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Review

A Systematic Review on Estimation of Reference Evapotranspiration under Prisma Guidelines

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Abstract

Reference evapotranspiration (ET_o) is considered an essential factor in determining the meticulous estimation of crop water requirement and effective irrigation scheduling. The accurate estimation of crop water requirement is of critical importance to minimize over and under irrigation problems. Several empirical/semi empirical equations have been developed in the past to quantify ET_o. The Penmen-Montieth equation (FAO-PM56) has been globally accepted for estimation of ET_o but certain limitations were found to its implementation. The use of soft computing models in estimation of ET_o has received enormous interest in recent decade. Many studies have been reported in the literature to apply soft computing models on the improvement of ET_o estimation. This study intended to review these studies on basis of accuracy, structure and its flexibility/usefulness, and also made some possible suggestions for future research in this domain.

Keywords: reference evapotranspiration, empirical/semi-empirical equation, soft computing models, challenges and issues, diverse climatic stations

Introduction

Mitigation of water shortage has become a critical issue of the 21st century and labeled as blue gold. The agriculture sector is ranked as the highest consumptive user of water in most of the countries. The water withdrawal from the total amount of water in developing counties is estimated nearly 81% while it is accounted for 71% globally. In addition, more than 55% of all the world's fresh water withdrawals are allocated towards irrigation use [1]. Reference evapotranspiration (ET_o) is the principal component of the global hydrological cycle which affects irrigation, water requirement and crops yield. It consists of evaporation and transpiration processes. The phenomenon in which water moves from the land surface to the atmosphere is called evaporation while transpiration is the process in which plant roots

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extract water from the root zone and transport it to the leaves where it is lost through stomata [2]. For the purpose of the reference surface, a substantially uniform field of alfalfa (or grass) is considered worldwide. The characteristic of a reference surface crop includes the soil's properties, uniform height and total amount of water use under standard meteorological and agronomical conditions [3].

Estimation of ET_o is considered an essential element in the regional and global scale, preparation of water budget, crop irrigation requirements and influence of climate variation [4]. According to Lu et al. [5] and Zhao et al. [6], quantification of ET_o has always been difficult due to an imperceptible process exclusively in an ecosystem or a watershed spatial scale with the desired level of accuracy. Determining the soil water balance (especially ET_o component) is of great importance for good irrigation planning and management. As the soil has limited capacity to contain water, knowing the soil water balance overcomes the risk to apply excessive amounts of water which results in high percolation or overflow [6].

The estimation of ET_o through lysimeter is considered the best choice for direct measurement but a hard chore because it is time consuming and also requires potential financial aid. This method is not viable due to tedious and imprecise planning. Consequently, the indirect and soft computing models have gained much importance for estimating ET_o from climatic data [7]. McMahon et al. [8] have categorized indirect methods into following types: (1) empirical and semi empirical equations (2) Pan-evaporation method (3) energy budget method (4) mass transfer equations (5) combination equations (6) radiation base methods. In addition, empirical/semi-empirical equation based priestly-Taylor and penmen montieth methods have been widely used for estimation of ET_o [9]. Numerous methods/approaches have been developed for the estimation of $ET_{o.}$ These methods/approaches were used in different regions of the world and it worked efficiently where they were developed. When such approaches/ methods were applied in other climatic regions, the results were quite inefficient and not satisfying in comparison to conventional adopted methods [10].

One of the well-known indirect methods has been introduced by Food and Agriculture Organization (FAO) of United Nations which is accepted worldwide for ET_o estimation. This method includes incorporation of Penman-Monteith equation which was altered and reformed by Allen et al. [11] as symbolized as FAO-PM56. This method must be affected and controlled by several aerodynamic, surface resistance and climatic parameters. These consist of maximum and minimum air temperature, wind speed and solar radiation, deficit of saturation vapor pressure, slope vapor pressure curve, maximum and minimum relative air humidity and psychrometric constant. There is an anomaly to air temperature available at several weather stations. The remaining variables are usually incomplete and not always found reliable for several locations [12]. In the developed countries this may be not valid but in cases of developing countries, it considers a big challenge, where quantity and quality of data, always remain questionable. The reliable weather data sets of radiation, wind speed and relative humidity are often limited in developing countries as reported by Trajkovic and Kolakovic [13]. In addition, the geographic data (latitude, longitude, altitude) is also necessary in FAO-PM56 for the local adjustment of the various weather parameters, e.g. extraterrestrial radiations, atmospheric pressure, and daylight hours [14].

