Comparative Performance of Empirical and Heuristic Daily Reference Evapotranspiration Models in the Lower Donga River Basin, Nigeria

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ORIGINAL RESEARCH

Abstract—The need to accurately estimate evapotranspiration (ET_0) in tropical regions with limited climatic data is prodigious, considering its influence on hydrology, agriculture, and agro-meteorology. Evaluation of the ET_0 model is particularly essential in developing countries where meteorological data needed to estimate ET_0 using Penman-Monteith FAO-56 (PMFAO-56) model are limited or not available. The purpose of this study is to compare a few empirical ET_0 models with the corresponding heuristic data-driven models to test their efficacy in the lower Donga basin, Taraba State, Nigeria. For this purpose, a temperature-based model (Hargreaves) and a combination-based (PMFAO-56) model was evaluated and validated with observed ET_0. Data-driven models consisting of Artificial Neural Networks (ANNs) and Gene Expression Programming (GEP) were employed for evaluating models using 32 years of daily meteorological data. The results were compared with the empirical models with respect to coefficient of determination, (R^2), Nash Sutcliffe efficiency coefficient (NSE), root mean square error (RMSE), and scatter plots. ANNs and GEP models have the least RMSE with NSE and R^2 of up to 1 and 0.95 at the training and testing periods, respectively. However, GEP models produced a set of equations as compared to ANNs and are therefore preferred for engineering applications. The proposed approach produced simple, yet reliable estimates for ET_0 evaluations in the basin, which can serve as promising alternatives to the conventional methods.

Keywords— ANN, empirical, evapotranspiration, GEP, Heuristic, lower Donga basin.

1 Introduction

Evapotranspiration (ET) refers to the combined process of evaporation and transpiration from the surfaces of soil, water and stomata of leaves (Ahmad et al., 2017). It constitutes an essential component of the hydrological cycle, which finds wide applications in water resources managements as well as irrigation practice (Gonzalez del Cerro et al., 2020). Consequently, the estimation of potential evapotranspiration (ET_0) is crucial for adaptation strategy (Gavili et al., 2018). In hydrological practice for instance, ET_0 can be measured directly by lysimeter, pan evaporation or the water balance measurement method (Ali Benzaghta, 2012; Gavili et al., 2018). Using a lysimeter at all times, may be tasking and time consuming (Li et al., 2018; Ghozat et al., 2020). In the light of this, mathematical models as alternatives are commonly used to estimate ET_0 from relevant meteorological datasets including relative humidity, solar radiation, air temperature and wind speed (Islam et al., 2020). With these variables, the development of different ET_0 models like radiation-based, temperature-based, and combination-based models had been achieved over the years by different researchers across the world.

Although, majority of these methods have limited validity over the global range, but are rather commonly used under local/regional calibrations (Gavili et al.,2018; Ali Benzaghta, 2012; Allen et al., 1998). Penman-Monteith (PM) model is particularly complex but robust, as compared to other ET_0 models. Reports have shown PM to perform satisfactorily in different climates and regions of the world, without any need for local calibration (Rahimikhoob et al., 2020). Moreover, its accuracy has been reported to be verified by lysimeter over a global range. This superior features of the PM lead to the official recommendation of the model by Food and Agricultural Organization of the United Nations (FAO) (Allen et al., 1998; Gavili et al., 2018) leading to the formulation of FAO56 Penman-Monteith (PMFAO-56). Hence, the PMFAO-56 equation has been widely applied in previous literature as a reference model (Allen et al., 1998) and it is currently being used by scientists for calibration. However, the major shortcoming of the PMFAO-56 method lies in its large meteorological data requirements (Trajkovic et al., 2020), which are not realistic in many regions, particularly developing countries like Nigeria.

Heuristic approaches are computational intelligence (CI) inspired by intuition and wisdom of human beings to solve complex problems. They are robust tools, suitable for solving non–linear, complex water resources problems, owing to their ability to learn and experience. Moreover, they are skilful in adapting themselves to conditions and are able to make the best decisions (Chandwani et al., 2015). Some of the new approaches to the estimation of ET_0 in recent literatures, include; Artificial Neural Networks (ANNs) (Pandorfi et al., 2016; Nema et al., 2017; Ali Benzaghta, 2012), Adaptive Neuro-Fuzzy Inference Systems (ANFISs) (Dou and Yang, 2018; Gavili et al., 2018; Goyal et al., 2014; Shiri et al., 2014), Fuzzy Logic (FL) (Goyal et al., 2014), Gene Expression Programming (GEP), Support Vector Machine (SVM) (Shiri et al., 2014), and Extreme Learning Machine (ELM) (Dou and Yang, 2018). However, the efficacy of these

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modern techniques has not been tested in the lower Donga basin, Taraba State.

