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Review

Parameter Optimisation-Based Hybrid Reference Evapotranspiration Prediction Models: A Systematic Review of Current Implementations and Future Research Directions

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Abstract: A hybrid machine learning (ML) model is becoming a common trend in predicting reference evapotranspiration (ETo) research. This study aims to systematically review ML models that are integrated with meta-heuristic algorithms (i.e., parameter optimisation-based hybrid models, OBH) for predicting ETo data. Over five years, from 2018–2022, the articles published in three reliable databases, including Web of Science, ScienceDirect, and IEEE Xplore, were considered. According to the protocol search, 1485 papers were selected. After three filters were applied, the final set contained 33 papers related to the nominated topic. The final set of papers was categorised into five groups. The first group, swarm intelligence-based algorithms, had the highest proportion of papers, (23/33) and was superior to all other algorithms. The second group (evolution computation-based algorithms), third group (physics-based algorithms), fourth group (hybrid-based algorithms), and fifth group (reviews and surveys) had (4/33), (1/33), (2/33), and (3/33), respectively. However, researchers have not treated OBH models in much detail, and there is still room for improvement by investigating both newly single and hybrid meta-heuristic algorithms. Finally, this study hopes to assist researchers in understanding the options and gaps in this line of research.

Keywords: reference evapotranspiration; hybrid model; machine learning; meta-heuristic algorithms; systematic review

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1. Introduction

Water has been termed "blue gold", and it will undoubtedly be a major problem in the twenty-first century [1]. Fresh water supplies for agricultural production are becoming less abundant, necessitating the urgent need to manage scarce water resources effectively while raising agricultural productivity [2]. The hydrologic cycle is dominated by evapotranspiration (ET), which returns almost 60% of the yearly precipitation that falls on the earth's surface back to the atmosphere [3]. Reference evapotranspiration (ETo) is made up of the transpiration and evaporation processes. Evaporation is the process by which water flows from the earth's surface to the atmosphere, whereas transpiration is the action of plant roots taking water from the root zone and moving it to the leaves, where it is then expelled through the stomata [4]. Additionally, it is measured as the amount of water lost from a surface that is covered in grass or alfalfa that is in an active growth stage, has a uniform height, a leaf area index of about three, is not subject to water restrictions, and has a fetch that is sufficiently large and well-irrigated to reduce advection towards the experimental area [5]. To date, the Penman–Monteith (FAO-56 PM) model has been the most extensively used empirical model to estimate ETo after being endorsed by the United Nations Food and Agricultural Organisation [6]. However, the FAO-56 PM model has a major drawback as it requires a lot of climatic variables, and automatic weather stations can also be costly and time-consuming to install and maintain [7–10]. As a result, this model has not been widely adopted, especially in developing nations [11]. However, machine learning is one of the most active solutions [12].

In recent years, the most popular technique in hydrology modelling has been machine learning, an artificial intelligence approach that aims to provide machines with a decision-making capacity. Furthermore, it has a high degree of accuracy and precision in predicting variables while being quick and inexpensive to implement [13]. Researchers have made significant efforts to model ETo using machine learning algorithms, e.g., artificial neural networks (ANN) [14], adaptive neuro-fuzzy inference systems (ANFIS) [15], random forests (RF) [16], support vector machines (SVM) [17], and extreme learning machines (ELM) [18]. It was also shown that these models had a good ability to model ETo data in various climates [19]. However, machine learning techniques have several drawbacks, such as a slow convergence rate and the issue of easily slipping into local minima [20]. Recently, hybrid modelling has advanced machine learning, allowing for the continued improvement of standalone models to achieve more promising accuracy [6]. For example, Maroufpoor, et al. [21] developed a hybrid technique that depends on the ANN approach and the GWO algorithm for ETo estimating. They discovered that the new hybrid ANN-GWO technique performed better than the single ANN model. Likewise, Tao, et al. [22] established a hybrid ANFIS-FA model for predicting daily ETo, and found that the hybrid ANFIS-FA model was superior to the standalone ANFIS model. According to Hajirahimi and Khashei [23], hybrid techniques can be categorised into many groups; this study focused on parameter optimisation-based hybrid models (OBH), which incorporate two or more techniques, one of which serves as the main model and the other as a pre-or post-processing [24]. Machine learning models have been combined with meta-heuristic optimisation algorithms [8], which, in a later section, will be classified and analysed. Therefore, one of the most important objectives of the study is to clarify the uses of the hybrid model.

On the one hand, the primary goal of this paper is to provide valuable insights into the hybrid techniques used in ETo forecasting. Particularly those that combine machine learning with meta-heuristic algorithms. Furthermore, this study aims to identify the most commonly used methods and determine the best ones. Moreover, it supports researchers by understanding the obtainable options and gaps in this line of research. Furthermore, it aims to shed light on the efforts of researchers in this field and map the research landscape into a coherent taxonomy. On the other hand, the previous reviews rarely touched on this aspect. For example, Krishnashetty, et al. [25] carried out a review of cognitive computing models used for the estimation of ETo by comparing only three models (ANN, SVM, and GP). While Jing, et al. [26] reviewed the implementation of evolutionary computing models to estimate ETo from 2007–2019. Finally, Raza, et al. [4] conducted a search for research articles in the Google Scholar Database only.

In this regard, the contributions of this paper can be presented in advance as the following list: (1) A coherent taxonomy of meta-heuristic algorithms based on their inspired theories will be presented; (2) the role of these algorithms will be emphasised in enhancing the accuracy of prediction results; and (3) the results of applying these algorithms in previous studies will be discussed and illustrated, including the most popular and effective types, as well as make some suggestions for future research. (4) The study's recommended taxonomy of the relevant literature also has important implications. (5) This investigation pinpoints prospective research avenues, has the ability to reveal research gaps, and provides a map of the academic literature on meta-heuristic algorithms for reference evapotranspiration.

The rest of the paper is organised as follows: Section 2 describes the methodology. Section 3 presents the details and results from this study's final set of publications. In Section 4, the discussion is presented. In Section 5, a bibliometric analysis was used.

Section 6 contains the most important recommendations. Finally, the conclusion of this review is presented in Section 7.

2. Methodology

The most significant keyword in the scope of this article is "reference evapotranspiration". This section excludes any paper in which meta-algorithms have not been used in ETo forecasting. Furthermore, the scope is restricted to the English literature.

2.1. Information Sources

To conduct the search for relevant articles, we used three online resources: (1) ScienceDirect, which provides access to scientific and technical literature; (2) IEEE Xplore, which houses technological and engineering literature; and (3) the Web of Science (WoS) service, which indexes studies from a variety of scientific fields. The goal of this selection was to present a comprehensive overview of the state of research in this area by drawing from a wide range of relevant publications.

2.2. Study Selection

Finding the relevant studies required a search of the relevant literature sources, followed by two rounds of screening and filtering. After removing any duplicates and unrelated articles from the findings by screening their titles and abstracts, the remaining articles were subjected to a more in-depth screening process that included reviewing the complete texts of the articles that had passed the first screening.

2.3. Search

Research began on the first of July 2022 in the ScienceDirect, IEEE Xplore, and WoS databases via their search boxes. A mix of keywords were used that contained "machine learning", "neural networks", "optimisation", "hybrid", "meta-heuristics", "tune", "tuning", and "reference evapotranspiration" in different variations, combined by the "OR" operator. In addition, the tools provided by each search engine were utilised to filter out book chapters and other report kinds in favour of journal and conference articles, which were thought to be the most likely to include recent and appropriate scientific publications.

2.4. Eligibility Criteria

All articles that matched the standards shown in Figure 1 were involved. These classes were created using extensive textual materials. All of the articles that failed to satisfy the eligibility requirements shown in Figure 1 were excluded once the duplicate articles had been removed. The criteria for exclusion were: (1) If there was no English in the articles. (2) If the use of machine learning models in tandem with meta-algorithms in ETo data modelling were not discussed in the articles.

2.5. Data Collection Process

The included articles were compiled from a wide variety of sources into a single Excel® file, where preliminary categorisations had already been made. All of the papers were read, and detailed notes were made on what was most interesting and how to organise the articles into a more accurate taxonomy. All highlighting and notes were done on the text itself. The findings were tabulated, summarised, and discussed at length. The list of survey articles, summary and description tables, source indices, objectives, review sources, validation methodologies, utilised datasets, and different related figures were all saved in separate Word and Excel documents. All of this necessary information was included with the outcomes for easy reference.

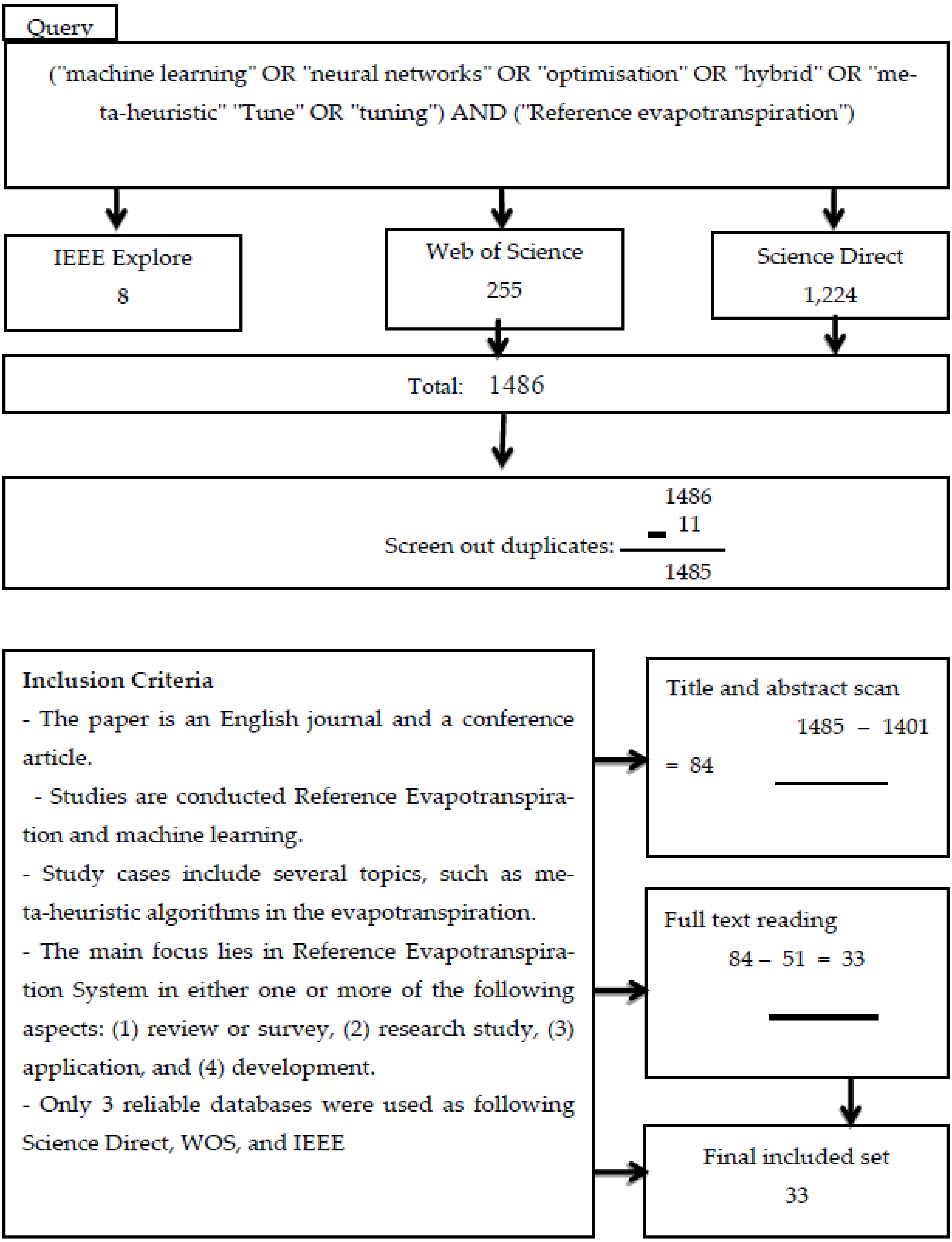

Figure 1. Search Query.

