.

Table (1): Comparison between the previous studies and the present study

Comparison criterion	**Amani & Shafizadeh-Moghadam (2023)**	**Wanniarachchi & Sarukkalige (2022)**	**Ezenne et al. (2023)**	**Taheri et al. (2025)**	**Tosan et al. (2025)**	**Khairan et al. (2023)**	**This review (ours)**
Comprehensive review *(Phys&SAI&OH-AI)*	✗	✗	✗	✗	✗	✗	✓
focus on PET *(not ETo-only)*	✓	✓	✓	✗	✗	✗	✓
Data sources coverage *(Sta + RS + Field)*	✗	✓	✓	✗	✗	✗	✓
Systematic screening *(criteria + counts)*	✗	✗	✗	✗	✓	✓	✓
Study-level extraction *(Inputs + Metrics + Best)*	✗	✗	✗	✗	✓	✓	✓

The diversity of current reviews shows a critical gap, as there is no comprehensive synthesis that takes OEM, SAI, and OH-AI together from various data sources at the same time. Most previous surveys concentrate on a single modeling modality or on a specific variable ETo without taking into account the PET estimation with the aid of multi-source data (ground stations, remote sensing, and field measurements). A narrative review is thus needed to fill the gap between traditional formulas and advanced data-driven modeling in order to provide a common classifier to correct interpretations and provide meaningful comparisons among studies.

3. Methodology

This research focuses mainly on the prediction and modeling of PET values. The review includes three categories of studies, namely: OEM, SAI and OH-AI. Studies that did not apply any of these methods in the context of PET estimation were excluded. In addition, the scope of the review was limited to articles published in English. Figure 1 summarizes the study selection process adopted in this review. Total of 82 records were initially identified through searches across multiple scientific databases. After removing duplicate records and screening titles and abstracts, 28 full-text articles were assessed for eligibility. Based on the predefined inclusion and exclusion criteria, 16 studies were finally included in this narrative review.

3.1 Information Sources

The scientific articles reviewed in this study were collected from reputable academic databases and digital libraries. Major sources included Science Direct (Elsevier), IEEE Explore, Springer Link, MDPI, Wiley Online Library, and Taylor & Francis. These platforms have been chosen because they provide extensive coverage of both environmental science and AI applications. The aim of relying on these sources was to provide a comprehensive picture of the reality of scientific research in this field, by making use of a wide range of relevant publications.
The selected databases were chosen because they provide broad coverage of peer-reviewed studies in hydrology, environmental sciences and AI.