In this study, ANN and GEP models were used to estimate ET_0 in Donga basin. These were compared with empirical models such as; PMFAO-56 and Hargreaves, with pan evaporation record as reference ET_0, to accurately estimate the daily evapotranspiration in the basin. The performances of the models were examined with respect to their statistical indices; such as Nash–Sutcliffe efficiency coefficient (NSE) coefficient of determination (R^2), and root mean square error (RMSE) for decision on the best model.

2 Materials and Methods

2.1 Description of the study site and Datasets

The study area comprises of the lower reaches of river Donga and some of its tributaries and Benue Littorals (south-eastern region of Benue); where River Donga debauches into River Benue, near Jibu in Taraba State, Nigeria. The catchment extends between latitudes 07° 13' and 08° 13' N and longitudes 09° 45' E and 10° 35' E, respectively. The basin is blessed with abundant water resources and extensive arable land suitable for irrigated agriculture. The Donga basin as a whole, commands a large catchment area of approximately 19,440 km² of which 17,000 km² lie within the Federal Republic of Nigeria, which is about 95 % of the total catchment. Thus, the remaining part conversely lies within the Federal Republic of Cameroun. The river system is the second largest tributary of river Benue after river Katsina-Ala. It took source from the border beyond Gembu (Mambilla Plateau) and drains a distance of approximately 310 km before draining into River Benue at Jibu. The river falls from over 1,800 m above mean sea level on the Mambilla Plateau in the south to about 90 m at the confluence with river Benue (MRT Consulting Engineers (Nigeria) Ltd, 1978). Figure 1 shows the study area map.

The climate of Donga basin is tropical with identified two distinctive seasons viz–a- vis: the dry and the wet seasons. The dry season starts from November to April; while the wet season extends from May to October. However, the upper reaches of the basin around Mambilla Plateau has cold climate. Thus, the dry season only span from November to February. 32 years records of daily meteorological variables at Ibi station were procured from Nigerian Meteorological Agency (NiMET), Abuja for this study. Similar records for Gassol and Gembu stations were obtained from Upper Benue River Basin Development Authority, Yola. These consist of rainfall, minimum and maximum temperatures, relative humidity, wind speed, sunshine hours, and evaporation. The quality of the datasets was assessed through comparisons with gridded datasets like the Climate Research Unit (CRU), and Global Precipitation Climatology Centre (GPCC) to ensure a reliable data source for building the ET_0 models. These datasets are widely embraced by researchers due to their good performance, globally and particularly over Nigeria (Olayiwola et al., 2024).

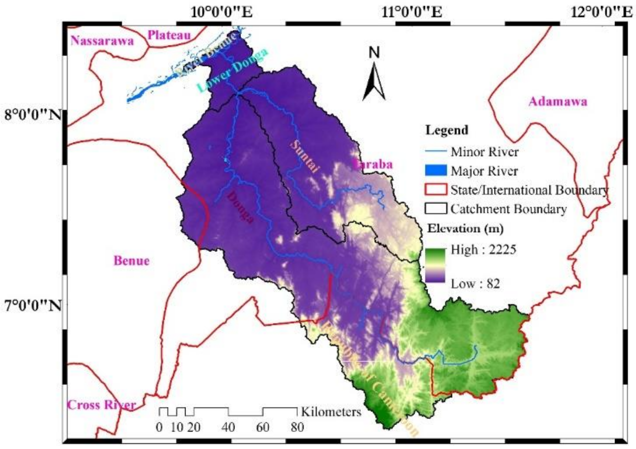

Figure 1. Map of the Study Area

2.2 Empirical Models

PMFAO-56: The Penman method, initially developed for estimating open water evaporation, was modified by Monteith to apply to cropped surfaces, resulting in the Penman-Monteith model. Further refinement defined a reference surface to establish crop-specific evaporation parameters at different growth stages (Allen et al., 1998), leading to the PMFAO-56 method. The equation defines ET_0 in mm/day as shown in Eq (1).