2.6. Articles Search Results and Statistical Information

The initial query results reached 1486 papers: 1224 from Science-Direct, 8 from IEEE Explore, and 255 from WOS, in a span of 5 years, from 2018 to 2022. Eleven duplicate papers were found among the databases utilised. After the title and abstract scanning, 1401 non-related papers were excluded, resulting in 84 papers. After reading the full text, 51 articles were excluded, and finally, 33 papers remained in the final set. These papers were read deeply to offer a general research plan in this field.

3. Results

The taxonomy displayed in Figure 2 was applied to review the primary research streams relying on meta-heuristic algorithms and their general practise in ETo forecasting. This taxonomy system demonstrates the all-encompassing growth of several investigations and implementations. The taxonomy suggests various classes and subclasses. The final class consisted of survey and review articles discussing the use of meta-heuristic algorithms in ETo modelling (33 papers).

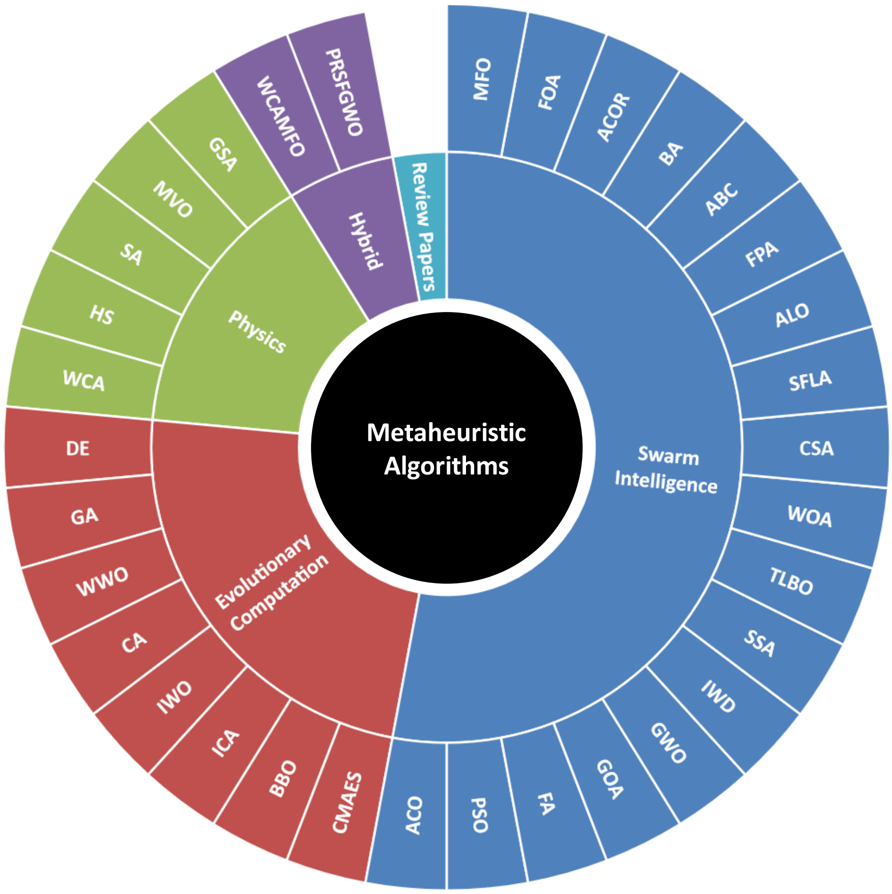

Figure 2. A taxonomy of research literature on using meta-heuristic algorithms in ETo modelling.

3.1. Meta-Heuristic Algorithms

The term "meta-heuristic" refers to an algorithmic structure that may be used generically for many different optimisation problems with just minor adjustments for problem-specific adaptations [27]. In recent years, actual engineering design optimisation issues have been solved using these algorithms as the principal techniques [28]. The meta-heuristic algorithms were classified into four groups depending on their behaviour: swarm intelligence-based algorithms, evolutionary computation-based algorithms, physics-based algorithms, and hybrid meta-heuristic algorithms [27,29].

3.1.1. Swarm Intelligence-Based Algorithms (SI)

Swarm intelligence imitates the group behaviour of constituent agents, including birds and insects. The decentralisation principle, which dictates that the candidate solutions be updated through local contact with one another and their surroundings, is the foundation upon which SI is primarily based. Particle swarm optimisation (PSO) and ant colony optimisation (ACO) are the two SI algorithms with the highest levels of popularity [27]. This category contains numerous algorithms, some of which will be discussed in the section below, as well as some of the research that used this type of algorithm in ETo modelling.

a Particle Swarm Optimisation (PSO)

It is a meta-heuristic optimisation algorithm that takes its cues from the swarm intelligence paradigm, which imitates the cooperative behaviour of fish and birds. It is successfully used in a variety of engineering and scientific applications [30]. The following section will describe and detail four studies that used the PSO and produced the best results.

Zhu, et al. [19] used the PSO algorithm to determine the ELM model's parameters in the best possible way. As a result, a novel hybrid ELM-PSO model was suggested for estimating daily ETo in the dry region of Northwest China with little input data (2002–2016). The ELM-PSO approach produced better results compared to the original ELM, RF, and ANN models, along with six empirical models (including empirical models based on mass transport, temperature, and radiation). In comparison to equivalent empirical models using the same inputs, the results showed that machine learning models generated more accurate ETo estimations. Furthermore, the statistical results showed that the hybrid ELM-PSO model performed better than the other models for the daily ETo estimate. Overall, the machine learning and empirical models were outperformed by the ELM-PSO model. When compared to the other models, the radiation-based ELM-PSO model performed the best, with a coefficient of determination (R^2), MAE, relative root mean square error (RRMSE), and Nash–Sutcliffe efficiency (NSE) values of 0.935, 0.470 mm/day, 17.1%, and 0.935, respectively. With average R^2, MAE, RRMSE, and NS of 0.917, 0.416 mm/day, 20.6%, and 0.917, respectively, the temperature-based ELM-PSO model likewise produced favourable results.

Roy, et al. [31] assessed a new methodology, which coupled the hierarchical fuzzy system (HFS) with the PSO algorithm to predict daily ETo. Two separate weather stations in Bangladesh's Gazipur Sadar Upazila of the Gazipur district and Ishurdi Upazilla of the Pabna district were used to collect meteorological data (2004–2019). The HFS-PSO model was evaluated by comparison to a fuzzy inference system (FIS), an M5 model tree (M5), and a regression tree (RT) model. The idea of Shannon's entropy, which takes into account a number of performance evaluation indices, was used to rank the models. Additionally, the dataset from a test station was used to assess the suggested models' generalisation abilities. The models' generalisation performances showed that they all performed similarly well on the test dataset. The HFS-PSO model offered the best performance (with correlation coefficient (R) = 0.93, the root mean square error (RMSE) = 0.59 mm/d, and Willmott's index of agreement (IOA) = 0.94), while the RT model displayed the worst performance (with R = 0.82, IOA = 0.83, and RMSE = 0.90 mm/d). Overall, the findings suggest that ETo could be reliably and efficiently modelled using the HFS-PSO model.

Yu, et al. [32] developed a hybrid technique by combining the extreme gradient boosting (XGB) model with the PSO algorithm. The model employs data from a greenhouse located in Beijing, China, from 2018 to 2019. Using the meteorological and soil moisture data gathered during the two-crop planting process as the experimental data and ETo calculated using the improved FAO-56 PM equation as the reference truth, the effectiveness of the model estimation was evaluated, and the impact of fewer input variables on the model estimation was tested. In order to more thoroughly assess the XGB-PSO model's capacity for model construction and the generalisation performance of fitting with data from a single planting process, the data obtained in this study comprised planting process data for spring and autumn crops. Additionally, the characteristic values were processed using the Min-Max normalisation approach to increase the precision and speed of model training. The findings demonstrated that the PSO algorithm could stabilise the XGB model's parameter optimisation and that the XGB-PSO model could reliably estimate ETo in a variety of data modes. Furthermore, the results show that all of the R^2 values for the verification set and all of the R^2 values for the test set were greater than 0.9 and 0.92, respectively.

Alizamir, et al. [33] examined the utility of two evolutionary neuro-fuzzy inference systems, the ANFIS with PSO and the ANFIS with a genetic algorithm (GA), in simulating monthly ETo. The data were obtained from two stations in Turkey, Antalya and Isparta, from 1982 to 2006. Furthermore, the hybrid models were compared with traditional ANFIS, ANN, and classification and regression tree (CART). The results show that the suggested evolutionary neuro-fuzzy models outperformed ANFIS, ANN, and CART in terms of estimates. Furthermore, the precision of ANFIS, ANN, and CART was raised by 40%, 32%, and 66% for the Antalya and by 14%, 44%, and 67% for the Isparta, respectively, by the ANFIS-PSO and/or ANFIS-GA.

b Ant Colony Optimisation (ACO)

An optimisation technique was put forth by Ali Dorigo et al. [34]. ACO draws its inspiration from several ant species' foraging strategies. These ants leave pheromone trails on the ground to indicate a good route for the colony's other ants to take. An analogous method is used in ant colony optimisation to address optimisation issues. ACO works in both discrete and continuous domains to solve a variety of static and dynamic optimisation problems by cooperating as a colony of artificial ants. It distributes the computing power to a group of artificial ants, which are comparatively basic agents that communicate covertly via pheromone trails. It is a probabilistic multi-agent method that switches between iterations using a probability distribution [35].

c Shuffled Frog-Leaping Algorithm (SFLA)

It is a memetic optimisation method that draws inspiration from biological phenomena such as frog social behaviour [36]. For SFLA, the population is divided into a number of memeplexes, and a number of frogs from each memeplex are chosen to form a submemeplex for local evolution. This is done in accordance with the principle that the worst frog learns from the best frog in the submemeplex or the best frog in the population. The memeplexes are then shuffled for global evolution after several generations of each memeplex [37].

Mehdizadeh, et al. [38] created and implemented two innovative hybrid models using two optimisation methods: the SFLA and invasive weed optimisation (IWO), coupled with the ANFIS. In addition, the proposed hybrid models were contrasted with four empirical models of various complexity, including Hargreaves–Samani, Romanenko, Priestley–Taylor, and Valiantzas. This study used Tabriz and Shiraz, two locations in Iran, as its study locations. The Iran Meteorological Organisation collected daily time-scale meteorological data from the study sites (2000–2014). According to the evaluation results, the developed coupled models outperformed the traditional ANFIS, with the ANFIS-SFLA surpassing the ANFIS-IWO, with RMSE being within 0.15 mm/day, RRMSE being within 4%, mean absolute error, (MAE) being within 0.11 mm/day, and both a high R^2 and NSE of 0.99 in the test phase at the two study sites. Furthermore, the hybrid ANFIS-SFLA models incorporating full predictors provided the study locations with the most precise estimates of the daily ETo.

d Firefly Algorithm (FA)

The idealised behaviour of the firefly served as the inspiration for the creation of FA Yang [39]. The flash behaviour of fireflies serves as the basis for the FA. In the FA method, the solution space is filled with a collection of fireflies, each of which stands for an initial solution. Each firefly's target function determines the fitness score, which is then assigned a light intensity. Fireflies with a high adjacent light will attract nearby fireflies with a low light intensity [8].