Thus, alternative computer based soft computing models have been developed and reported in the literature over a last decade to omit limitations of FAO-PM56 method and try to estimate ET_o by using limited climatic parameters. The formulation of ET_o model with use of novel learning algorithms, input/output dataset and activation functions in soft computing models attained much attention in achieving high performance. In this study, ET_o estimation by applying various soft computing models in comparison to FAO-PM56 and empirical/semi-empirical equations existed in literature have been reviewed on the basis of accuracy, structure and flexibility/usefulness.

Development of Soft Computing Models

Kumar et al. [15] have categorized ET_o estimation into energy based, temperature based, mass transfer and composite based methods. These methods are based on various empirical and semi-empirical equations which can be observed in Table 1. It can be perceived that selection of particular method depends upon weather type and nature of surface area. The weather divided into saturated, semi saturated, semi dry and dry conditions while surface area into valley, grassy land, vegetative surface, lake surface, water free surface and grass type. Beside each method, only composite method based on FAO-PM56 equations acknowledged as standard and considered viable for each type of weather and surface area. The applicability of FAO-PM56 equation become limited due to large amount of climatic and aerodynamic parameters requirement. Therefore, various researches conducted on ET_o estimation in different part of world and reported in recent decade.

The application of soft computing models have been widely used for non-linear phenomena in hydrological studies [16]. As the process of ET_o considered non-linear dynamic and complex in nature, soft computing models can be contemplated as alternative tool. These models are based on computational intelligent system to overcome imprecision and vulnerability in producing results. The topology in development of soft computing model for ET_o estimation is presented in Fig. 1. The selection of best suitable soft computing model depends upon model's structure, accuracy and usefulness.

Table 1. Types of ET_o estimation method based on empirical/semi-empirical equations.

Type	Equation	Weather condition	surface area
Energy based method	$ET = ET\frac{dN}{360}, ET' = C\left(\frac{10Ta}{I}\right)^a i = \left(\frac{Ta}{5}\right)^{1.51} = \sum_{j=1}^{12} j$	Saturated	Valley
	$ET = a\frac{\Delta}{\Delta+\gamma}\frac{R_s}{\lambda} - \beta$, $\alpha = 0.61$, $\beta = 0.12$	Saturated	Grassy land
	$ET = 0.013\frac{T}{T+15}(R_s+50)RH > 50$ $ET = 0.013\frac{T}{T+15}(R_s+50)(1+\frac{50-RH}{70})$	Saturated	Grassy land
	$ET = C_t(T-T_x)\frac{R_s}{\lambda}$ $Ct=0.025$; $T_x = -3$	Saturated and semi-saturated	Grassy land
	$ET = a\frac{\Delta}{\Delta+\gamma}\frac{R_n}{\lambda}$ $\alpha = 1.26$	Saturated Humid; wet surface	Hydrated surface
	$ET = 0.0135(T+17.8)\frac{R_s}{\lambda}$	Dry and semi-dry	Grassy land
	$ET = a\left(\frac{\Delta}{\Delta+\gamma}\frac{R_s}{\lambda}\right) + b$ $b = 0.03$	Saturated	Grassy land
Temperature based method	$ET = 0.55D^2Pt$ $\quad ET = Kp(0.46T + 8.13)$	Dry and semi-dry	Vegetative surface
	$Pt = \frac{4.95e^{(0.062T_a)}}{100}$	All type	Vegetative surface
	$ET = \frac{\frac{500T_m}{100-A} + 15(T_a - T_d)}{(80 - T_a)}$	All type	Lake surface
	$ET = 0.34\rho {T_a}^{1.3}$	Dry	Vegetative surface
Mass transfer method	$ET = 0.35(1 + \frac{0.98}{100U_2})(e_s - e_a)$	Saturated	Water free surface
	$ET = 0.44(1 + 0.27U_2)(e_s - e_a)$	Dry and semi-dry	Water free surface
Composite method	$ET = \frac{0.48\Delta(R_N) + \gamma\frac{900}{(T_a+273)}U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)}$	All type	Grass