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)} \qquad (1)$$

where R_n is net irradiance at the crop surface (MJm^{-2} day^{-1}), γ = psychrometric constant (kPa °C^{-1}), G = ground heat flux density measured in (MJm^{-2} day^{-1}), U_2 = wind speed at 2 m (ms^{-1}), T = mean daily air temperature at 2 m (°C), e_s = saturation vapour pressure (kPa), Δ = slope vapour pressure curve (kPa °C^{-1}), e_a = actual vapour pressure (kPa), $e_s - e_a$ defines saturation vapour pressure deficit (kPa).

HARGREAVES: Hargreaves et al. developed the equation shown in Eq. (2) to calculate daily ET_0 from daily averages based on extensive work carried out on grass lysimeters. The model is widely used in the research community for ET estimation for practical applications, owing to its acceptable level of accuracy and simplicity. The model requires only three readily available parameters for evaluation.

$$ET_0 = 0.0023(T_{mean} + 17.78)(T_{max} - T_{min})^{0.5}\left(\frac{R_a}{2.45}\right) \quad (2)$$

where T_{mean}, T_{max}, and T_{min} refer to mean, maximum and minimum daily air temperature at 2 m (°C), respectively, and R_a is extra-terrestrial radiation (MJm^{-2} day^{-1}).

PAN EVAPORATION: The pan evaporation method gives evaporation from free water surface. The effects of several meteorological variables such as; rainfall, humidity, air temperature, windspeed and solar radiation are integrated. The ET model from pan evaporation is expressed as follows.

$$ET_0 = k_p E_p \qquad (3)$$

where, k_p = pan coefficient and E_p = pan evaporation (mm). The values of k_p depend on the pan type. In any

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case, reports have shown humidity, wind and fetch to have a more significant effect on k_p values than other meteorological variables (Ahmad et al., 2017).

2.3 ARTIFICIAL INTELLIGENCE

Using two different heuristic methods along with the above stated universally accepted empirical models are deemed sufficient to accurately estimate the ET_0 in lower Donga basin, considering the size of the catchment.

ANN MODEL: The ANN network, consists of interconnected nodes otherwise known as neurons which are arranged in three distinctive layers as: input, hidden and output. Basically, the input layer is used to feed data to the network, but makes no computations; data are processed in the hidden layer; while the output layer produces results for a given input data. This type of network which passes information in one-way manner is known as feed forward network (FFN) (Dawson and Wilby, 1998).

The ANN models comprise of feed forward backpropagation (FFBP) models alongside Bayesian Regularization (BR), and Levenberg–Marquardt (LM) algorithms. FFN are commonly used for hydrological applications due to their simplicity, accuracy and associated high processing speeds (Tayfur et al., 2006). Moreover, the most widely used supervised training algorithm in literature in the multilayer FFN is Back-propagation, owing to its ability to modify weights by minimizing errors between the target (observed) and the model (simulated) outputs. (Tokar and Johnson, 1999). Figure 2 shows Multilayer perceptron ANN network topology.

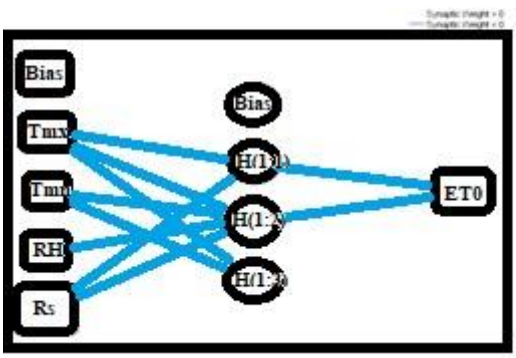

Figure 2. ANN Architecture

GEP MODEL: The GEP, genetic algorithms (GAs) and genetic programming (GP), are similar in principle, since they all use basic genetic operators to select from populations of individuals based on fitness and consequently institutes genetic variation (Ferreira, 2001). Despite the fact that they share similar evolutionary computational algorithms, there exists fundamental difference between the three categories. The GAs for instance, consist of linear strings of fixed length known as chromosomes; whereas, the GP are made up of nonlinear entities of varying sizes and shapes referred to as parse trees; consequently, the GEP combined the features of both GAs and GP (Ferreira, 2001; Muhammad et al., 2018). The mingled attributes gave rise to each entity being encoded as linear strings which are later expressed as nonlinear entities