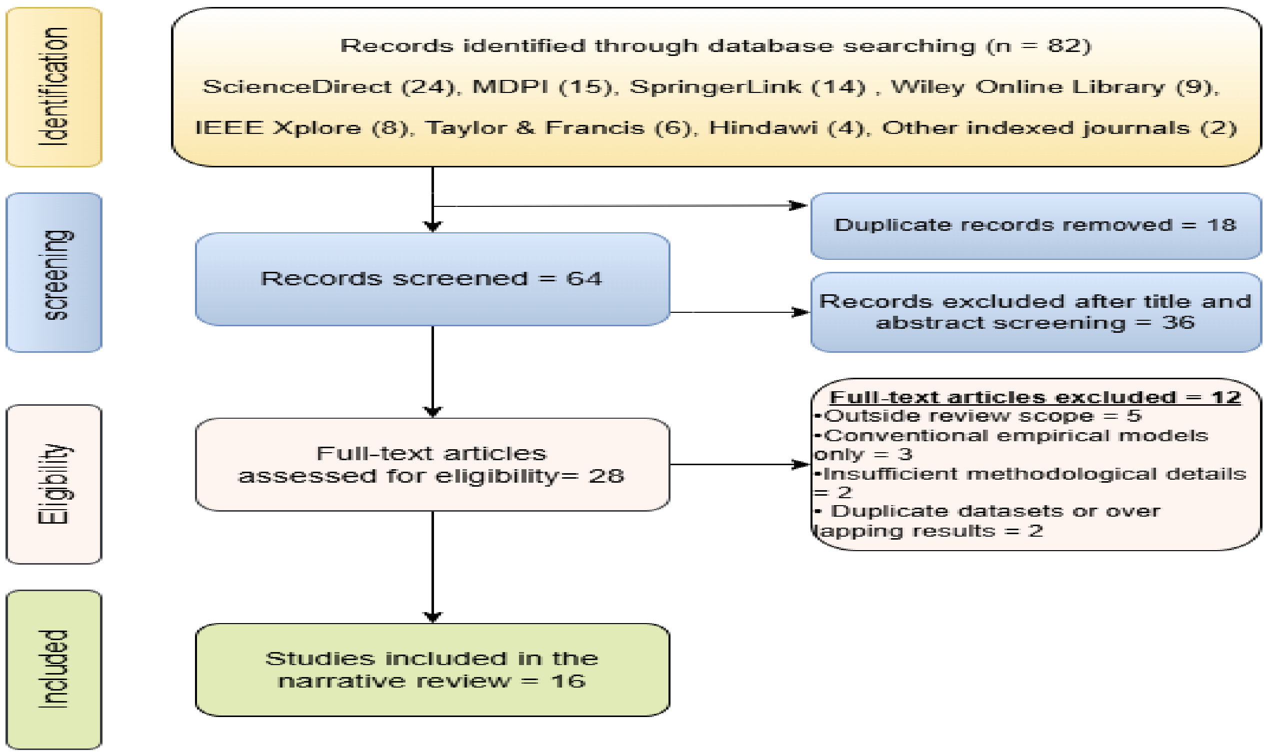

Figure (1): PRISMA-inspired flow diagram of the selection study process

3.2 Search Strategy

The research process started in November 2025 based on the previously mentioned academic databases. A set of appropriate keywords was used to identify studies related to PET prediction and AI techniques. The search keywords included terms such as: “potential evapotranspiration”, “PET”, “artificial intelligence”, “AI”, “meta-heuristic optimization”, “machine learning”, “deep learning”, “ML”, “DL”, “swarm”, and “hybrid models”. Boolean operators, mainly “OR” and “AND", were also used to build flexible and comprehensive search phrases. The research was limited to articles written in English and published in recognized scientific journals or in the Proceedings of scientific conferences. Figure 2 illustrates the temporal distribution of the studies included in this review between 2020 and 2025.

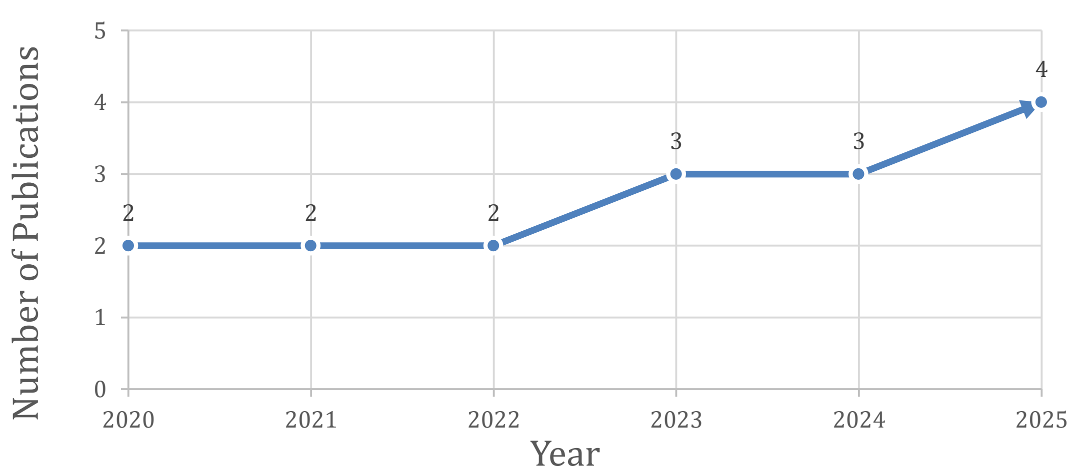

Figure (2): Temporal distribution of the studies included in this review (2020-2025).