Roy, et al. [40] combined the ANFIS model with four different optimisation algorithms: FA, PSO, biogeography-based optimisation (BBO), and Teaching-Learning-based optimisation (TLBO) to predict the daily ETo. The daily weather data from three meteorological stations: Gazipur Sadar Upazilla, Blue Cypress Marsh, and Pine Upland in Bangladesh and South Florida, USA, were used in this study. Additionally, the performance of these models was contrasted with that of the typical ANFIS model, whose parameters were fine-tuned using the Integrated Least Squares and Backpropagation Gradient Descent (LSGD) algorithm. Furthermore, decision theories were used to rank prediction models based on eight statistical indicators and evaluate how accurate the forecasts were. The results showed that ANFIS-FA produced the most precise ETo forecasts.

Roy, et al. [31] proposed the ANFIS model combined with fifteen optimisation algorithms, namely: FA, BBO, Artificial Bee Colony (ABC), Bee Algorithm (BA), continuous ant colony optimisation (ACOR), Covariance Matrix Adaptation Evolution Strategy (CMAES), Cultural Algorithm (CA), Differential Evolution (DE), GA, Harmony Search (HS), Imperialist Competitive Algorithm (ICA), IWO, PSO, Simulated Annealing (SA), and Teaching-Learning-based optimisation (TLBO), for daily ETo prediction in Bangladesh (2004–2019). These hybridised ANFIS models' performances were compared to the traditional ANFIS model adjusted using a combined Gradient Descent technique and Least Squares Estimate (GD-LSE) methodology. Eight statistical indices and decision theories based on Shannon's entropy, Variation Coefficient, and Grey Relational Analysis were used to rank the performances of these ANFIS models. According to the results, the ANFIS-FA model is the best model (R = 0.993, NSE = 0.986, IOA = 0.996, Kling–Gupta Efficiency (KGE) = 0.989, Median Absolute Deviation (MADE) = 0.054 mm/d, RMSE = 0.149 mm/d, and normalised root mean square error (NRMSE) = 3.819%), which can be used to forecast daily ET0 values for regions with similar climatic circumstances.

Tao, et al. [22] integrated ANFIS with the FA and compared it with the ANFIS model to predict daily ETo. Three meteorological stations in Burkina Faso's Sudanian, Sahelian-Sudanian, and Sahelian regions provided data on a daily time scale: Bobo Dioulasso, Bur Dedougou, and Ouahigouya, from 1998 to 2012. According to six different models, six alternative climate input variable combinations were examined. In addition to the Taylor diagram, several numerical indicators were taken into account while assessing the performance of the models. The results revealed that for all three stations, the hybrid ANFIS-FA model (Scatter Index (SIndex) = 0.043, R^2 = 0.97, mean absolute percentage error (MAPE) = 0.035, and RMSE = 0.24) beat the traditional ANFIS-based model (SIndex = 0.068, R^2 = 0.89, MAPE = 0.037, and RMSE = 0.378), and the model with the complete inputs of climatic data produced the best results. The results also showed that using the FA significantly enhanced the performance of the traditional ANFIS model.

Shiri, et al. [41] provided a thorough comparison of 12 soft computing models, including SVM coupled with the FA (SVM-FA), gene expression programming (GEP), neural network coupled with PSO algorithm (NN-PSO), neural network-differential evolution (NN-DE), RF, boost regression tree (BT), model tree (MT), SVM, ELM, and neuro-fuzzy with grid partitioning (NF-GP). Data from two humid stations in northern Iran (Babolsar and Sari) from 2001 to 2012 were used to create and test the models. Models based on radiation and temperature were also developed. The data gathered showed that all of the methods used were extremely efficient. The temperature-based SVM-FA models (RMSE = 0.324 mm, SIndex = 0.210, MAE = 0.225 mm, R^2 = 0.960, NSE = 0.960) often exhibited the highest accuracy when estimating the ETo. Furthermore, among the radiation-based models, the NF-GP (RMSE = 0.272 mm, SIndex = 0.100, MAE = 0.203 mm, R^2 = 0.973, NSE = 0.974) had the highest level of accuracy for computing the ETo of both stations.

Wu, et al. [8] suggested a novel kernel extreme learning machine model combined with the K-means clustering and firefly algorithms (Kmeans-FA-KELM). Furthermore, the RF, M5P, ANFIS, and KELM-FA models were created to estimate the monthly mean daily ETo. A total of 26 weather stations in the Poyang Lake basin of South China were utilised to collect meteorological data from 1966 to 2015, which were then used to train and evaluate the models. Furthermore, prior to training and testing, the raw weather data were standardised to 0–1 to suit the needs of the machine learning models. According to the results, the FA-KELM model and the ANFIS model fared better than the RF and M5 prime model tree (M5P) models. Additionally, the KELM-FA model was surpassed by the Kmeans-FA-KELM model.

e Grasshopper Optimisation Algorithm (GOA)

GOA was first developed by Saremi, et al. [42]. It mimics the behaviour of grasshoppers to tackle several real-world optimisation problems. Together, grasshopper populations create a network, and each individual grasshopper is connected through this network to coordinate and modify its position. The direction of the other network members' predation can be cooperatively determined by individuals. Individual grasshoppers are subject to gravitational and repulsive forces. Grasshoppers can search for the right place thanks to the repelling force, and they can explore some new places thanks to the gravitational force. The optimal adaptation region is where an individual grasshopper is located when gravity and the repulsive force are equal. Since they did not initially know the target area, the target position was determined to be the optimal adaptation area. The grasshopper will move towards the network objective. The appropriate range region will be automatically altered as the grasshoppers' locations are regularly updated, to strike a balance between global and local searches. Eventually, all the grasshoppers will congregate and approach the ideal solution.

f Grey Wolf Optimiser Algorithm (GWO)

Depending on the traits of the grey wolf population, Mirjalili, et al. [43] initially presented the grey wolf algorithm. It has been demonstrated that it can efficiently discover the nonlinear function's optimal solution and that it has both a better estimation accuracy and a faster processing speed. Due to these benefits, the GWO approach is one of the most often applied bio-inspired algorithms in recent years. The fundamental goal of the GWO algorithm is to mimic the grey wolf's social standing and hunting habits [9].

Maroufpoor, et al. [21] used the GWO algorithm to enhance the ANN model for estimating daily ETo. The models were built using data collected between 2012 and 2017 and were based on the 31 provinces of Iran. The accuracy of ANN-GWO was evaluated in comparison to standalone ANN and least square support vector regression (LSSVR). The outcomes demonstrated that the ANN-GWO model was more accurate than ANN and LS-SVR, and that the GWO algorithm worked as an effective tool for optimising the ANNs structure.

Lu, et al. [44] developed a new hybrid model called XGB-GWO, which uses the PSO algorithm to optimise the extreme gradient boosting (XGB) parameters while using XGB as the primary regression model for forecasting multi-step ahead ETo (1–3 months ahead). This was done in comparison with three conventional machine learning models, namely the Multi-Layer Perceptron (MLP), the standalone XGB, and the M5 model tree (M5). Monthly meteorological data were gathered for this study from nine weather stations in South China. The results showed that the XGB-GWO model generally outperformed the other three machine learning models, with very few differences among the three models. The model was then followed by the XGB, M5, and MLP models. The GWO-XGB technique had the best performance in the autumn (RMSE = 0.431 mm/day, NSE = 0.840 and MAE = 0.335 mm/day). Furthermore, the MLP model fared somewhat better than the other three models in the summer.

Tikhamarine, et al. [45] improved the performance of the ANN approach by combining it with five optimisation algorithms: the GWO algorithm, the PSO algorithm, the multi-verse optimisation (MVO) algorithm, the whale optimisation algorithm (WOA), and the ant lion optimisation (ALO) algorithm, to predict monthly ETo. The models were tested in two different locations: Dar El Beida Station in Algiers, the capital of Algeria, and Ranichauri Station, located in the foothills of the Indian central Himalayan area (Uttarakhand State, India), from January 1994 to December 2012. Three models, Valiantzas-1, 2, and 3, were used to compare the estimations produced by the hybrid machine learning models. The comparison results reveal that the ANN-GWO technique with five predictors (Tmin, Tmax, RH, Us, and Rs) produces better predictions at both research sites. (RMSE = 0.0592/0.0808, NSE = 0.9972/0.9956, R = 0.9986/0.9978, and index of scattering (IOS) = 0.9993/0.9989) was the evaluation result.

Tikhamarine, et al. [46] investigated the feasibility of a novel hybrid AI model for calculating monthly ETo in the northern Algerian stations of Algiers, Tlemcen, and Annaba, from 2000 to 2013. This model uses support vector regression (SVR) combined with the grey wolf optimiser (SVR-GWO). The suggested hybrid SVR-GWO approach was contrasted with combined SVR-GA, SVR-PSO, ANN, and empirical models (Turc, Ritchie, and Thornthwaite, and three variations of Valiantzas techniques). The outcomes show that the SVR-GWO offers highly promising and occasionally competitive outcomes in comparison to other ML and empirical methods at research stations. Therefore, at the Algiers, Tlemcen, and Annaba stations, the evaluation result was (RMSE = 0.0776/0.0613/0.0374 mm, NSE = 0.9953/0.9990/0.9995, R = 0.9978/0.9995/0.9998, and IOS = 0.9988/0.9997/0.9999).

Dong, et al. [9] explored the performance of the kernel-based nonlinear extension of Arps decline (KNEA) optimised with four bio-inspired algorithms named: GWO, PSO, GOA, and salp swarm algorithm (SSA), to forecast monthly ETo. The 51 weather stations located in China's seven climate zones between 1966 and 2015 were used for model training and testing. The FAO-56 PM formula findings were utilised as a control, and four alternative combinations of meteorological data were applied as a model input. The results revealed that the KNEA-GWO model outperformed the other three coupling models in general (on average, R^2 was 0.9666, RMSE was 0.3033 mm/day, MAE was 0.2308 mm/day, and NRMSE was 0.105).

g Intelligent Water Drops (IWD)

This algorithm was first proposed by Hosseini [47]. The IWD algorithm is dependent on water droplets flowing in nature, where each drop answers via moving through space and altering its surroundings. In nature, countless water trains cooperate in providing the best path to the destination. In other words, this is a method that relies on communal intelligence.