Several factors including hidden/output layer, weights and neurons, activation functions, network and other tuning parameters helped in determining suitable model. These factors are explicitly explained in Raza et al. [17-18]. It was noted that these models produced good results using fewer inputs which resembled with field calculations. The development of these models using limited dataset without involving physical process information made them superior over conventionally adopted empirical/semi-empirical equations and urge to use [19].

Review Methodology: PRISMA Guidelines

The guidelines of preferred reporting items for systematic review and meta-analysis (PRISMA) were followed for conducting systematic review in this study.

Data Source

The searching of research articles was performed in google scholar database only. The following keywords were used individually and along with combinations for seeking relevant results: reference evapotranspiration, soft computing, machine learning, artificial neural network, climatic variables, climatic stations, Penmen Montieth equation, ET_o.

Screening of Articles and Data Collection

The following inclusion criteria for the selected research articles was carried out: only English language based scientific articles, published articles available in full text and indexed in scientific journals. However, the studies belong to incompatible results, dissertations, books and unpublished work were excluded in this study. A total of 143,000 research articles were significantly identified. Based on inclusion and exclusion criteria,

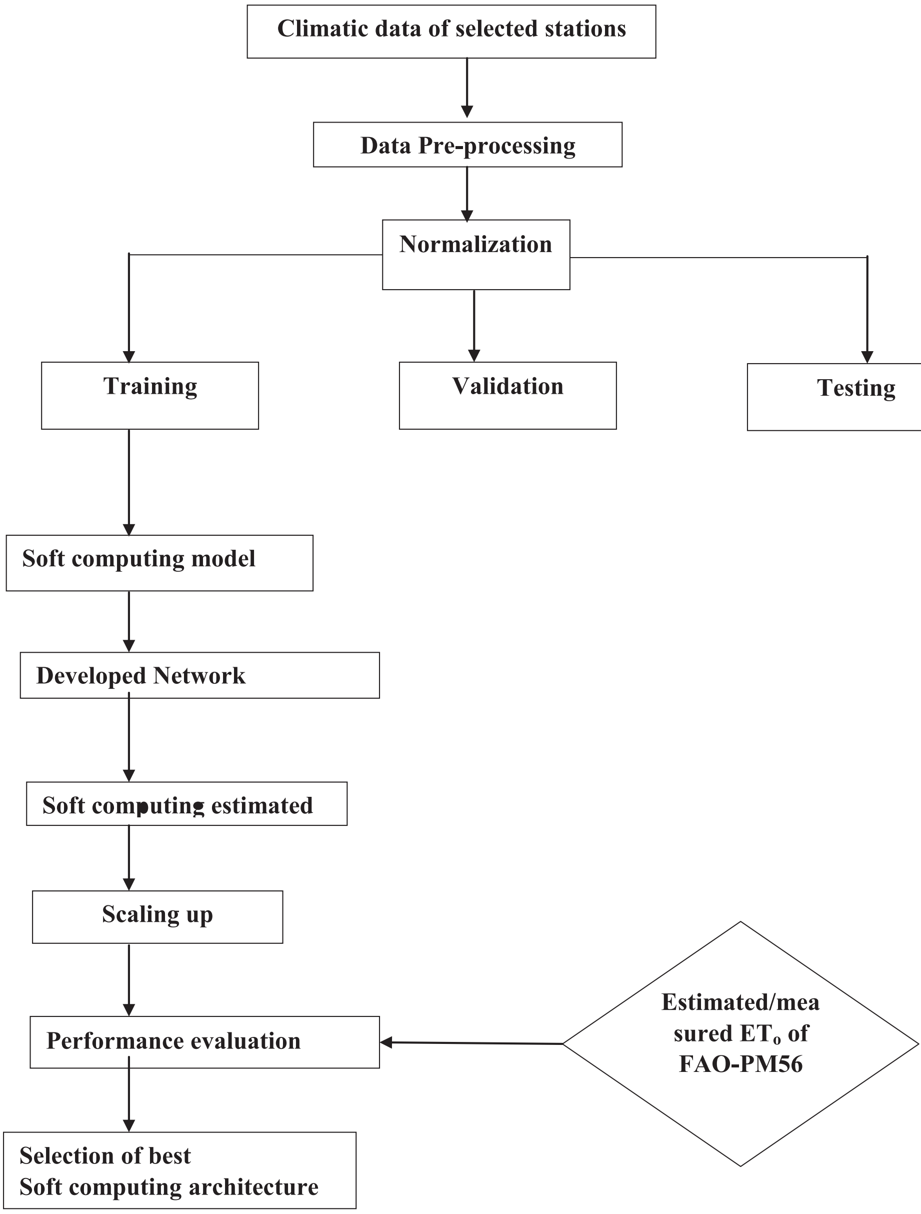

Fig. 1. Development of soft computing model.

only 29 full-text research articles were considered suitable and completely investigated in this study. The PRIZMA flow diagram as per instructions was made which is presented in Fig. 2. The research articles in accordance with inclusion criteria were downloaded. The adopted methodology and obtained results of these selected articles were evaluated and finally included in this review. The following attributes were noted from included articles: (i) input/target data, (ii) study duration, (iii) time step, (iv) study origin, (v) best soft computing model, (vi) model evaluation parameters, (vii) study used other countries climatic data.

Data Type and Size

Before the implementation of a soft computing model, it is necessary to check the type of selected data. Numerous researches indicate that different data division ratios were performed in training and testing phases when using soft computing models. There is no hard and fast rule to divide the data of training and testing phases in specific ratio but rarely 50/50 or 60/40 or 90/10, while mostly 70/30, have been applied in previous studies. A case study conducted on computation of daily solar radiation using wavelet and support vector machines divided available data set into 90/10 ratio for training and testing phases [20]. The reported articles [21-23] divided climatic dataset into 50%, 20% and 30% for training, validation and testing phases. With the recent development in soft computing models, the data points inside the training phase could be validated, therefore dataset could only be divided into training and testing phases [24-27].