As show in Figure 2, the number of eligible studies increased in recent years, indicating growing research interest in AI-based PET modeling.

4. Literature analysis

This section covers studies related to PET, including their publication year, geographical location, and all related details. It also includes an analytical study of these papers.

4.1 Main Information

Table 2 summarizes the main information of the selected 16 studies, including study region, data period and temporal scale, input variables, AI models, meta-heuristic optimizers, and the best-performing configuration with the adopted evaluation metrics.

Table (2): Summary of the Selected PET Studies.

Ref.	Location	Size of data	Predictors	Models Used	Best Model	Highest Accuracy
[13]	Philippines	2021	Tmin, Tmax, Ta, RH, U2, SD, dT, VPD, Rn	HG, HamonV1, Penman, PM with GA, GWO, MFO, BWO, SSO	SSO-Penman	MAE=2.5e-6 deviation=3.08% error=0.51
[14]	Philippines	2022 90 days	N, Tm, I, α	TW, ASO-TW, DE-TW, MVO-TW	ASO-TW	PETTh-mod=6.420×10^{-3}
[15]	India	2012-2021	P, Tmin, Tmax, RH, WS, SR, DEM, LU-LC, Soil	SWAT, SWAT-CUP(SUFI-2), NSGA-II	SWAT-CUP(SUFI-2)	R^2=0.510,r=0.714, NSE=0.320
[16]	Indonesia	2001-2020	Elev, T, NDVI, MODIS-16 PET	MODIS-16(PM-based), ANN-MODIS-16(PMbased), ANN	ANN-MODIS-16	r=0.94, MAE=11.60, RMSE=14.41, NRMSE=7.72%
[17]	Brazil	1984-2017	Tmax, Tmin, Tmean	ANN (MLP)	ANN (MLP)	R=0.959, R^2=0.920, RMSE=0.327, MAE=0.298, MAPE=37.793%
[18]	South Korea	2019-2021	RSR, DSR, ASR, OLR, DLR, ULR, NDVI, SPI6, Ta, Ts, RH, WS, ESR, DEM	ANN (MLP)	ANN (MLP)	RMSE=0.649 , R=0.954, bias=−0.134
[19]	Indonesia	2018	Tavg, RH, P, E, WV, SR	ANN	ANN	R=0.875, MSE=1.731
[20]	China	1960–2014	PET(t−1…t−240)	BPNN, LSTM	LSTM	R^2=0.93, NSE=0.90, RMSE=8.57, MAE=6.54, MAPE=9.87%
[21]	China	1969–2018	Tmean, Tmax, Tmin, RH, n, uz	SVR, RF, ELM; HS, PT, PM; FAO-PM (ref)	RF	PBIAS=−1.05, AICc=−2.13
[22]	Turkey	1979–2021	Tmean	CNN, SVM, RF	RF	R^2=1.000, MSE=0.326, RMSE=0.571
[23]	South Korea	2010–2024	Tmax, WS, Tmin, Tavg	DNN, LSTM	DNN	RMSE=0.3082, NSE=0.8600, CC=92.74%, PBIAS=−2.0630%

Ref.	Location	Size of data	Predictors	Models Used	Best Model	Highest Accuracy
[24]	Turkey	1964–2017	Tmean, Tmax, Tmin, RHmean, Psum, WSmean, WSmax	XGBoost, GBM, RF, BT, DL	XGBoost	R^2=0.9844, RMSE=6.5434, MAE=5.2812
[25]	Greece	2012–2023	Tmean, Tmin, Tmax, RHmean, RHmin, RHmax, Ra	SVR, RFR, GBR, KNN	RFR	R^2=0.917, RMSE=0.468, MAPE=0.119
[26]	Turkey	1983-2020	T, RH, WS, P, Rs, SH, G	ANFIS, ANFIS-SO, DBN	DBN	R^2=0.99, R^2adj=0.99, NSE=0.99, WI=0.99
[27]	Malaysia	1987-2003	Tmean, Rs	MLR-ET, MLR-PSO	MLR-PSO	R^2 = 0.993
[28]	China	1958-2019	Tmax, Tmin, RH, U10, SD	ELM-GWO, ELM-SSA, MLP-GWO, MLP-SSA, RF-GWO, RF-SSA	ELM-GWO	R^2 = 0.980