Ahmadi, et al. [48] applied SVR and gene expression programming (GEP) as independent models. Then, by combining the conventional SVR with the IWD algorithm (i.e., SVR-IWD), a novel combined technique was presented in order to simulate the monthly ETo. Six stations in Iran were employed as the study areas. The semi-arid climate is present in three of the six chosen stations (Arak, Mashhad, and Shiraz), whereas the arid climate is present in the remaining three (Bandar Abbas, Tehran, and Yazd). The advances of current research include the hybrid SVR-IWD model as well as the use of the two pre-processing techniques, Kendall, and entropy, to determine the most significant weather characteristics of ETo. Two types of empirical equations—the original and calibrated versions of the Priestley–Taylor and Hargreaves–Samani equations—were also used. It was determined that the calibrated versions performed better than the original ones. The outcomes demonstrated that the pre-processing techniques used added various climate inputs to the models. The overall findings of this study showed that the suggested hybrid SVR-IWD model performed better than the standalone SVR one. The evaluation yielded the following results: At the Arak (RMSE = 0.404 mm/day, MAE = 0.303 mm/day, R = 0.980), Mashhad (RMSE = 0.540 mm/day, MAE = 0.414 mm/day, R = 0.983), Shiraz (RMSE = 0.299 mm/day, MAE = 0.219 mm/day, R = 0.989), Bandar Abbas (RMSE = 0.457 mm/day, MAE = 0.370 mm/day, R = 0.962), Tehran (RMSE = 0.559 mm/day, MAE = 0.446 mm/day, R = 0.978), and Yazd (RMSE = 0.399 mm/day, MAE = 0.314 mm/day, R = 0.986).

h Salp Swarm Algorithm (SSA)

The salp population movement and foraging activity served as inspiration for the creation of the SSA by Mirjalili, et al. [49]. Salpidae is the class that includes salps. They resemble jellyfish greatly in both their shapes and movements, as well as having a translucent body. The body swims by spraying water. Salps typically float in a chain in the ocean, so they may move and forage more easily. One could think of salp's movement patterns as a mathematical model. Salps naturally form two groups: leaders and followers. The actions of the team are guided by the leader, and each individual follower works in turn. The SSA employs infinitely spaced salps to iteratively approach the best solution, calculating the best fit of each salp to determine its position [9].

i Whale Optimisation Algorithm (WOA)

The WOA was put forth by Mirjalili and Lewis [50], where it mimics humpback whales' foraging habits. It was seen that humpback whales would construct bubble nets to enclose their prey while engaged in hunting behaviour. The whales (search agents) are separated from one another throughout the searching phase to maximise search effectiveness.

Mohammadi and Mehdizadeh [51] utilised the SVR model for the modelling of daily ETo at three weather stations in Iran that experienced various climatic conditions: Isfahan (arid), Urmia (semi-arid), and Yazd (hyper-arid), from 1 January 2000 to 31 December 2014. The best input combinations for the SVR were determined using a variety of pre-processing techniques, including relief (RL), random forests (RF), principal component analysis (PCA), and Pearson's correlation (COR). Data were normalised using the Min-Max normalisation strategy to compare pre-processing techniques. The inputs used by the RF strategy (i.e., RF-SVR) produced superior outcomes than those introduced by the other approaches, despite the fact that they introduced various predictors to the SVR approaches. Additionally, a brand-new hybrid model that combines SVR with the WOA was created and is used for daily ETo modelling. The RMSE, NRMSE, MAE, R^2, and NS were applied to examine the performance of the models. The outcomes revealed that the hybrid RF-SVR-WOA technique had the best performance of the hybrid models, which outperformed the SVR-only models. (RMSE = 0.294 mm/d, NRMSE = 7.931%, MAE = 0.204 mm/d, R^2 = 0.981, E = 0.981 for training period; RMSE = 0.265 mm/day, NRMSE = 6.945%, MAE = 0.193 mm/day, R^2 = 0.986, E = 0.986 for testing period).

ELM-based estimation of ETo has become the norm due to its outstanding computing efficiency and reduced reliance on data. However, when stochastic tuning is absent, convergence to a local rather than a global optimum frequently occurs. Chia, et al. [10] made an effort to address this problem by combining three optimisation algorithms, including the WOA, the ELM, the PSO, and the moth-flame algorithm (MFO), with various levels of fitness. In this study, daily data were collected from three stations in the states of Sabah and Sarawak in East Malaysia from 2014 to 2018. The findings demonstrated that the ELM-WOA outperformed the ELM-PSO and ELM-PSO in terms of the average rank score, particularly when the simple Taylor skill score was applied as the fitness function. The use of various fitness functions did not result in any notable results. Furthermore, as the ideal optimisation algorithm for this study, the WOA was recommended.

Chia, et al. [6] utilised the MLP, SVM, and ANFIS as the basic models to estimate daily ETo. Additionally, three methods were utilised to hybridise the underlying models: bootstrap aggregating, Bayesian model averaging (BMA), and an ELM-based non-linear neural ensemble (NNE). Alor Setar, Kota Bharu, Kuala Lumpur International Airport, and Kuantan were the four stations chosen for this study, all of which are located in Peninsular Malaysia and have typical tropical climates (2000–2019). In order to compute the results of the combined judgments made by the MLP, SVM, and ANFIS for predicting ETo, the WOA optimised the ELM. A hybrid model with improved accuracy and generalisability was produced by the ELM-WOA, which was free to combine the positive characteristics and features of the underlying models. The ELM-WOA was the best model, according to the Global performance Index (GPI) ranking algorithm, obtaining the highest value.

For the purpose of estimating the daily ETo at four stations in the desert part of China and four stations in the humid region of China, for the period (1966–2015), Yan, et al. [11] suggested a unique hybrid extreme gradient boosting (XGB) model with the WOA. With seven incomplete combinations of meteorological data, its performances were specifically assessed under the local and three exterior scenarios. The findings showed that, in comparison to their corresponding simplified FAO-56 PM models, the locally tested and trained XGB-WOA models performed significantly better, with an average reduction in RMSE of 40.1% and 38.9% in arid and humid regions, respectively. Furthermore, the externally trained XGB-WOA models' prediction accuracy with local or external testing data fell by 18.1% or 69.9% in the arid region and 16.8% or 67.9% in the humid region, respectively, as compared to the local XGB-WOA models. This is a promising method that enables a more precise daily ETo calculation in the absence of complete current or long-term historical data.

Tikhamarine, et al. [52] used hybrid SVR along with the whale optimisation algorithm (SVR-WOA) at the Algiers and Tlemcen meteorological stations, located in the north of Algeria (2000–2013), to calculate the monthly ETo. Through performance metrics, the combined SVR-WOA technique's accuracy was evaluated against the hybrid SVR-MVO (Multi-Verse Optimiser) and SVR-ALO (ant lion optimiser) techniques. In comparison to the SVR-MVO and SVR-ALO models, the suggested hybrid SVR-WOA model was found to be more suitable and effective for calculating the monthly ETo in the research region. For the testing period at both stations, the following values were recorded: MAE = 0.0658/0.0489 mm/month, RMSE = 0.0808/0.0617 mm/month, IOS = 0.0259/0.0165, and the highest values of NSE = 0.9949/0.9989, R = 0.9975/0.9995, and IOA = 0.9987/0.9997.

j Cuckoo Search Algorithm (CSA)

Yang and Deb [53] introduced the CSA, an optimisation technique based on the breeding behaviour of cuckoos mixed with Levy flights. The CSA mimics the cuckoo's egg-laying and breeding behaviour. Some cuckoos are nest parasites, which means that they lay their eggs in the nests of other birds. The host birds would either remove the eggs or build a new nest after spotting these ones. To increase the chance of the eggs surviving, they imitate this behaviour. Each egg in the nest represents a particular answer, and the cuckoo egg represents a brand-new solution. The cuckoo frequently replaces the undesirable eggs in the nest with superior ones. This method uses breeding behaviour to replace the poorest answer with a new one. Each time a cuckoo bird lays an egg, it only chooses one nest at random to place it in. The number of nests with eggs of a high calibre is subsequently passed on to the next generation. An alien egg is likely to be found by a host cuckoo if there are a certain number of accessible host nests. The alien egg will either be discarded at this point or a new nest will be constructed [54].

k Flower Pollination Algorithm (FPA)

Yang [55] created the FPA, which is an optimisation algorithm. It simulates the biological traits of self-pollination and the cross-pollination of flowering plants in nature using a stochastic global optimisation technique. Plants can be classified into two categories based on their pollination components: self-pollination and cross-pollination.

Wu, et al. [54] integrated the ELM with four optimisation algorithms: FPA, ACO, GA, and the cuckoo search algorithm (CSA) to estimate the daily ETo. Eight meteorological sites in China with varying climates provided data from 2001 to 2015 that were used to train, validate, and test the models. These models were contrasted with the traditional ELM model parameterised using the grid search method. The findings demonstrated that the ETo values predicted by all ELM models and the matching FAO-56 PM values were in good agreement. During testing, the ELM-FPA model (R^2 = 0.9930, RMSE = 0.1589 mm/day, NRMSE = 5.5406%, and MAE = 0.1188 mm/day) fared a little better than the ELM-CSA, both of which outperformed the ELM-ACO and ELM-GA models, with the standalone ELM model coming in third. The findings supported the ability of bio-inspired optimisation algorithms, particularly the FPA and CSA, to enhance the daily ETo prediction accuracy of the traditional ELM model in China's various climates.

l Artificial Bee Colony (ABC)

The ABC Karaboga [56] is an optimisation algorithm designed to mimic the rational, inherently social behaviour of real honey bees when constructing meals. A swarm is made up of a group of honeybees that have been given specific duties to complete and have done so successfully through social cooperation. Honeybees use a variety of unusual techniques, such as the waggle dance, to precisely find food sources and look for new ones. Due to their distinctive behaviour, honeybees are a perfect option for the development of intelligent search algorithms. The ABC algorithm uses the behaviours of three different bee kinds: employed bees, observers, and scout bees, which are associated with three different sorts of actions: (1) searching for new food sources; (2) hiring bees to collect the food; and (3) abandoning exploited food sources [40].

m Bee Algorithm (BA)

Pham, et al. [57] developed the Bees Algorithm, which uses the honeybees' organic foraging habits as inspiration to obtain the best answer. The algorithm conducts a neighbourhood search that is both exploitative and exploratory [58].

n Continuous Ant Colony Optimisation (ACOR)

The first ant-based continuous optimisation method that fits into the ACO framework, Socha and Dorigo [59], ACOR, is a straightforward extension of ACO. It is possible to classify ACOR as a competitive strategy. Additionally, ACOR's performance may be modified to meet goals for either greater robustness or greater efficiency. Furthermore, ACOR is a definite victor when compared to other ant-related continuous optimisation methods that have been put forth in the past. ACOR outperformed these techniques by roughly two orders of magnitude.

o Ant Lion Optimiser (ALO)

Mirjalili [28] presented the ant lion optimiser (ALO) method and demonstrated its efficacy by resolving three traditional engineering problems in addition to nineteen different mathematics benchmark problems. The ALO algorithm was influenced by the ant lions' clever hunting techniques and interactions with their preferred ant prey. As a result, the ALO algorithm includes a mathematical representation of the primary processes in ant lion hunting [60].

p Moth-Flame Optimisation Algorithm (MFO)

MFO was developed by Mirjalili [61] and was primarily motivated by the way that moths naturally travel in spirals towards flames or artificial light.

q Teaching-Learning-Based Optimisation (TLBO)

It is a population-based meta-heuristic search technique that converges to the overall best solution using a population of solutions. The foundation of TLBO approaches is the concept of teaching and learning processes in a classroom, or the impact of a teacher on students [62]. This algorithm takes into account the teacher and learner phases, which are the two fundamental learning processes: learning from the teacher and learning from other students' interactions [63]. The TLBO approach is based on how a teacher's influence affects the students' performance in a class [64].

r Fruit fly Optimisation Algorithm (FOA)

The FOA, is based on how fruit flies acquire their food. The fruit fly has superior sensory and perceptive abilities to those of other species, particularly in osphresis and eyesight. Fruit flies have osphresis organs that can detect a wide range of aromas in the air, and they can even detect food sources 40 km distant [65].