The GEP optimisation technique made it suitable to solve symbolic regression problems. The fact that the chromosomes are simple entities which are relatively small, linear, compact, and easy to manipulate genetically gave it upper hand over other classical optimisation algorithms (Ferreira, 2001). Furthermore, the GEP produces expression trees, which expresses their respective chromosomes; upon which the selection acts and, are selected to reproduce with modification based on fitness, and are subsequently transmitted to the next generation. Nonetheless, the GAs and GP have limitations. In any case, reports have shown GAs to be easy to manipulate genetically, but suffers serious setback in functional complexity; consequently, the GPs are particularly difficult to reproduce with modification even if they demonstrate some degrees of functional complexity. Based on these features, GEP have been reported to outperform other EAs due to its versatility and computational capability in solving complex engineering problems (Ferreira, 2001; Fernando et al., 2009; Salaudeen et al., 2016).

2.4 METHODS OF ESTIMATION

In estimating ET_0 for the selected study area, being an agricultural catchment, PMFAO-56 and Hargreaves models were chosen as recommended by FAO using daily averages of 32 years (1981-2013) meteorological variables as input data. The resulting ET_0 were accordingly compared with those developed using ANN and GEP architectures relative to the reference observational ET_0. In each model, two separate input datasets are considered. The PMFAO-56 dataset comprises of minimum and maximum temperatures, wind speed, solar radiation and relative humidity. While in the case of Hargreaves; minimum, maximum and mean temperatures, and extra-terrestrial radiation are considered as the input parameters. About 70 % of the datasets are used for the training; while the remaining 30 % are used for testing the models.

Sensitivity analysis using a Monte Carlo simulation was run about 1,000 times, each time with randomly sampled input values assuming a uniform probability distribution. Thus, the variability of the output in response to input changes were analyzed statistically, allowing the identification of the most sensitive inputs.

2.5 GOODNESS OF FIT MEASURES

Nash-Sutcliffe Efficiency Coefficient (NSE): NSE [Eq. (4)] is a statistical tool commonly used to measure the predictive power of hydrologic models. This finds wide applications in hydrology because of its flexibility for use for various types of mathematical models. It is the complement to unity of the ratio between the mean square error of measured and simulated values and the variance of the observations. An NSE = 1 denotes a perfect match, while a NSE less or equal to 0 signifies a weak model (Gupta and Kling, 2011; Ritter and Muñoz-Carpena, 2013).

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$$NSE = 1 - \frac{\sum_i \left(ET_{i,pred} - ET_{i,obs}\right)^2}{\sum_i \left(ET_{i,obs} - \overline{ET}_{obs}\right)^2} \qquad (4)$$

Where $ET_{i,obs}$, $ET_{i,pred}$ and $\overline{ET}_{obs}$ are the observed, predicted and mean observed evapotranspiration, respectively.

The Root Mean Square Error (RMSE): RMSE [Eq. (5)] is the square root of mean square error (MSE) - is a statistical estimator which quantitatively measures the average of the squares of the errors between the observed and predicted values. The units of the predicted values are expressed in terms of the units of the observed variables. The value ranges from 0 to ∞. where RMSE = 0 indicates a good model (Ritter and Muñoz-Carpena, 2013).

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(ET_{Obs} - ET_{Pred})^2}{n}} \qquad (5)$$

where ET_{obs} = observed evapotranspiration, ET_{pred} = Predicted evapotranspiration, and n = number of observations.

Coefficient of determination (R^2): R^2 Eq. (6) is the square of the Pearson's product - moment correlation coefficient. This measures the degree of collinearity between simulated and observed data. Thus; it gives a meaningful indication of the prediction accuracy of a hydrologic model (McCuen, 1989). The values range between 0 and 1 with higher values indicating perfect match. Although, R^2 has been widely for quantitative assessment of model performance, this statistic is known for its high sensitivity to outliers and consequently, insensitive to additions and proportional difference between model predictions and measured data (Legates and McCabe, 1999).

$$R^2 = \frac{\sum_i^n (ET_{pred} - ET_{mean})^2}{\sum_i^n (ET_{obs} - ET_{mean})^2} \qquad (6)$$

Graphical presentation: Scatter plot is another useful tool to visualize the fitness between the measured and simulated data. It presents the degree of association between the variables. These can either be positive or negative.