4.2 Optimized Empirical Models

A few portions of the literature look at studies that aim to link traditional physical modelling with modern optimization techniques. In this field, the attention is on improving the accuracy of empirical equations without move to AI architecture. These models maintain the basis physical structure. For example, Penman, Hargreaves and Thornthwaite. the Penman method combine energy balance and mass transfer which make it very reliable for PET estimation[29]. Hargreaves equation is simpler alternative it only needs max and min temperature and radiation data[30]. the Thornthwaite model use monthly average temperature and day length to estimate water loss[31]. All these methods is useful for different climate study depending on what data actually existing. Also, applying meta-heuristic optimization algorithms to adjust their parameters to fit local climatic conditions.

Extended Mendigoria et al**.**[13] The idea of optimizing equations. Across multi PET formula such as **(**Hargreaves, HamonV1, and Penman**)** by use bio-inspired optimizer (GA, MFO, GWO, BWO and SSO). This algorithm used to find optimal meteorological parameter settings. While Penman-Monteith used as a benchmark, noted the MAE is near-zero for swarm methods and highlighted SSO-penman as best (MAE = 2.5×10^{-6}). This mix of meta-heuristic algorithms with traditional empirical models very improved the accuracy of PET estimate. Daily dataset of a volume of 365 records in 2021 in the Philippines was used. And the predictors were T_{min}, T_{max}, Ta, RH, U2, SD. Beyond that, Concepcion et al**.**[14] use Atom Search Optimization (ASO) algorithm, Differential Evolution (DE) and Multiverse Optimizer (MVO) to develop optimized version of the Thornthwaite PET formula for controlled *Carica papaya in* Philippines. Among the tested handling, the ASO-optimized Thornthwaite setting showed the strong plant responses, providing more precise irrigation requirements for papaya cultivation in controlled environments across replicated 90-day experiment in 2022. In much the same way, some researchers focus on enhancing complex physical models. Best model was ASOTh with results N=10.033, Tm=31.664, I=14.100, $\alpha=-5.528$ and PETTh-mod=6.420×10^{-3}.Among them, Archana K. et al. [15] that use Non-dominated Sorting GA II (NSGA-II) to optimize the outputs of the SWAT model, leading to best water resource management in semi-arid regions. The period of dataset that used to estimate PET was daily data from 2012 to 2021 in India. SWAT-CUP(SUFI-2) was the best model and achieved R^2=0.510, r=0.714 and NSE=0.320.

4.3 Standalone AI models (SAI)

AI models used in hydrological research by depend on the AI algorithms to identify complex patterns [32]. This done without the need any pre-defined physical structure or meta-heuristic optimizers. They work like systems based on data that focus on empirical evidence instead theoretical assumptions**.** These architectures excel at processing high-dimensional datasets from satellite remote sensing and meteorological networks. It's provided a scalable and flexible framework that can steady under change climatic conditions where traditional equations often fail. This provides a powerful alternative that overcomes the drawbacks of classical modeling. The following is explanation the papers that used many AI algorithms such as RF, ANN, and other to predict PET.