Using generalised regression neural networks (GRNN) and mathematical morphology clustering (MMC), Ruiming and Shijie [66] created a prediction model for the daily ETo of Tieguanyin. The GRNNs smoothing factor was enhanced using the FOA. The proposed model (MMC-GRNN-FOA) was trained and tested using meteorological data collected between January 2018 and October 2019 in the Dabaofeng tea garden in Anxi County, Fujian Province, China. Following a correlation analysis of the microclimate features of the tea garden, the average air temperature, sunlight hours, and relative humidity were chosen as the best acceptable input indexes for GRNN. The model validity coefficient (MVC), RMSE, and MAE were utilised to assess its performance. The outcomes of various seasons' predictions (March, June, August, and October) demonstrate how effective and accurate the suggested model is, as well as how well-suited it is to changing weather circumstances. The analysis produced the following findings: MVC = 0.982, 0.976, 0.985 and 0.981, respectively; MAX = 0.431, 0.472, 0.345 and 0454, respectively; RMSE = 0.271, 0.189, 0.223 and 0.283 respectively.

3.1.2. Evolutionary Computation-Based Algorithms (EC)

Evolutionary algorithms are approaches to finding the answer to an optimisation problem that draw on concepts from biological evolution, such as reproduction, mutation, and recombination. In order to arrive at progressive approximations of the ideal answer, the principle of survival was applied to a set of probable solutions [67]. This section lists only a few of the most popular algorithms of this type reported in the literature and cites references that have used these algorithms for ETo modelling.

a. Genetic Algorithm (GA)

The GA developed by Holland [68] is reliable, strong, and optimised, based on the laws of natural selection and evolution. The natural processes of biological evolution served as the basis for the GA, which has been frequently used to produce excellent answers to optimisation problems [24]. Briefly stated, the approach starts by generating a random population of chromosomes that represent potential answers to a certain problem. The fitness function that determines the likelihood of the selection stage should then be determined for each chromosome. The crossover operation is performed on a pair of chosen chromosomes to combine two different chromosomes in order to create a new, superior progeny. As a result, genes located at several randomly chosen chromosome locations are changed. This last genetic modification is referred to as a "mutation". The descendants of genetically altered individuals will be the next population to be studied [69].

Jiao and Hu [70] used the GA with the backpropagation network (BP) and three other optimisation techniques (RF model, the LSSVR model, and the Bi-LSTM model) to simulate the ETo values. Daily weather information from eight meteorological sites was used in northern Xinjiang, China, between 2000 and 2020. The models were evaluated using five statistical performance evaluations: the formulas for the GPI, MAE, mean bias error (MBE), R^2, and RMSE. The findings demonstrate that the GA-BP model's total simulation impact is the best, with an RMSE = 0.2542 mm/day, MAE = 0.1706 mm/day, MBE = -0.0039 and R^2 = 0.9918.

b Differential Evolution (DE)

DE is a straightforward, evolutionary process that combines the parent individually with several other individuals from the same population to produce new candidate solutions. Only when a candidate is fitter than the parent does it take its place. This is an avaricious selection strategy that frequently outperforms traditional strategies [71].

Majhi and Naidu [30] examined how well a differential evolution-based radial basis function neural network (RBFDE) can simulate weekly ETo as a function of climatic variables in various agro-climatic zones in a wet, sub-humid region in East-Central India (2001 to 2019). The new RBFDE model's performance is compared against models based on particle swarm optimisation, radial basis function neural networks, multilayer artificial neural networks, and the traditional empirical equations of Hargreaves, Turc, Open-Pan, and Blaney–Criddle. The results revealed that the soft computing models generate better ETo estimates than empirical techniques. RBFDE outperforms other soft computing models such as RBFPSO, RBFNN, and MLANN.

c Biogeography-Based Optimisation (BBO)

BBO was first developed by Simon [72], who details the process by which many biological organisms move from one habitat to another. It also discusses how each species came into being and went extinct. Geographically remote places that are home to various animals or plant species are referred to in this method as habitats or islands.

d Covariance Matrix Adaptation Evolution Strategy (CMAES)

CMAES is a powerful global evolutionary optimisation technique that does not use derivatives to solve continuous optimisation issues, Hansen, et al. [73]. Recombination, mutation, and selection are the three essential processes that the CMAES executes to carry out the optimisation tasks, just like any other evolutionary optimisation method.

e Imperialist Competitive Algorithm (ICA)

The ICA, introduced by Atashpaz-Gargari and Lucas [74], is motivated by the socio-political behaviours of people as a strategy for human social evolution.

To predict the daily ETo, Zeinolabedini Rezaabad, et al. [63] combined the ANFIS with four optimisation algorithms: ICA, IWO, BBO, and TLBO. The data were collected from the synoptic station of Kerman, Iran, from 2000 to 2015. Additionally, the ETo values were estimated using relatively new empirical equations and compared with the FAO-56 PM equation. The results showed that the hybrid models were more capable of estimating the ETo values than empirical equations. Furthermore, when compared to other models, ANFIS-ICA (R = 0.99, RMSE = 0.5, and NSE = 0.98) performed better in terms of both statistical and graphical approaches and error distribution; as a result, it was deemed to be the best model.

f Invasive Weed Optimisation (IWO)

Mehrabian and Lucas [75] initially presented the IWO as a kind of rational and evolutionary optimisation algorithm that draws inspiration from the way weeds grow, survive, and adapt. According to the IWO definition, a weed is a plant that grows and produces in undesirable locations, poses a major threat to other plants, and impedes their development. The basic and natural characteristics of weeds, as well as seed generation, development, and survival conflict in a colony, are the basis of this set of rules, which, while simple, are very successful and quick in identifying the ideal parameters [38].

g Cultural Algorithms (CA)

CA are an evolutionary model that Reynolds [76] introduced as being drawn from the natural process of cultural evolution. It comprises areas for beliefs and populations, as well as a communication link between them, to regulate the standard of common knowledge and its kind.

h Water Wave Optimisation (WWO)

WWO is derived from shallow water wave theory [77]. It provided a number of benefits, including a balanced approach to exploitation and exploration. Additionally, it employs various operators, including refraction, propagation, and breaking operators, to broaden the population [78].

Sayyahi, et al. [78] assessed the capacity of soft computing models to simulate the daily and monthly ETo using MLP and in combination with the WWO, PSO, and GA algorithms. The data were gathered between 1987 and 2000 by the Iranian meteorological station in the Aidoghmoush basin. Prior to creating the model, monthly and daily ETo values were subjected to a principal component analysis (PCA) in order to identify the significant delays, i.e., the inputs that have the greatest impact on daily and monthly ETo values. Soft computing models were utilised to estimate daily, and monthly ETo using the variables lagged up to seven days and seven months. The outcomes demonstrated that, in comparison to the MLP-PSO, MLP-GA, and MLP models in the daily scale models, the MAE of the MLP-WWO is 1.3%, 2.5%, and 3.3% lower. Additionally, in comparison to the MLP-PSO, MLP-GA, and MLP models on a monthly basis, the MAE of the MLP-WWO was 7.2%, 14%, and 17% lower.

3.1.3. Physics-Based Algorithms (PH)

In these sections, we briefly review all the studies that applied physics-based algorithms that are used in ETo modelling. Quantum theory, electrostatics, electromagnetics, Newton's gravitational law, and the laws of motion are some of the key topics covered by these algorithms. Examples of physics-inspired algorithms include:

a Gravitational Search Algorithm (GSA)

The effective meta-heuristic GSA [79] was modelled after Newton's equations of motion and gravitation. The performance of the solutions is viewed in GSA as the mass of the objects, with search agents playing the role of interacting with physical objects. Based on the gravitational force, the particles can draw in additional entities. By this force, lighter things are pushed towards the heavier ones. Although heavy objects are thought to be superior solutions, they will travel more slowly than lighter objects. The research that used this algorithm and got the best results was conducted by Muhammad Adnan, et al. [80], who used two machine learning models: least squares support vector regression with a gravitational search algorithm (LSSVR-GSA) and the dynamic evolving neural-fuzzy inference system (DENFIS), to predict the monthly ETo. The models were built and tested using data collected from three stations in China's Jinsha River basin between 1961 and 2012. Furthermore, these techniques were compared with the M5 model tree (M5) approach. Three statistics—the determination coefficient, mean absolute error, and root mean square error—are used to gauge how accurately the models estimate. The results show that the accuracy of LSSVR-GSA is somewhat higher than that of the DENFIS and M5RT models.

b Multi-Verse Optimiser (MVO)

Three cosmological notions—the white hole, black hole, and the wormhole—serve as the foundation for this algorithm's primary sources of inspiration. These three concepts each have mathematical models that have been established for exploration, exploitation, and local search, respectively. The MVO was developed by Mirjalili, et al. [81]. Tikhamarine, et al. [52] and Tikhamarine, et al. [46] used this algorithm, but it did not produce the best results.

c Simulated Annealing Optimisation Algorithm (SA)

The SA was first developed as a search engine for combinatorial optimisation problems [82]. It is an iterative meta-heuristic search algorithm that simulates the gradual cooling process of metals.

d Harmony Search (HS)

HS, a meta-heuristic optimisation algorithm that has been created to imitate musicians' improvisation, was initially suggested by [83]. The algorithm is based on the fact that the main goal of listening to music is to seek out perfect harmony, which is incorporated into the search process to find the best solution to a problem requiring optimisation, as in Roy, et al. [40], who used it and also did not achieve the best results.

e Water Cycle Optimisation Algorithm (WCA)

The WCA takes its inspiration from nature and is based on observations of the water cycle and how rivers and streams naturally flow in the direction of the sea, and it was developed by Eskandar, et al. [84].

3.1.4. Hybrid Meta-Heuristic Algorithms

Hybrid algorithms are sets of two or more algorithms that work in concert and complement one another to create a positive synergy. An algorithm's capacity to search better is thanks in large part to hybrid algorithms. In order to create a hybrid algorithm, hybridisation seeks to integrate the positive aspects of each algorithm while also minimising any significant negative aspects. The results of hybridisation can typically be improved in terms of either computational correctness or speed [85,86]. Hybridisation boosts the algorithms' effectiveness and precision. The problems of randomisation, intensification, and trapping in local minima are overcome by combining the optimisation procedures [87].

a Adaptive Dynamic Algorithm Coupled with the Grey Wolf Optimiser (PRSFGWO)

El-Kenawy, et al. [13] developed a new hybrid adaptive dynamic PRSFGWO that was coupled to several machine learning regressors, such as the Decision Tree Regressor (DET), the Multi-Layer Perceptron Regressor (MLP), the Support Vector Regressor (SVR), the Random Forest Regressor (RFR), and the K-neighbours Regressor (KNR), in order to construct novel combined ensemble techniques for forecasting the daily ETo under the semi-arid climate of Andalusia, Spain. The study's objective was to improve the accuracy and reliability of the base learners by comparing them with other widely used optimisers such as GWO, PSO, GA, and WOA. The prediction models' predictive capability was assessed using various statistical metrics combined with ANOVA testing. The results show that the KNR algorithm performed better as a base learner. The MLP, SVR, and KNR-based techniques displayed improved performances when combined with PRSFGWO, which reduced prediction errors by up to 68%.

b Water Cycle-Moth Flame Optimisation (WCAMFO)

For the purpose of resolving numerical and restricted engineering optimisation problems, Khalilpourazari and Khalilpourazary [88] devised a combined method based on the Water Cycle and Moth-Flame Optimisation techniques. The Water Cycle algorithm incorporates the spiral movement of moths from the Moth-Flame Optimisation algorithm to improve its ability to be exploited. Additionally, the streams in the Water Cycle algorithm can alter their positions utilising a random walk in the new hybrid method to further boost randomisation (Levy flight). The Water Cycle algorithm's capacity for exploration is considerably enhanced by the random walk.