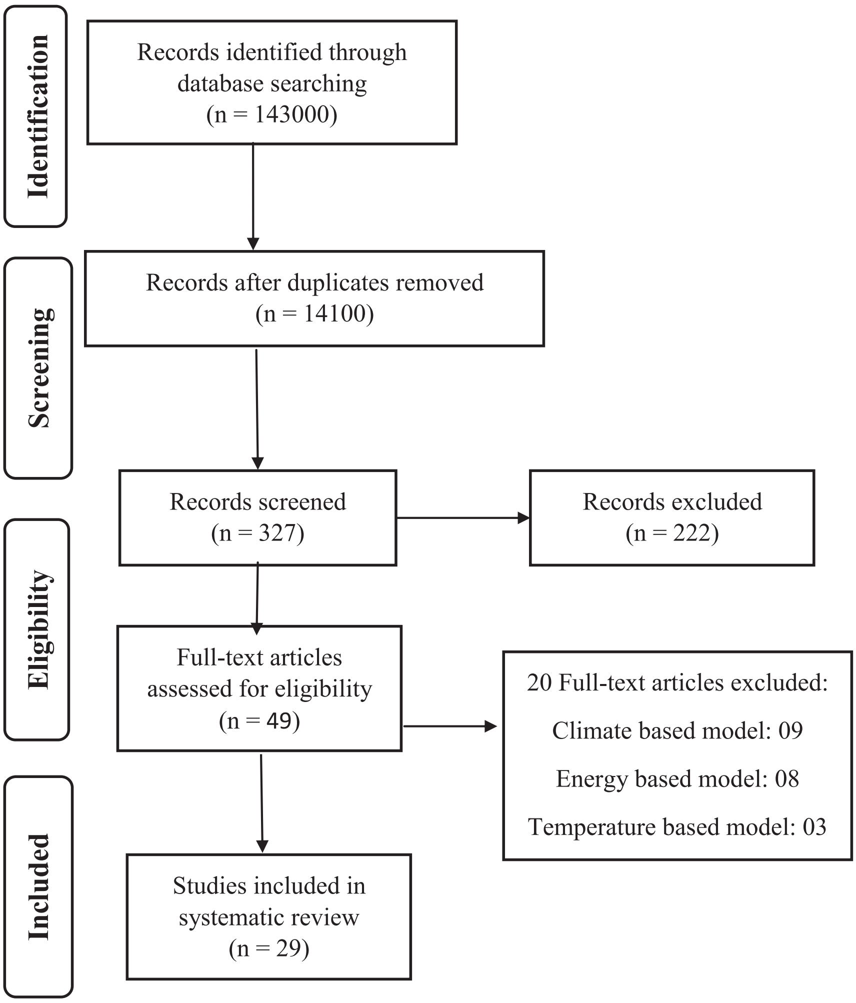

Fig. 2. PRISMA flow diagram.

Selected Reviewed Articles

The recently published studies on ET_o estimation not later than 8 years ago (2012-2020) were included and evaluated which are in the English language and available in full text.

Evaluation and Assessment

In this study, reported articles (2012-2020) have been reviewed on basis of accuracy, structure and its usefulness.

Accuracy

The accuracy of soft computing models was investigated through a set of various indicators and/or indices. The commonly used performing indices are Pearson correlation coefficient (r2), Linear regression coefficient (R2), Nash-sutcliffe efficiency (NSE), Mean absolute error (MAE), Root mean square error (RMSE), Mean absolute percentage error (MAPE) and scatter index (SI) which can be determined as:

$$r^2 = \frac{[n\times\{\sum_{i=1}^{n}\{(ET_{obs}\times\overline{ET}_{est})\}]-[\{(\sum_{i=1}^{n}ET_{obs})\times(\sum_{i=1}^{n}ET_{est})\}]}{\sqrt{[n\times\{\sum_{i=1}^{n}(ET_{obs})^2]-[\{(\sum_{i=1}^{n}ET_{obs})\}^2]\times[n\times\{\sum_{i=1}^{n}(ET_{est})\}^2]-[\{(\sum_{i=1}^{n}ET_{est})\}^2]}} \tag{1}$$

$$R^2 = \frac{[(\sum_{i=1}^{n}(ET_{obs}-\overline{ET_{obs}})\times(ET_{est}-\overline{ET_{est}})]^2}{[(\sum_{i=1}^{n}(ET_{obs}-\overline{ET_{obs}})\times(ET_{est}-\overline{ET_{est}})]} \tag{2}$$

$$NSE = 1-\frac{\sum_{i=1}^{N}(ET_{obs}-ET_{sim})}{\sum_{i=1}^{N}(ET_{obs}-\overline{ET}_{obs})} \tag{3}$$

$$MAE = \sum_{i=1}^{N}\frac{|ET_{obs}-ET_{sim}|}{N} \tag{4}$$

$$MAPE = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{ET_{obs}-ET_{est}}{ET_{obs}}\right| \tag{5}$$

$$RMSE = \sqrt{\sum_{i=1}^{N}\frac{(ET_{obs}-ET_{est})^2}{N}} \tag{6}$$

$$SI = \frac{RMSE}{ET_{mean}} \tag{7}$$

Structure

The structure of soft computing model depends upon its input/output dataset, neurons and activation

Table 2. Reviewed studies on ET_o estimation applied soft computing models (2012-2020)