Astuti et al. [16] used an ANN to predict MODIS-16 PET to better match ground-station PET in Indonesia. The dataset was monthly data collected from 2001 to 2020.The best ANN setting used a 70:15:15 split. Levenberg-Marquardt training, and two hidden layers. The best input was native MODIS-16 PET and temperature from MODIS LST). The highest performance was r = 0.94, RMSE = 14.41 mm, NRMSE = 7.72% and MAE=11.60 mm. this result show major improves in reduced the exaggeration that shown in result before use ANN. Likewise, Meneses et al. [17] estimated daily Penman-Monteith PET in Brazil. Using 34 years of daily data from 1984 to 2017. They developed ANN based on a Multi-Layer Perceptron (ANN-MLP) to predict daily PET using air-temperature inputs only. The best architecture was MLP 2-5-1. The model achieved high result was r = 0.959 and R^2 =0.920, with low errors RMSE =0.327 mm day, MAE = 0.298 mm. They concluded ANN-MLP is effective for estimating PM-based daily PET in the region. Also, Jang et al. [18] are developed an ANN-based (optimized MLP) approach to estimate daily PET in South Korea. This done by use geostationary satellite variables, passive microwave composite data, numerical weather prediction data and static ancillary layers. The model use station-based Penman-Monteith PET from KMA ASOS from 2019 to 2021. Compare the reference PM-PET, the model achieved RMSE = 0.649 mm and bias = −0.134 mm, R = 0.954, and IOA = 0.975. The study note that the ANN-derived PET surpassed on Terra/MODIS PET over the same region. This superiority was due the use of ANN-MLP model. Nusantara and Nadiar [19] used an ANN model to predict daily PET in a tropical region of Indonesia. The target PET values computed using the Modified Penman method. These studies use daily 2018 climate data from BMKG Juanda station. The Predictors was temperature (Tavg), wind velocity (WV), rainfall (P), relative humidity (RH), evaporation (E), and solar radiation duration (SR). They implemented the ANN model with a 70-15-15 for train-validation-test split. By testing 6-input MLP with hidden single layer. The best model was 6-5-1. Result validation was MSE = 0.305 with R = 0.981 and testing R = 0.875, overall R = 0.903. Then compared this best 6 input model with multiple 5 input models (removing one variable in each time) to identify the most influential variables. The rank of importance (descending) was WV, RH, SR, Tavg, P and E.

Jiang et al. [20] studied the Three-River Headwaters Region in China. They built predictive AI time-series models to forecast monthly PET. They used dataset from 14 stations from 1960 to 2014. They compared two ML predictors. Back-Propagation Neural Network (BPNN) and an LSTM network to predict monthly PET to next 30 year. The LSTM was tuned by 240 input nodes and two hidden layers with Adam optimizer. Based on the result that show, LSTM was achieved R^2 =0.93, NSE = 0.90, MAE = 6.54, MAPE = 9.87%, and RMSE = 8.57, higher than BPNN which achieved NSE = 0.89, MAE = 6.76, MAPE = 10.76% and RMSE = 8.89. therefore, LSTM is the best model in this study.

Liu et al. [21] develop 3 ML models, it was SVR, RF, and extreme learning machine (ELM). To predict daily PET in the Yellow River Basin in China. The study used FAO-PM PET as the reference target and daily station meteorological data from 115 stations during the period 1969-2018. They tested 4 input scenarios. Each scenario contains number of input different from other scenarios. They concluded that Scenario 2 which includes T_{mean} and sunshine hours (n) is the best and most practical setup. Where it achieved a median KGE bigger than 0.82 across the 115 stations. Generally, RF was the best model, especially when using two or more inputs. It is showed the strongest stability in Scenario 2 with a lower RMSE-change sum (12.51) compared with SVR (18.37) and ELM (20.23).
As well, Hasan and Yuce [22] predicted monthly PET for the Murat River Basin in Turkey. That was first used computing PET with the Thornthwaite equation and then training AI models. Three models used CNN, SVM, and RF. The dataset was collected from 28 meteorological stations during the period 1979-2021. They used the trained models to estimate PET for the next 42 years. The best model was RF. It achieves R^2 = 1.000 (100%) across the sub-basins, with MSE = 0.326-0.640 and RMSE = 0.571–0.800. In contrast, the CNN model achieves R^2 = 96.2-98.7%, RMSE = 0.541-0.649 and SVM achieve R^2 = 94.5-95.6%, RMSE = 0.990-1.014.

Lee et al. [23] proposed an explainable AI framework to estimate daily PET for ungauged regions in South Korea. Daily meteorological data collected during the period 2010-2024 was used. They trained two models (DNN and LSTM) and used SHAP to quantify the contribution of each meteorological variable and to design scenarios that work with limited-data conditions. The best model was the DNN in Scenario 6, where achieved RMSE = 0.3082, NSE = 0.8600, CC = 92.74%, and PBIAS = −2.0630. SHAP highlighted the T_{max} and average wind speed as the most effective predictors.