Adnan, et al. [89] examined the potential of a new hybrid neuro-fuzzy approach called ANFIS-WCMFO for simulating the monthly ETo. The case study locations for this study are the Bangladeshi districts of Dhaka and Mymensingh, which are situated on the Buriganga River and east of the Jamuna River (1982–2017). Various statistical criteria and graphical tests were employed to compare the outcomes of this method with those of standalone ANFIS and the two hybrid methods, ANFIS-WCA and ANFIS-MFO. This demonstrated the need for hybrid techniques for fine-tuning the ANFIS algorithm for the ETo estimate. Among the hybrid techniques, ANFIS-WCMFO outperformed ANFIS-WCA and ANFIS-MFO. The evaluation result showed that the improvements in RMSE were obtained by applying the ANFIS-WCA, ANFIS-MFO, and ANFIS-WCMFO hybrid approaches as 2.7%, 6.9%, and 15.1% for one station and 0.6%, 7.3%, and 12.4% for another station, respectively.

3.2. Review and Survey Articles

This subsection will highlight the past review papers in order to provide academics and researchers with insight into this area.

This review by Raza, et al. [4] indicated that the use of soft computing models in the estimation of ETo had received enormous interest in recent decades. Additionally, many studies have been reported in the literature to apply soft computing models to the improvement of ETo estimation. Furthermore, in this review, they relied on dividing the papers according to accuracy, structure, and flexibility, and also provided some possible suggestions for future research in this area. Krishnashetty, et al. [25] reviewed the research on cognitive computing models that have been applied to the calculation of ETo. The analysis demonstrates that the ANN technique performs better than both the SVM and GP. The second-order neural network (SONN), one of the ANN models, shows the most promise. Jing, et al. [26] performed a thorough analysis to determine the viability of evolutionary computing (EC) models and their potential for modelling ETo in a variety of situations. Using the review as a foundation, an evaluation and assessment of the techniques are also offered. Finally, a number of potential future study directions for the examinations of ETo employing EC are suggested.

4. Discussion

The main objective of this research is to offer valuable information on hybrid metaheuristic algorithms with ML models to forecast ETo data. The accurate estimation of ETo data is crucial for several reasons. It helps manage water resources, calculate crop water needs, choose crop patterns for agricultural lands, analyse water balances, and calculate water budgets, especially in arid environments where fresh water is scarce and resources are limited. Therefore, decision-makers have valuably benefited from using hybrid ML models that offer them a clear scientific view. This paper reviews the recent ETo forecasting research, where the OBH models have been studied in detail. The publications selected for this review showed that there had been a growing tendency towards applying hybrid techniques in the field of ETo modelling recently. Additionally, meta-heuristic algorithms have enhanced single ML models by choosing the most appropriate hyperparameters for the nominated model, saving time, and avoiding slipping into local minima instead of a global solution.

This survey differs from many earlier reviews in both its recentness and its focus on the literature that uses OBH models. Furthermore, it contributes to a suggested taxonomy of the related literature. Evolving a taxonomy of the published works imposes a sort of organisation on the mass of publications. On the other hand, the taxonomy's structure offers scholars the crucial context for their research. It begins by outlining prospective avenues of investigation for the area. Second, a taxonomy might highlight research gaps that can be considered for potential future directions.

In this study, meta-heuristic algorithms are divided into four categories: swarm intelligence-based algorithms, evolutionary computation-based algorithms, physics-based algorithms, and hybrid meta-heuristic algorithms. Based on the analysis of the results, the following must be highlighted:

About 47% of the total papers reviewed in this study integrated the ML models (i.e., ANN, ANFIS, and SVR) with one meta-heuristic algorithm. It was noted that the hybrid techniques were superior to the standalone ML approaches in terms of prediction accuracy, depending on the various statistics adopted in these papers.

Furthermore, around 47% of the total papers reviewed in this study used several meta-heuristic algorithms to optimise the ML models. It was observed that the swarm intelligence-based algorithms were superior to both the evolutionary computation-based and physics-based algorithms.

Finally, about 6% applied hybrid meta-heuristic algorithms to tune the ML models, and the results were compared with ML models that integrated with several single meta-heuristic algorithms. The comparison shows that the hybrid meta-algorithms were more accurate than single meta-heuristic algorithms when combined with the ML models. Accordingly, the development of the field of meta-heuristic algorithms works in parallel ways that either create new meta-heuristic algorithms or hybridise two current algorithms to achieve the benefits of both algorithms.

5. Analysing Scientific Maps

Although there is a steady flow of both applied and theoretical literature, staying abreast of the literature is a complex process. To arrange the results of the prior literature, highlight issues, and determine research gaps, some scholars have proposed the method of systematic reviews and meta-analyses. Systematic reviews increase understanding, improve the study, and summarise the findings of previous studies. Systematic reviews already have problems with trustworthiness and impartiality because they depend on the author's viewpoint to rearrange the results from the preceding literature. To end, various authors have proposed ways for holistic academic research and analysis based on the R-tool and VOS viewer to promote transparency in presenting the outcomes of the previous research (Aria and Cuccurullo, 2017). High dependability and openness in drawing conclusions from the research are hallmarks of the bibliometrics method. Additionally, these tools are easy to use and are widely available since they are developed and shared by the public. As shown in the following sections, the bibliometric approach was used for this research.

5.1. Main Information

Table 1 provides information on the chosen studies, including the authors, location, time frame, techniques, predictors, target prediction, and rating criteria. The following are the results of an examination of many papers on ETo forecasting:

Table 1. Summary of application of various kinds of hybrid models in reference evapotranspiration forecasting.

Authors	Location	Size of Data	Scale	Predictors	Target	Models Used	Best Model	Measures of Accuracy
[51]	Iran	2000–2014	Daily	Tmin, Tmax, RH, U2, Rs, SSD	ET_O	SVR, RL-SVR-WOA, RF-SVR-WOA, PCA-SVR-WOA, COR-SVR-WOA	RF-SVR-WOA	NSE, NRMSE, MAE, R^2, RMSE
[30]	India	2000–2019	Weekly	Tmin, Tmax, Rs, BSS, WS, RH1, RH2, EP	ET_O	ML-ANN, RBF-PSO, RBF-NN, RBF-DE	RBF-DE	NSE, RMSE, R^2, MAPE
[62]	Bangladesh and USA	2004–2019, 2009–2014, 2007–2010	Daily	Tmin, Tmax, WS, RH, SSD, sensible heat flux, latent heat	ET_O	ANFIS, ANFIS-BBO, ANFIS-FA, ANFIS-PSO, ANFIS-TLBO, LSGD,	ANFIS-FA	R, UC, RRMSE, SI, MAE, MBE, Tstat, U95, GPI, NSE, KGE, U, UB, UV, Shannon's entropy, COV, GRA
[31]	Bangladesh	2004–2019, 2015–2020	Daily	Tmin, Tmax, RH, WS, SSD, Rs	ET_O	RT, FIS, M5Tree, HFS, HFS-PSO	HFS-PSO	R, RMSE, NRMSE, Acc, NSE, IOA, MAE, MADE, Shannon's entropy
[9]	China	1966–2015	Monthly	Tmin, Tmax, RH, WS, Rs, Ra	ET_O	KNEA, KNEA-SSA, KNEA-PSO, KNEA-GWO, KNEA-GOA	KNEA-GWO	NRMSE, RMSE, MAE, R^2
[13]	Spain	2000–2020	Daily	Tmean, Tmin, Tmax, RH, WS	ET_O	PRSFGWO, MLP, RFR, SVR, KNR, DET	PRSFGWO	MAE, RMSE, RRMSE, R^2, IOA, ANOVA tests
[66]	China	2018–2019	Daily	Tmean, SSD, RH	ET_O	MMC, GRNN, GRNN-FOA	GRNN-FOA	MVC, MAE, RMSE
[48]	Iran	1973–2018	Monthly	Tmean, Tmin, Tmax, RH, SSD, U2	ET_O	SVR-IWD, SVR, GEP	SVR-IWD	R, MAE, RMSE
[78]	Iran	1987–2000	Daily and Monthly	the lagged ETo values	ET_O	MLP, MLP-GA, MLP-WWO, MLP-PSO	MLP-WWO	NSE, PBIAS, MAE, Scatter plots
[22]	Burkina Faso	1998–2012	Daily	Tmin, Tmax, RH, WS, Rs, Vp	ET_O	ANFIS-FA, ANFIS	ANFIS-FA	TD, MAPE, RMSE, RMSRE, MRE, MAE, R^2, RE, SIndex
[41]	Iran	2001–2012	Daily	T, RH, WS, Rs	ET_O	ELM, NF-GP, NF-SC, MARS, MT, RF, BT, SVM, GEP	SVM-FA and NF-GP	NSE, RMSE, SIndex, MAE, R^2
[32]	China	2018–2019	Hourly	Tmean, VPD, RH, RS, SSWC	ET_O	XGB-PSO, CatBoost, Bagging, XGB, AdaBoost, RF, ANN, KNN, Tree	XGB-PSO	RMSE, MSE, MAE, R^2
[8]	China	1966–2000, 2001–2015	Monthly	Tave, Tmax, Tmin, RH, WS, SSD	ET_O	RF, M5P, ANFIS, KELM-FA, Kmeans-FA-KELM	Kmeans-KELM-FA	NSE, RMSE, MAE, SI, R^2
[54]	China	2001–2015	Daily	Tmin, Tmax, RH, WS, Rs	ET_O	ELM, ELM-FPA, ELM-ACO, ELM-GA, ELM-CSA	ELM-FPA	MAE, RMSE, NRMSE, R^2