3 RESULTS AND DISCUSSION

In this study, PMFAO-56, Hargreaves, ANN and GEP models were compared with the observed ET_0 in Donga lower basin to test the efficacy of CI in simulating the non – linear complex parameters involved in estimating ET_0 considering daily time step. There exists extensive arable land for irrigation practice alongside the abundant water resources which require accurate estimate of ET_0 to boost agricultural produce in the basin. Thus, the comparisons were limited to the two most prominent ET_0 models recommended by FAO. In the light of this, ANN and GEP models were developed to optimise the input parameters without necessarily compromising the output results. Consequently, about 50 % of the datasets (1981-1996) were used for the training, while the remaining 50 % (1997-2013) for testing of the models. Table 1 gives the overview of the summary statistics of the meteorological data used for the study at Ibi station; whereas the results of the analyses are presented and discussed as follows.

Table 1. Statistics of Training and Testing Datasets

Statistics	ET_0 (mm d⁻¹)	RH (%)	T_{max} (⁰C)	T_{min} (⁰C)	R_a (mm d⁻¹)	U_2 (m/s)
			Training			
Mean	4.93	53.82	32.67	22.06	14.54	2.64
Stdev	0.85	19.1	2.59	2.28	0.79	0.47
Skew	0.03	-0.41	0.30	-0.47	-0.79	-0.34
CV	0.17	0.35	0.08	0.10	0.05	0.18
			Testing			
Mean	4.98	54.79	33.68	22.33	14.54	2.69
Stdev	0.9	20.52	2.84	2.49	0.79	0.48
Skew	-0.01	-0.37	0.24	-0.48	-0.79	0.29
CV	0.18	0.37	0.08	0.11	0.05	0.18

3.1 MODELS TRAINING RESULTS

The results from the training of the daily averages of the available data are as shown in Figure 3 (a-c). Figure 3(a) compares results from observed ET_0 with those of PMFAO-56 and Hargreves; 3(b) and 3(c) compare ANN and GEP models with observed data, considering Hargreaves and PMFAO-56 datasets. Similar to Figure 3, Figure 4 (a-f) present the scatter plots comparing between the observed ET_0 and simulated values. The idea was to optimise the parameters such that; the best of the models can be chosen for practical applications. Based on the obtained results, GEP appeared to be the best of all, having NSE and R^2 equal to unity, with least error of 0.019 mm/day. The PMFAO-56 method was observed to overestimate the ET during the winter months and consequently underestimate the model during the summer period. The NSE, R^2 and RMSE are 0.65, 0.90 and 0.50 mm/day respectively. Table 3 presents the quantitative performance measures for the models. The CI methods were noted to have significant superiority over the empirical models in terms of robustness and simplicity. More importantly, the GEP method provides models with practical applications; though its learning speed is slower than that of ANN approach but with overall best performance.

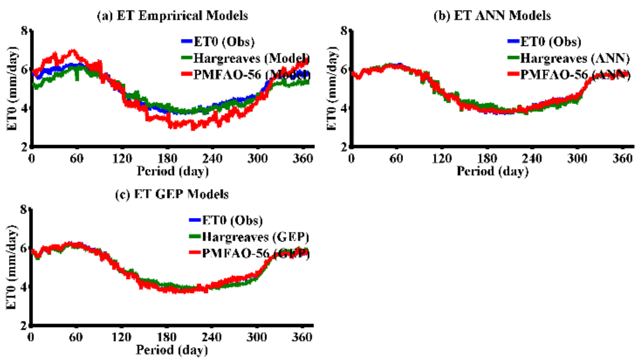

Figure 3 (a)-(c). Comparison between the observed and predicted ET_0 models during training (a) Empirical Models (b) ANN models using Hargreaves and PMFAO-56 datasets (c) GEP using Hargreaves and PMFAO-56 datasets.

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3.2 Models Testing Results

The performances at the testing period followed similar trends with those of the training period as evident from the time series plots, scatter plots and the quantitative performance measures (see Figure 4 (d-f) and Figure 5 (g-l).