Studies	Applied models	Input/output	Time Step	Best model	Accuracy indices	Usefulness (selected region)
Shiri et al. [28]	GEP, empirical equations, ANFIS	$T_{(max, min, mean)}$, R.H, R_s, U-ET_o	Daily	GEP	RMSE, R^2, SI	1-country (Spain)
Traore and Guven [29]	GEP	R_s, T_{mean}, R.H, U-ET_o	Daily	GEP	RMSE, r	1-country (Burkina Faso)
Jean et al. [30]	GEP, FAO-PM56	T_{mean}, R_s, soil Ǿ, R_n, U- ET_o	Monthly	GEP	RMSE, R^2	1-country (Datong Basin)
Eslamian et al. [31]	ANN-GA, ANN	$T_{(max, min, mean)}$, R.H, R_s, U-ET_o	Monthly	ANN-GA	MSE, NMSE, MAE, r	1-country (Iran)
Shiri et al. [32]	GEP, empirical equations, ANFIS	$T_{(max, min, mean)}$, R.H, R_s, U-ET_o	Daily	GEP	MAE, SI, NS, R^2	1-country (Iran)
Traore and Guven [33]	GEP	$T_{(max, min, mean)}$, R.H, P,N U-ET_o	Daily	GEP	RMSE, R^2	1-country (Burkina Faso)
Shiri et al. [34]	ANN, empirical equations, SVM, ANFIS, GEP	$T_{(max, min, mean)}$, R.H, R_s, U-ET_o	Daily	GEP	RMSE, R^2, SI, MAE	1-country (Iran)
Shiri et al.[35]	GEP1–3	$T_{(max, min, mean)}$, R.H, R_s, U-ET_o	Daily	GEP	RMSE, R^2, AARE, MAE	1-country (Iran)
Kisi et al. [36]	GEP, ANFIS-GP/SCANN	Geographic data (Lat, Long, Alt)-ET_o	Monthly	ANFIS-GP/SC	RMSE, R2	1-country (Iran)
Martí et al. [37]	Empirical equations, GEP	Calibrated/Calculated ET_o	Daily	GEP	RMSE, R^2, MAE	1-country (Spain)
Gocić et al. [38]	GP, SVM-WA/FFA, FAO-PM56, ANN	T_{max}, T_{min}, V.P, N, U-ET_o	Monthly	SVM-W	RMSE, R2, r, MAE, MAPE	1-country (Serbia)
Yassin et al. [39]	ANN, GEP, FAO-PM56	$T_{(max, min, mean)}$, $R.H_{(max, min, mean)}$, R_s, U-ET_o	Daily	ANN	RMSE, R^2, OI, MAE	1-country (Saudi Arabia)
Alazba et al. [40]	GEP	$T_{(max, min, mean)}$, $R.H_{(max, min, mean)}$, R_s-ET_o	Daily	GEP	RMSE, R^2, MAE	1-country (Saudi Arabia)
Yassin et al. [41]	GEP	$T_{(max, min, mean)}$, $R.H_{(max, min, mean)}$, R_s, U-ET_o	Daily	GEP-MOD/8	RMSE, R^2, OI, MAE	1-country (Saudi Arabia)
Kumar et al. [42]	ELM, SVM, ANN, GP	$T_{(max, min)}$, $R.H_{(max, min,)}$, R_s P, U-ET_o	Daily	ELM	RMSE, R^2, Time	1-country (India)
Karimi et al. [43]	SVM, GEP	$T_{(max, min)}$, R.H, R_s, U-ET_o	Daily	GEP	MAE, CRM	1-country (Republic of Korea)
Kiafar et al. [44]	Empirical equations, GEP	$T_{(max, min, mean)}$, R.H, R_s, U-ET_o	Daily	GEP	RMSE, R^2, CRM	2-country (Iran, Spain)
Mehdizadeh et al. [45]	GEP, MARS, SVM	$T_{(max, min, mean)}$, R.H, R_s, U-ET_o	Monthly	MARS	RMSE, R^2, MAE	1-country (Iran)
Traore et al. [46]	GEP, FAO-PM56	$T_{(max, min, mean)}$, R.H, R_s, N, U-ET_o	Daily	GEP-MLP	RMSE, r, MAE, RRSE	1-country (China)
Shiri [47]	Empirical equations, GEP	$T_{(max, min, mean)}$, R.H, R_s, U-ET_o	Daily	GEP	SI, MAE, NSE	1-country (Iran)
Feng et al. [48]	GRNN, DTF	$T_{(max, min)}$ R.H, R_s, N_D, U-ET_o	Daily	DTF	RRMSE, MAE, NSE	1-country (China)
Landeras et al. [49]	GEP, MLP	$T_{(max, min, mean)}$, $R.H_{(max, min, mean)}$, N_D, U-ET_o	Daily	GEP	RMSE, MAE, SI	1-country (Ghana)
Mattar and Alazba [50]	GEP, MLR, FAO-PM56	$T_{(max, min)}$ $R.H_{mean}$, R_s, U-ET_o	Monthly	GEP	RMSE, R, MAE	1-country (Egypt)
Mattar [51]	Empirical equations, GEP	$T_{(max, min)}$, $R.H_{mean}$, R_s, U-ET_o	Monthly	GEP	RMSE, OI, IA	1-country (Egypt)
Mehdizadeh [52]	MARS, GEP	T_{mean}, R.H, R_s, U-ET_o	Daily	GEP1-ARCH	RMSE, R2, MAE, MAPE	1-country (Iran)