Table 1. *Cont.*

Authors	Location	Size of Data	Scale	Predictors	Target	Models Used	Best Model	Measures of Accuracy
[63]	Iran	2000–2015	Daily	Tmin, Tmax, RH, U2, Rs, SSD, Epan, ETo-FAOPM56	ET_O	ANFIS, ANFIS-IWO, ANFIS-BBO, ANFIS-TLBO, ANFIS-ICA	ANFIS-ICA	NSE, MAE, IOA, R, RMSE
[33]	Turkey	1982–2006	Monthly	Tave, RH, WS, Rs	ET_O	ANN, CART, ANFIS-PSO, ANFIS-GA, ANFIS	ANFIS-PSO, ANFIS-GA	R^2, NSE, RMSE
[10]	Malaysia	2014–20	Daily	Tmean, Tmin, Tmax, RH, Rs, U2	ET_O	ELM, ELM-WOA, ELM-PSO, ELM-MFO	ELM-WOA	R^2, RMSE, MAE
[6]	Malaysia	2000–2019	Daily	Tmean, Tmin, Tmax, RH, Rs, WS	ET_O	ANFIS, SVM, MLP, BMLP, BSVM, BANFIS, BMA-E, ELM-WOA-E	ELM-WOA-E	MBE, RMSE, R^2, MAE
[70]	China	2000–2020	Daily, Monthly, and Seasonal Scales	Tmean, RH, WS, Rainfall, VPD, Ra	ET_O	BP-GA, Bi-LSTM, LSSVR	BP-GA, LSSVR	GPI, MAE, MBE, R^2, RMSE
[80]	China	1961–2012	Monthly	Tave, Ra, ETo	ET_O	LSSVR-GSA, DENFIS, M5RT, LSSVR	LSSVR-GSA	R^2, MAE, RMSE
[89]	Bangladesh	1982–2017	Monthly	Tmin, Tmax, RH, U2	ET_O	ANFIS, ANFIS-WCA, ANFIS-MFO, ANFIS-WCAMFO	ANFIS-WCAMFO	R^2, MAE, NSE, RMSE
[38]	Iran	2000–2014	Daily	Tave, Tmax, Tmin, RH, U2, Rs, SSD	ET_O	ANFIS, ANFIS-SFLA, ANFIS-IWO	ANFIS-SFLA	NSE, RRMSE, MAE, R^2, RMSE
[21]	Iran	2012–2017	Monthly	Tmin, Tmax, RH, U2, SSD, P	ET_O	ANN-GWO, ANN, LSSVR	ANN-GWO	GPI, R^2, MAE, U95, SI, TD
[11]	China	1966–2015	Daily	Tmin, Tmax, RH, U2, SSD	ET_O	XGB-WOA, XGB	XGB-WOA	NSE, MAE, RMSE
Lu, et al. [44]	China	1966–2015	Monthly	T, RH, WS, SSD	ET_O	XGB- GWO, MLP, M5, XGB	MLP best in summer, XGB- GWO best in autumn	RMSE, NSE, MAE
[45]	India and Algeria	1994–2012, 1990–2016	Monthly	Tmin, Tmax, RH, WS, Rs	ET_O	ANN, ANN-ALO, ANN-GWO, ANN-MVO, ANN-PSO, ANN-WOA,	ANN-GWO	IOA, NSE, R, IOS, RMSE Scatter plots and TD
[52]	Algeria	2000–2013	Monthly	Tmin, Tmax, RH, WS, Rs	ET_O	SVR, SVR-ALO, SVR-MVO, SVR-WOA,	SVR-WOA	NSE, RMSE, IOA, R, MAE, IOS, and graphical interpretation (time-variation and scatter plots, and TD).
[46]	Algeria	2000–2014	Monthly	Tmin, Tmax, RH, WS, Rs	ET_O	SVR, SVR-PSO, SVR-GA, SVR-GWO	SVR-GWO	IOA, NSE, R, RMSE

Table 1. *Cont.*

Authors	Location	Size of Data	Scale	Predictors	Target	Models Used	Best Model	Measures of Accuracy
[40]	Bangladesh	2004–2019	Daily	Tmin, Tmax, RH, WS, SSD	ET_O	ANFIS, ANFIS-ABC, ANFIS-BA, ANFIS-BBO, ANFIS-ACOR, ANFIS-CMAES, ANFIS-CA, ANFIS-DE, ANFIS-FA, ANFIS-GA, ANFIS-HS, ANFIS-ICA, ANFIS-IWO, ANFIS-PSO, ANFIS-SA, ANFIS-TLBO, ANFIS-LSE-GD	ANFIS-FA	NRMSE, NSE, IOA, KGE, RMSE, MAE, MADE, R
[19]	Northwest China	2002–2016	Daily	Tmin, Tmax, RH, U2, Rs	ET_O	ELM-PSO, ANN, RF, ELM,	ELM-PSO	R^2, RRMSE, NSE, MAE

5.2. Country Scientific Production

The country scientific production map shows the publication production of authors, institutions, and nations. One of the most important ways to help academic and industrial institutions thrive is to increase the number of published scientific papers. Figure 3 shows a graphic map of OBH models to predict the ETo time series. This figure has four colours. The darkest blue refers to the highest scientific productions, while the bright blue relates to the fewest scientific productions. The grey area shows the lack of scientific production output. China and Iran have the highest scientific production, which can improve researchers' and policymakers' scientific views.

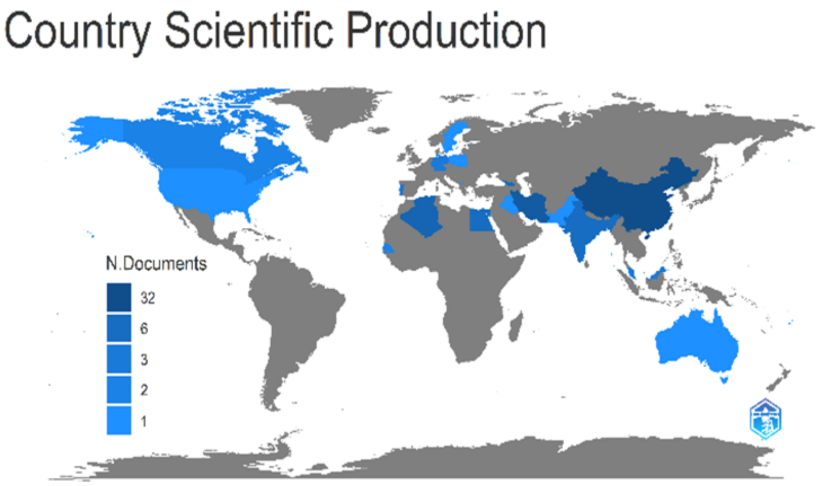

Figure 3. A graphic map of OBH models to predict ETo time series.

5.3. Cloud of Words

The most frequently used and significant terms from the titles of previous studies are explored in this word cloud. In order to offer a summary and reorganise the data, Figure 4 delivers the key terms from the research literature. It can be seen in various word sizes. Larger word sizes indicate greater occurrence rates in the studies. Terms with fewer occurrences in the established literature tend to be thinner. Daily and monthly reference evapotranspiration prediction and optimisation algorithms are all crucial parts of the existing body of knowledge in this regard. The literature outcomes recommend that optimisation algorithms are essential considerations for improving ML techniques in the ETo prediction models.

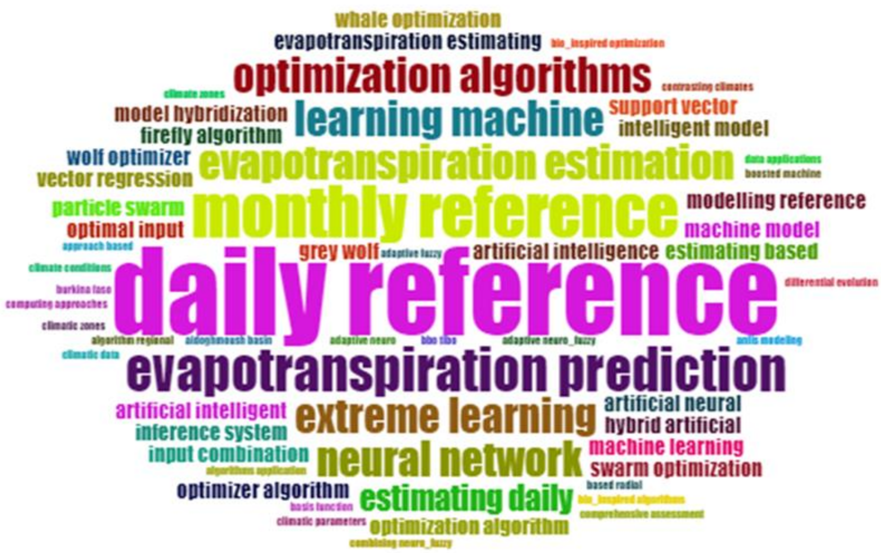

Figure 4. A delivers key terms from the research literature.

5.4. Distribution Based on Affiliations

Twelve different affiliations were represented in the papers included in this analysis that discussed the prediction of ETo using OBH models (see Figure 5).

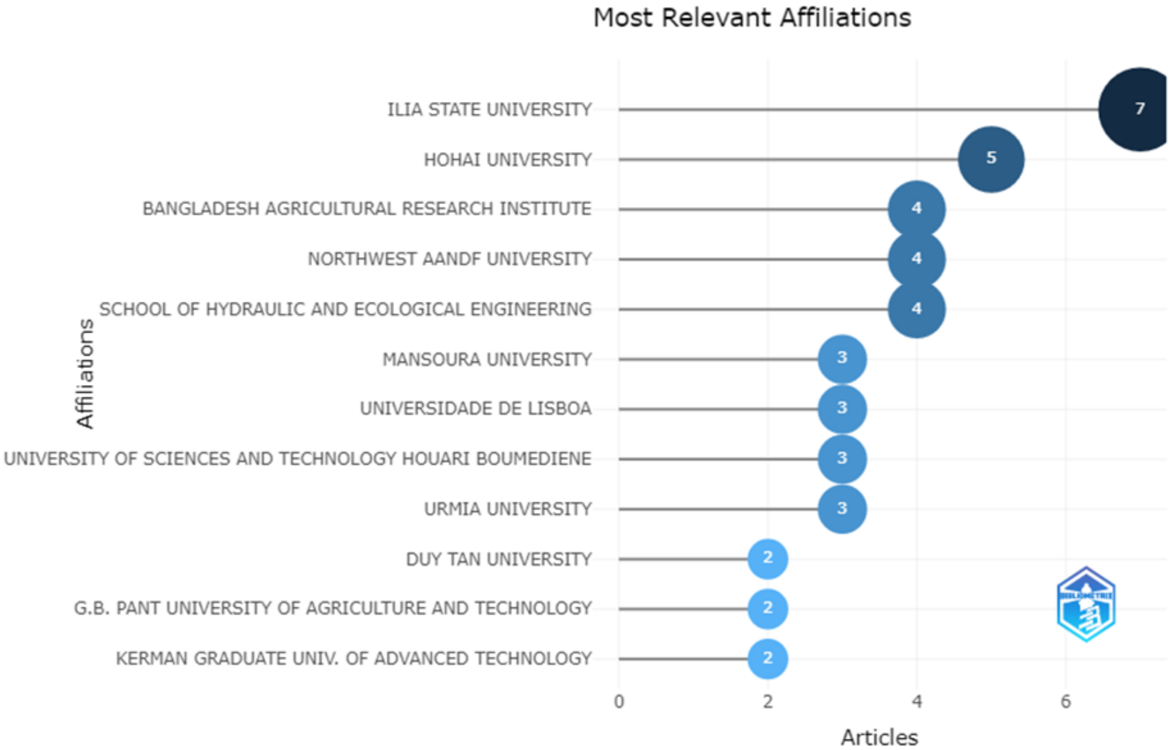

Figure 5. A delivers key terms from the research literature.

There are a total of 33 papers. The number distribution of the selected articles on the prediction of ETo reveals that the most prolific writers are found at Ilia State University (7 papers). Then, Hohai University (5 papers), followed by Bangladesh Agricultural Research Institute, Northwest Aandf University, and School of Hydraulic and Ecological Engineering, each of which had four papers. The following universities each contributed three papers: Mansoura University, Universidade de Lisboa, University of Sciences, Technology Houari Boumediene, and Urmia University,. At last, we have Duy Tan University, G.B. Pant University of Agriculture and Technology, and Kerman Graduate univ. of Advanced Technology, all of which contributed two papers each.

5.5. Co-Occurrence

Co-occurrence networks are built using frequently occurring terms from the existing literature. Academics, researchers, and practitioners in a given field may greatly benefit from the co-occurrence analysis network structure, which can shed light on the underlying theoretical frameworks of that discipline. In order to better comprehend commonly used terms, Figure 6 exhibits their co-occurrence networks.

The network of topics in the prior literature is reflected in the co-occurrence. It is constructed of interconnected lines and knots. Regarding the literature, the largest knots represent the most common themes. Since researchers may use data networks to aid their attempts to reorganise the available information and results, optimisation algorithms are among the most frequently used phrases by previous academics in the ETo prediction models.