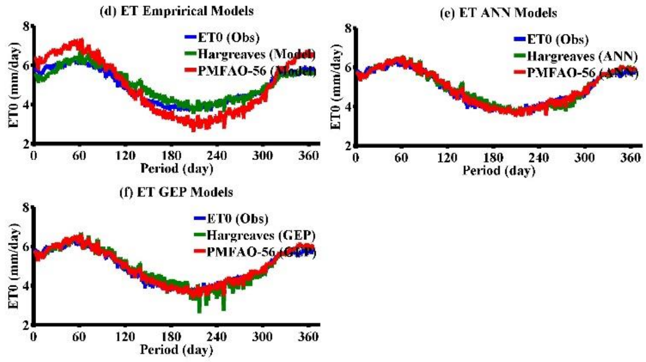

Figure 4 (d)-(f). Comparison between the observed and predicted ET_0 models during training (d) Empirical Models (e) ANN models using Hargreaves and PMFAO-56 datasets (f) GEP using Hargreaves and PMFAO-56 datasets.

The CI approaches outperformed the existing models in consonant with the training periods. The ANN and GEP models using PMFAO-56 datasets have the best performances as indicated by the NSE, R^2 and RMSE of 0.95, 0.94, 0.96 0.95 0.195 mm/day and 0.208 mm/day respectively (see Table 2).

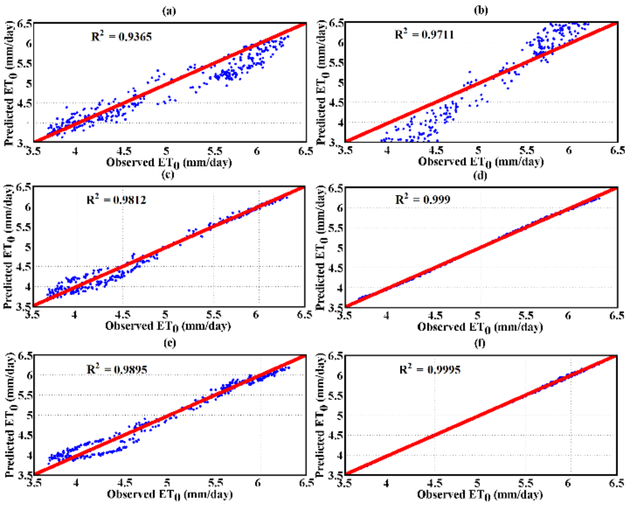

Figure 6. (a)-(f). Comparison of ET_0 between measured and simulated by data – driven models in the training period (a) PMFAO-56 (b) Hargreaves (c) ANN (PMFAO-56) datasets (d) ANN (Hargreaves) datasets (e) GEP (PMFAO-56) datasets (f) GEP (Hargreaves) datasets.

3.3 GEP Models

Equations (4) and (5) are the two sets of equations obtained from GEP model. Eq (4) consists of three parameters only for estimating ET_0 in lower Donga Basin. These are: minimum, maximum temperatures in degree Celsius and solar radiation in mm/day. Similar to this, Eq (5) requires extra–terrestrial radiation in mm/day in addition to the temperature data. The 3-parameter equations can be simply implemented and can as well provide accurate estimates of ET_0 in lower Donga basin. This can reliably be used to replace the PMFAO-56 and Hargreaves with accuracy of up to 95 %.

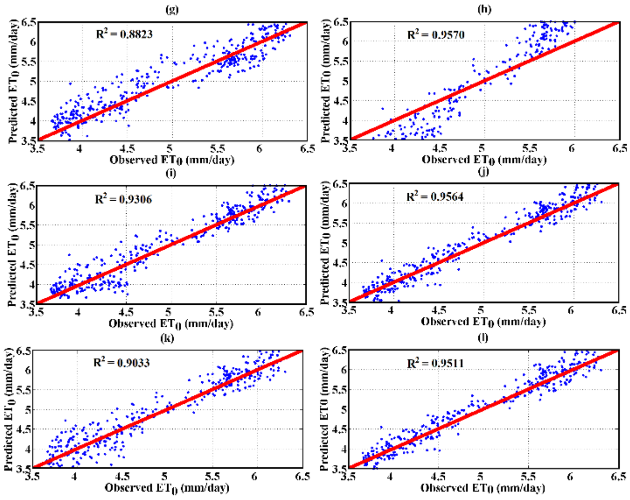

Figure 5(g)-(l). Comparison of ET_0 between measured and simulated by data – driven models in the training period (g) PMFAO-56 (h) Hargreaves (i) ANN (PMFAO-56) datasets (j) ANN (Hargreaves) datasets (k) GEP (PMFAO-56) datasets (l) GEP (Hargreaves) datasets.