Table 2. Continued.

Jovic et al. [53]	GP	$T_{(max, min, mean)}$, R.H, N, U-ET_o	Monthly	GP-6	RMSE, R	-
Mohammad et al. [54]	GEP, SVM, ANFIS	$T_{(max, min, mean)}$, R.H, N, U-ET_o	Daily	SVM	MSE, R2, MAE	1-country (Iran)
Shiri [55]	GEP	$T_{(max, min, mean)}$, R.H, N, U-ET_o	Monthly	E1/E2-GEP4,	IA, RMSE, NS	1-country (Island)
Sanikhani et al. [56]	GEP, MLPNN, GRNN, RBFNN, ANFIS-GP/SC	$T_{(max, min, mean)}$, R.H, N, U-ET_o	Monthly	RBNN, GEP	RMSE, R2, MAE, CRM, NS	1-country (Turkey)
Shiri et al. [57]	Empirical equations, GEP	$T_{(max, min, mean)}$, R_a, R_s - ET_o	Daily	GEP	SI, NSE	1-country (Iran)
Raza et al. [17]	SDT, TB, DTF, FAO-PM56	$T_{(max, min, mean)}$, $R.H_{(max, min, mean)}$, U, N-ET_o	Monthly	TB	RMSE, R2	4-country (Pakistan, China, New Zealand, USA)
Raza et al. [18]	MLPNN, CCNN, GMDH, GRNN, SVM, FAO-PM56	$T_{(max, min, mean)}$, $R.H_{(max, min, mean)}$, U, N-ET_o	Monthly	SVM	r^2, R^2, M.E, RMSE, MAE, MAPE, SI	4-country (Pakistan, China, New Zealand, USA)

functions. In case of artificial intelligence (AI) based soft computing models [17], neurons in input/hidden/output layers accounted preeminent factor for determining structure of model. Alternatively, the structure in tree based soft computing models could be determined by considering its depth, size and level [18]. However, the models based on gene expression programming (GEP) formulated an equation for determining input-output relationship.

Flexibility/Usefulness

The empirical/semi empirical equations for estimation of ET_o developed in past studies are limited to site specific or particular climatic region (Table 1). When these equations applied in other climatic condition, the results found are not acceptable. Although, FAO-PM56 equation removed this barrier and applied worldwide for calculation of ET_o but restricted its applicability in absences of climatic data. The information of maximum and minimum temperature only accessible in climatic stations of developing countries which restricted the use of FAO-PM56 equation in these locations. Therefore, development of alternative approaches/methods/models with less require climatic parameters is essential for ET_o estimation. The flexibility/usefulness of ET_o studies applied soft computing models were evaluated on basis of number of various climatic regions and fewer meteorological input.