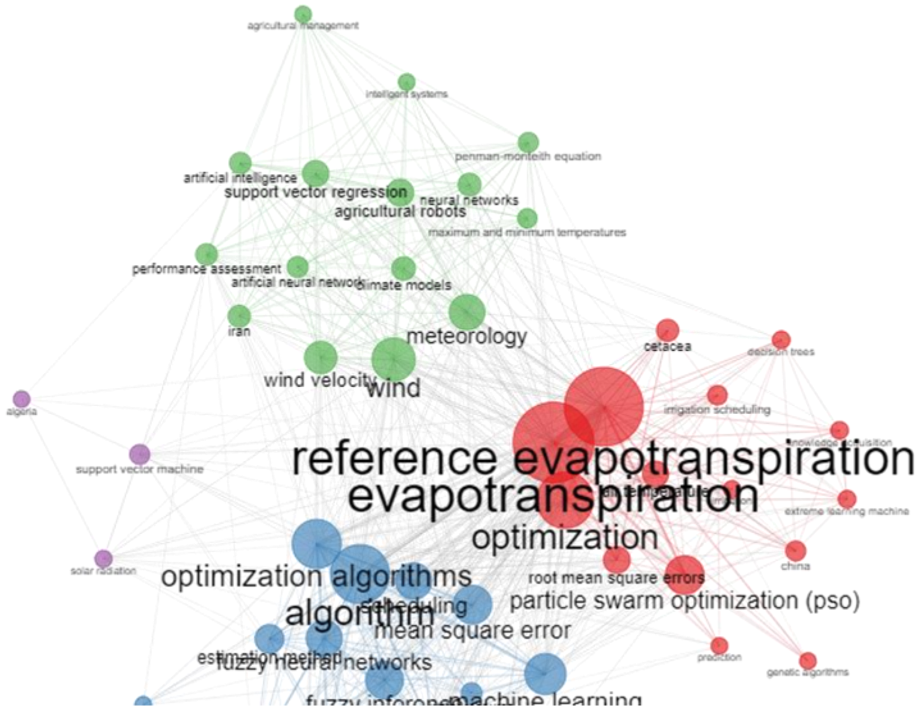

Figure 6. A co-occurrence networks structure.

6. Recommendations

The most significant suggestions provided by recent previous studies for potential future ETo modelling research are outlined in this section.

Mohammadi and Mehdizadeh [51] recommended combining AI methods such as ANFIS and MLP with optimisation algorithms such as GA, PSO, FFA, and KHA to create different hybrid models. Mehdizadeh, et al. [38] expressed a similar viewpoint when they proposed merging the ANFIS and SVM with additional bio-inspired optimisers, such as the FA, WOA, GOA, krill herd algorithm (KHA), and the dragonfly algorithm (DFA) to provide a variety of hybrid models for ETo modelling. Furthermore, Roy, et al. [31] advised that future studies may focus on examining and contrasting additional bio-inspired optimisation algorithms for the HFS models' parameter tweaking procedures. Zhu, et al. [19] mentioned that the hybrid PSO-ELM model is an effective way to estimate the daily ETo under various input configurations. Roy, et al. [62] demonstrated how, in some places, the seasonal variance of ETo is frequently far larger than the variation in daily anomalies. Future studies might focus on creating AI-based prediction models that take into account this seasonal change in the ETo values. El-Kenawy, et al. [13] recommended re-evaluating the same hybrid method (i.e., PRSFGWO) in various climatic conditions. Ahmadi, et al. [48] suggested combining AL-based ANN and ANFIS approaches with a variety of optimisation methods, including GA, PSO, FA, and SFLA, to suggest other forms of combined models. Furthermore, it is recommended that the novel hybrid techniques (i.e., SVR-IWD) be applied to hydrological research studies in order to simulate the time series of hydrological parameters such as evaporation, precipitation, stream flow, and other variables.

According to Sayyahi, et al. [78], using the proposed model in their study (MLP-WWO) was recommended to predict hydrological phenomena and other hydrological variables such as precipitation, temperature, and runoff. Maroufpoor, et al. [21] recommend using one of the most effective technologies for supplying meteorological information: the geographic information system (GIS) and satellite data. The lack of meteorological stations may be resolved by analysing AI models with satellite input data to estimate ETo. Tikhamarine, et al. [45] suggested that additional meta-heuristic algorithms, such as the GOA, MFO, and the crow search algorithm, may also be employed to estimate monthly ETo.

From the above analysis and observations, we may highlight some insights that should be helpful for any future developments in this field:

The SI algorithms are superior to the other meta-heuristic types based on the findings of earlier studies and identifying the best models. So, it advises using it going forward for that reason.

Recently, hybrid meta-heuristic algorithms, such as WCAMFO (i.e., combining swarm intelligence-based and physics-based algorithm types), have proven efficient. Accordingly, extending the existing results by investigating various hybrids of meta-heuristic algorithms would be a beneficial next step.

The use of the OBH technique in ETo forecasting has recently increased. Nevertheless, there is still an opportunity for improvement by investigating different combinations of types of ML models and meta-heuristic algorithms.

7. Conclusions

The worldwide shortage of freshwater has worsened substantially in recent years. Consequently, there has been a growing trend towards integrating ML models with meta-heuristic algorithms in the field of ETo modelling to offer policymakers a scientific view that supports sustainability. Accordingly, this study systematically reviewed in detail the available information on OBH models for ETo prediction in the last five years by considering three reliable sources (i.e., Web of Science, ScienceDirect, and IEEE Xplor). This study offers a substantial contribution through classification and taxonomist publications. There are distinct patterns that can be drawn from the mass of writings on ETo prediction, approximately categorising the paper into five groups: swarm intelligence algorithms, evolutionary computation algorithms, physics algorithms, hybrid algorithms, and review papers.

The outcomes of this research indicate that 47% of the total papers used one meta-heuristic algorithm to optimise the ML model and compared the results with the standalone ML model. The results show the superiority of the hybrid ML technique in all cases. Furthermore, it concluded that 47% of the total papers integrated the ML model with several meta-heuristic algorithms to increase validation. The results show that the swarm intelligence-based algorithms were superior to evolutionary computation-based and physics-based algorithms. Moreover, hybrid meta-heuristic algorithms offer more accurate predictions than several single meta-heuristic algorithms when combined with ML models.

Overall, this study strengthens the idea that meta-heuristic algorithms accurately optimise ML models. Additionally, it has been one of the first attempts to thoroughly analyse the performance of different meta-heuristic algorithms (categorised into four main groups) combined with ML models. These findings contribute in several ways to our understanding of OBH models. Further studies regarding the role of meta-heuristic algorithms would be worthwhile because academics still have room to improve OBH models for ETo prediction models. Finally, accurate ETo data led to a balance between requested and delivered water demand that achieved sustainability.

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Abbreviations

Abbreviations	**Explanation**
ABC	Artificial Bee Colony
Acc	Accuracy
ACO	Ant Colony Optimisation
ACOR	Continuous Ant Colony Optimisation
AI	Artificial Intelligence
ALO	Ant Lion Optimizer
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
BA	Bee Algorithm
BBO	Biogeography-Based Optimisation
BMA	Bayesian Model Averaging
BSS	Bright Sunshine Hours
CART	Classification and Regression Tree
CMAES	Covariance Matrix Adaptation Evolution Strategy
COR	Pearson's correlation
CSA	Cuckoo Search Algorithm
DE	Differential Evolution
DENFIS	Dynamic Evolving Neural-Fuzzy Inference System
DET	Decision Tree Regressor
DFA	Dragonfly Algorithm
EC	Evolutionary Computing
ELM	Extreme Learning Machine
EP	Weekly Cumulative Pan Evaporation
Epan	Pan Evaporation
ET	Evapotranspiration
ETo	Reference Evapotranspiration
FA	Firefly Algorithm
FIS	Fuzzy Inference System
FOA	Fruit Fly Optimisation Algorithm
FPA	Flower Pollination Algorithm
GA	Genetic Algorithm
GOA	Grasshopper Optimisation Algorithm
GP	Genetic Programming
GPI	Global Performance Index
GSA	Gravitational Search Algorithm
GWO	Grey Wolf Optimizer
HFS	Hierarchical Fuzzy System
HS	Harmony Search
ICA	Imperialist Competitive Algorithm
IOA	Willmott's Index of Agreement
IOS	Index Of Scattering
IWD	Intelligent Water Drops
IWO	Invasive Weed Optimisation
KGE	Kling–Gupta Efficiency
KHA	Krill Herd Algorithm
KNR	K-Neighbours Regressor
LSSVM	Least Square Support Vector Machine
LSSVR	Least Squares Support Vector Regression
M5	Model Tree
MAD	Mean Absolute Deviation
MADE	Median Absolute Deviation
MAE	Mean Absolute Error
MAX	Maximum Absolute Error
MAPE	Mean Absolute Percentage Error
MBE	Mean Bias Error

MEMD	Multivariate Empirical Mode Decomposition
MFO	Moth-Flame Optimisation Algorithm
MLP	Multilayer Perceptron
MLR	Multiple Linear Regression
MRE	Mean Relative Error
MSE	Mean Square Error
MVC	Model Validity Coefficient
MVO	Multi-Verse Optimizer
NNE	Non-Linear Neural Ensemble
NRMSE	Normalised Root Mean Squared Error
NSE	Nash–Sutcliffe Coefficient of Efficiency
P	Precipitation
PBIAS	Percent bias
PCA	Principal Component Analysis
FAO-56 PM	Penman–Monteith Model
PRSFGWO	Adaptive Dynamic Algorithm Coupled with the Grey Wolf Optimizer
PSO	Particle Swarm Optimisation
R	Correlation Coefficient
R^2	Coefficient of Determination
Ra	Extraterrestrial Solar Radiation
RF	Random Forest
RFR	Random Forest Regressor
RH	Relative Humidity
RH1	Morning Relative Humidity During
RH2	Afternoon Relative Humidity
RL	Relief
RMSE	Root Mean Square Error
RMSRE	Root Mean Square Relative Error
RRMSE	Relative Root Mean Square Error
Rs	Global Solar Radiation
RT	Regression Tree
SA	Simulated Annealing Optimisation Algorithm
SFLA	Shuffled Frog-Leaping Algorithm
SIndex	Scatter Index
SONN	Second-Order Neural Network
SSA	Salp Swarm Algorithm
SSD	Sunshine Duration
SSWC	Average Surface Soil Water Content
SVM	Support Vector Machine
SVR	Support Vector Regression
T	Air Temperature
Tave	Average Temperature
Tmax	Maximum Temperature
Tmean	Mean Air Temperature
Tmin	Minimum Temperature
TD	Taylor Diagram
Tstat	T-statistic Test
TLBO	Teaching-Learning-Based Optimisation
U2	Wind Speed at a Height of 2 m
U95	Uncertainty with 95% Confidence Level
U	Theil Inequality Statistic
UB	Bias Proportion of Theil Inequality Statistic
UC	Covariance Proportion of Theil Inequality Statistic
UV	Variance Proportion of Theil Inequality Statistic

Vp	Vapour Pressure
VPD	Saturated Water Vapour Pressure Deficit
WCA	Water Cycle Optimisation Algorithm
WCAMFO	Water Cycle-Moth Flame Optimisation
WoS	Web of Science
WOA	Whale Optimisation Algorithm
WS	Wind Speed
WWO	Water Wave Optimisation
XGB	Extreme Gradient Boosting

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