Akar et al. [24] predicted monthly PET in Turkey. This done using monthly meteorological data from 1964 to 2017. They compared several tree-based algorithms: XGBoost, GBM, RF, and Bagged Trees with custom DL model. Temperature, humidity, precipitation, and wind variables with split 70 train – 30 tests were used. Authors concluded that use all available Predictors is the most effective overall, and that XGBoost provides the best overall performance. The results show the strongest XGBoost performance reached R^2 = 0.9844 and RMSE = 6.5434, and MAE = 5.2812, this reinforces the importance of XGBoost in overall assessment.

Stefanidis et al. [25] investigated if the data-poor meteorological conditions could support daily PET prediction in forest in Central Greece. Were used four ML regression, SVR, Random Forest Regression (RFR), Gradient Boosting Regression (GBR), and K-Nearest Neighbors (KNN). RFR used limited data, temperature, relative humidity, and solar radiation (Ra), daily dataset between 2012-2023. FAO-56 Penman-Monteith (PM) PET was used as the reference target to training and testing. The best-performing was RFR, which achieve R^2 = 0.917, RMSE = 0.468, and MAPE = 0.119. This result indicates the RFR is strong model that can perform PET prediction under limited data conditions.

4.4 Optimized Hybrid AI models (OH-AI)

The evolution of meta-heuristic algorithms dates back for early stages of computational optimization at the 1960s, when evolutionary principles such as GA and Simulated Annealing were proposed to handle complex non-linear problems exceed the capability of classical mathematical methods [33]. In the 1990s, the research interest shifted toward population-based and nature-inspired paradigms, giving rise to swarm intelligence [34] .Over the past two decades, meta-heuristics have varied rapidly, It included physics, chemistry, social behavior, and human cognition.More recently evolving into hybrid frameworks that integrate multiple search mechanisms for improved robustness and convergence speed [35]. In modern scientific research, meta-heuristic algorithms have acquired remarkable significance because of their versatility, scalability, and problem-independent nature [33], [34].They are extensively used for feature selection, model optimization, scheduling, engineering design, and other tasks. The following section below well describe studies that used the OH-AI model.

Akiner and Ghasri,[26]. compared DBN, ANFIS and ANFIS-SO for predict daily PET in Antalya, Turkey. This research used a huge record from 9 stations during 1983 to 2020, and the data was split to training (1983-2009) and testing (2010-2018) and unseen part (2019-2020). For hybrid model, they used Snake Optimizer (SO) to tune ANFIS parameters. The results show that ANFIS-SO was better than normal ANFIS, reaching R^2 between 0.94 and 0.99. But, the Deep Belief Network (DBN) was the best model overall. It reached R^2= 0.99 and NSE = 0.99 across all stations. Finally, they recommended DBN because it outperformed other models and hybrid variants for PET prediction in this province.

Ahmad, et al. [27] utilized the Multiple Linear Regression (MLR) algorithm optimized with PSO to develop a novel hybrid model for estimating PET in Peninsular Malaysia. the dataset was daily meteorological begin from 1987 into 2003 for 17 years. The study proved the temperature and solar radiation is key inputs also evaluated many PSO configuration with the FAO Penman-Monteith index. The results show the MLR-PSO model surpass in difference explanation achieving R^2 range from 0.942 to 0.993. especial in the South region the model reached its peak performance with R^2 was 0.993 and RMSE of 0.14 and a percentage error (PE) as low as 0.4 %. The study concluded that the MLR-PSO hybrid provides a high reliable and data-efficient alternative for PET estimation in data-scarce tropical regions.