Table 2. Performance measures between the observed and predicted models for the training and testing

Statistic	Harg.	PM	ANN (Harg.)	ANN (PM)	GEP (Harg.)	GEP (PM)
Training						
NSE	0.9	0.65	0.98	1	0.97	1
RMSE	0.27	0.5	0.12	0.03	0.15	0.02
R²	0.94	0.97	0.98	1	0.97	1
Testing						
NSE	0.87	0.48	0.92	0.95	0.89	0.94
RMSE	0.31	0.61	0.24	0.2	0.29	0.21
R²	0.88	0.96	0.93	0.96	0.9	0.95

Harg. = Hargreaves model, PM = PMFAO-56 model.

$$ET_0 = \mathrm{Exp}\left(\frac{1.3050 \times 10^{-5} - E_R}{D}\right) + R_s + \left(8.2356 \times 10^{-9} \times \mathrm{Exp}\left(\frac{-4.3145}{T_{min}}\right)\right) - \mathrm{Exp}\left(\frac{1.1315 \times 10^{-35} - E_R}{D}\right) \quad (4a)$$

where:

$$E_R = Exp(R_s^3) \quad (4b)$$

$$D = T_{min}(R_s + T_{max}) \quad (4c)$$

$$ET_0 = \log(0.049 + T_{max}T_{diff}) + \log(\mathrm{B}) + \mathrm{Sin}(8.9065 - \sqrt{A}\,) \quad (5a)$$

where:

$$T_{diff} = T_{max} - 1 \quad (5b)$$

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$$A = 3.0417T_{max} + 1 \quad (5c)$$
$$B = 2T_{max} - 0.4632R_a + Sin(T_{max}) \quad (5d)$$

3.4 Sensitivity analysis Results

The 1,000 Monte Carlo Simulation results compared favourably with the ET_0 model results in terms of mean, percentiles and standards error of estimates as shown in Table 3. The closely matched ET_0 model mean with the Monte Carlo mean suggests that the model provides reasonable estimates. Similarly, comparing the ET_0 model's results to the Monte Carlo percentiles highlights how optimistic the ET_0 model is relative to the range of simulated outcomes. Consequently, the low standard errors from both the model and Monte Carlo results implies the ET model appropriately captures uncertainty. In this case, the range lies between +5 and -5% which translates to 0.5 to about 1°C change in the air temperature and approximately 0.3 to 0.65 (mm/d) increase in the extra-terrestrial radiation values

Table 3. Comparison of ET_0 model output with Monte Carlo Simulation Results

Statistics (mm/day)	ET_0 Model results	Monte Carlo simulated results	% Change
Daily mean	5.22	5.50	5.1
25th percentile	4.28	5.02	14.7
50th percentile	5.02	5.51	8.8
75th percentile	5.63	5.98	5.8
99.5th percentile	6.66	6.52	-2.2
Standard Error	0.017	0.018	5.7

The findings in this study in terms of accuracy and predictive capabilities, flexibility and computational efficiency aligned with studies by Jamali et al. (2021), Achite et al., (2022), and Heramb et al. (2023).

8 Conclusion

The availability and reliability of high-quality meteorological data, particularly in developing countries, is often limited. As a result, there is a need to create simple yet robust models for estimating reference evapotranspiration (ET_0) in the lower Donga basin. Artificial intelligence (AI) presents a promising solution, as it can learn from data without requiring prior knowledge. In this study, the performance of the Hargreaves temperature-based ET_0 model and the combination-based PMFAO-56 model were compared to observed ET_0 data. Artificial neural networks (ANN) and gene expression programming (GEP) were employed to train and test 32 years of meteorological data. The models developed using the Hargreaves and PMFAO-56 datasets were evaluated against conventional methods. The soft computing techniques demonstrated superior performance, outperforming existing models with only three parameters. Although site-specific, these models proved robust and accurate, with an efficiency of up to 95%. Additionally, they require fewer meteorological parameters. However, the limitations of AI models lie in data dependency, black box nature, the tendency for overfitting and higher computational demands. As a result, future research that will incorporate transfer learning technique is recommended for better water resources planning and management in diverse environments.

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