The advantages of soft computing models are: (1) based on human reasoning which is inspired by the human brain in decision making, (2) ability to solve complex problems using multiplex algorithms, (3) ability to quickly learn from given dataset, (4) approximation, uncertainty and partial truth used as key elements to attain high level results, (5) unlike numerical modeling, develop approximation model using approximate reasoning and modeling, (6) provide solution with fast computing and zero cost. However, the main challenges and issues raised in various soft computing models are: (1) the evaluation of systematic and haphazard suspicions, (2) reduction in over fitting during training and testing process, (3) applicability of the model to provide efficient results for untrained data, (4) proper configuration of suitable tools for appropriate prediction, (5) the quality and quantity of available climatic data, (6) the availability of appropriate experimental observations.

Reviewed Articles

The summary of research articles reviewed in this study is presented in Table 2. It can be perceived that many studies have been conducted on ET_o estimation using soft computing models. The main reason for preferring soft computing models in estimating ET_o their capability to provide explicit formulation and ease of application. The formulation provided by GEP can be simply used in practical applications. Most studies have demonstrated a limitation in the predictability of soft computing models using fewer climatic parameters as input. This was observed more prominently in different climatic conditions such as arid, semi-arid and humid regions. This can best be explained by the ET_o processes being influenced by multiple climate variables and thus varying from one case to another. Based on the observations, soft computing models in such regions need several pieces of climate information for ET_o estimation to attain reliable results. The recently reported research articles on ET_o estimation using soft computing models have been addressed below.

Table 2 revealed that mostly studies applied full climate data as inputs in the FAO-PM56 method for ET_o estimation. The prime objective of the reported researches is to develop alternative soft computing model against FAO-PM56 because it requires large number of climate data as input and these data are not available at many stations, particularly in developing countries. So, it's not worth to design soft computing models using all the data that are usable, similar to FAO-PM56. Since, ET_o can be determined with the FAO-PM56 if data are available for all meteorological variables, development of soft computing models with all input parameters is not advisable.

The creation of a separate ET_o model with help of soft computing approaches for each station is another important matter. In addition, the development of a generalized ET_o model for the accurate ET_o estimation in all stations within an area has been considered by a small number of studies such as [17, 18, 44]. This becomes significant in case of developing countries where climatic data of mostly stations is missing or not available due to technical issues. Thus, the development of ET_o model with fewer climatic inputs (e.g. temperature data) is mainly requisite. Also, it should be further inspected to determine ET_o for those stations where nearby station or pooled data is considered.

Conclusion

In this review, the potential of soft computing models on ET_o estimation has assessed and evaluated in a detailed way. It was determined that soft computing models have been applied to develop ET_o models over the diverse climatic conditions. The results of accuracy indices indicated potential improvement in ET_o estimation using soft computing models. However, structural and usefulness of soft computing models found limited and needs to be more clearly addressed. Based on review of research articles, the study has made some possible guidelines as future direction: (1) apply soft computing models with only maximum and minimum temperature data as easily accessible for each location, (2) The simply temperature-based ET_o models should develop and use for the reliable projection of ET_o under climate change scenarios, (3) try to construct global soft computing model to estimate ET_o at least in homogeneous climatic region, (4) use of novel soft computing models based on different algorithms, hybrid, wavelet, extreme learning approaches which has not yet applied on ET_o estimation, (5) deep learning models have applied and found outperformed in other fields but not yet explore in ET_o estimation, (6) Integration of geographical information system (GIS) and satellite data in water resources management and hydrological modeling issues. Climatic data retrieved form geographic information system (GIS) and satellite must try for spatial modeling of ET_o. For this purpose, high-resolution satellite climatic data as input can be used. This strategy will be helpful where weather stations are uncommon or climatic data is missing. In addition, the developed ET_o models are station specific and even not work in station of same climatic region, therefore it is a dire need to include available data from all the stations and make a generalized model to estimate ET_o for a whole country or at least homogenous climatic regions. The recently modified form of soft computing models based on deep learning techniques outperformed due to fastest learning process and handling of millions or even billions of neurons-weights but not yet explore in ET_o estimation.

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Conflict of Interest

The authors claimed no conflict of interest in this article.

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