Pei, et al. [28] evaluated ELM, MLP, and RF models for estimating daily PET in the Source Region of the Yellow River Basin (SYRB) using 134,728 daily records (1958–2019) from ten meteorological stations of the China National Surface Weather Station dataset. Data from seven stations were used for training and validation and three (Xinghai, Dari, Maqu) for independent testing. Four statistical metrics: R^2, RMSE, MAPE, and PBIAS were used to assess the model's performance. Two meta-heuristic optimizers, GWO and SSA, were applied for hyper-parameter tuning across ten input combinations derived from T_{max}, T_{min}, RH, U10, and SD, with FAO-56 Penman-Monteith serving as the reference equation. The ELM-GWO model achieved the highest accuracy, achieving $R^2 = 0.995$ on validation and $R^2 = 0.980$ on testing in Scenario 1 (T_{max}, T_{min}, RH, U10, SD). Scenario 2 (T_{max}, RH, U10, SD) and Scenario 5 (T_{max}, RH, U10) also performed strongly with R^2 values of 0.976 validation, 0.955 test and 0.973 validation, 0.957 test, respectively. The ELM-GWO model also maintained superior stability when inputs were reduced, remaining above $R^2 = 0.76$ even for the two-variable case (T_{max}, RH). Overall, the GWO-optimized ELM model demonstrated the most reliable and computationally efficient PET estimation across all scenarios in the SYRB region.

5. Critical analysis

Based on the analysis of the 16 reviewed studies, the studies were divided into 3 groups. 1st section was OEM, and their number was 3, 2nd section was SAI and their number was 10, and 3rd section was OH-AI and their number was 3. The main contribute of all OEM studies examine classical PET equations to local climatic conditions and enabling PET estimate with limited input availability. And their primary gaps is don't use data-driven learning, which limit adapt and transferability the domain. The SAI studies improved PET and ET estimation accuracy using ML or DL models with either meteorological or remote-sensing inputs. They often show gaps related to limited external multi-climate validation, inconsistent benchmarking across baselines, and insufficient interpretability While OH-AI models have made significant contributions to the field of PET prediction, each study has combined an AI model with a Meta-heuristic optimization algorithm, resulting in higher prediction accuracy and better parameter adjustment. OH-AI models achieved the best overall performance by integrating AI models with Meta-heuristic optimization algorithm, resulting in improved prediction accuracy and parameter optimization. These models generally involve higher computational complexity and require repeated optimization runs to ensure stable and reliable results. Overall the reviewed studied indicate clear shift from empirical method toward AI-driven and hybrid approaches, highlighting OH-AI models as the most promising direction for future PET prediction.

6. Challenges

This Narrative review provides a comprehensive overview of methods for estimating PET, however, some limitations of this review should be noted. Firstly, the scope of the search included six main databases (Science Direct, IEEE Xplore, Springer Link, MDPI, Wiley, and Taylor & Francis) and published only in English, which means that there may be directly related studies that were excluded because they were written in other languages. Secondly, the timeframe for the selected studies is limited to the period from 2020 to 2025 and focuses primarily on the latest developments. Finally, although we analyzed 16 studies in detail, the scope focused more specifically on AI and AI models optimized with Meta-heuristic algorithms. This means that some conventional empirical and traditional statistical models were not fully covered, and there may be other studies that have used these models. These limitations provide a clear direction for researchers to expand the scope of their research further in the future.

7. Future perspectives

From the literature reviewed here, many future directions as show in Figure 3, can help make PET modelling more reliable and useful to real applications. Several needs are methodological, and some are data-related. Both are important. For example, Mendigoria et al. [13] focused on bio-inspired optimizers are random, so repeated runs and strong checks are important to avoid unstable "best" solutions. Another key point is PET variable is high location-dependent, which means that models should be tested in other regions and climates before drawing broad conclusions. As the researchers suggested increase ET prediction by add rainfall and water availability to support water-balance decisions. In the SAI side, Jatava et al. [36] suggest evaluate model performance at different climatic conditions and across crop growth stages. Because stage-wise accuracy is critical for irrigation decisions and water resources management. They also point out that data availability can limit practical use, so future work should examine how models behave when not available high-quality inputs or instruments. Ahmad et al. [27] used FAO-PM outputs as a benchmark because direct PET notice was not available. Which makes field-based test a clear next step. They also note that PSO has no general optimal control settings, so stability studies that tune PSO parameters systematically are still need. Also, this review allows us to summarize some future perspectives:

1. Validate PET models across multi-climates and new sites, not only in one region, to test generalization.
2. Improve reliability of optimization-based models by examine optimizers multiple times, report strengths and avoid the result that achieved only once.
3. Suggest a novel Meta-heuristic algorithm such as Robust adaptive Arithmetic Optimization Algorithm (RaAOA) to coupling with AI models (e.g., ANN) to estimate the PET value.
4. Incorporate Explainable Artificial Intelligence (XAI) techniques, namely SHAP, that interpret the model outputs to providing transparency and understanding of the factors affecting the prediction. XAI techniques used to increasing the interpretability of prediction models with the developed PET values. Although ML models and optimization-based hybrid models can achieve high predictive accuracy, the decision-making method within these models is not always immediately obvious. Therefore, SHAP used to show how much each input variable contributes to the final prediction
5. Combine hybrid Meta-heuristic algorithms (two or more algorithms) with AI models to improve PET prediction accuracy.

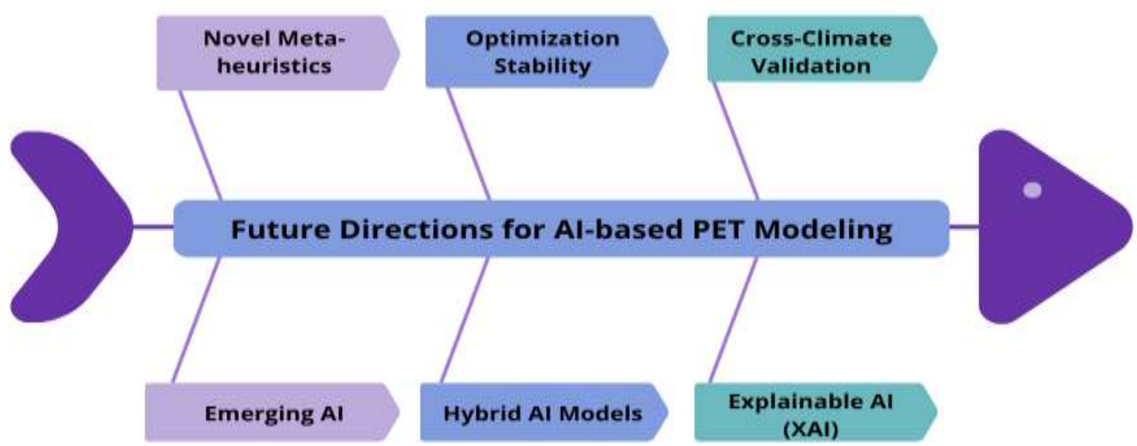

Figure (3): Fishbone diagram illustrating future research perspectives for PET modelling.

8. Conclusion

This Narrative review provides the comprehensive view of the current state of modeling and forecasting PET for the period from 2020 to 2025. 16 carefully selected scientific studies were studied and analyzed using the PRISMA inspired protocol. The narrative review classified the methodologies used to three main method: 1st OEM, 2nd SAI models, and 3rd OH-AI. The result shows the optimized empirical models remain high value because their ability to maintain the physical meaning of hydrological processes, accuracy of (OEM) increases significantly when combining with meta-heuristic algorithms to adjust for local climatic parameters. When examining (SAI) models, the advantage of use framework such as LSTM and RF becomes quite clear in processing complex non-linear and high-dimension satellite-derive data. The LSTM model produce high stable forecasts in monthly and daily data because it temporal memory cells. For the (OH-AI) methods, the development involved creating hybrid models. The mix of swarm intelligence algorithms, such as PSO, has result models that outperform standalone counterparts in terms of accuracy and interpretation of statistical variance. These hybrid models represent an advance approach that addresses the challenges of limit climate data and high levels of environmental variability. The study concludes that the future work of PET forecasting involves in development multi-objective, adaptive hybrid systems and integrating XAI techniques to ensure accuracy and transparency in water resource management. To effectively manage water resources, these methods play a necessary role for fine-tuning irrigation requirements and boosting resilience to harsh climatic conditions in arid and semi-arid regions. This research suggests toward researchers to focus on addressing the gaps in current models by explore more flexible optimization algorithms and combine more climatic variables to improve long-term forecast consistent performance.

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