Journal of Agrometeorology

(A publication of Association of Agrometeorologists)
ISSN : 0972-1665 (print), 2583-2980 (online)
Vol. No. 27 (3) : 381-384 (September - 2025)
https://doi.org/10.54386/jam.v27i3.3008
https://journal.agrimetassociation.org/index.php/jam

Short communication

Adaptive Neuro-Fuzzy inference system (ANFIS) based models for estimation of reference evapotranspiration (ET_0)

MAHADEVA M.[1*] and SRIRAM A. V.[2]

[1]*Department of Civil Engineering, University of Visvesvaraya College of Engineering, Bengaluru, Karnataka, India and Department of Civil Engineering, RNS Institute of technology, Bengaluru, Karnataka, India*

[2]*Department of Civil Engineering, University of Visvesvaraya College of Engineering, Bengaluru, Karnataka, India*

[*]*Corresponding author email: mahadeva.rnsit@gmail.com*

The reference evapotranspiration is defined as the evapotranspiration from an ideal crop with a presumed height of 0.12 m with a surface resistance of 70s m^1 and albedo of 0.23, closely mimicking the evaporation of a large area of green grass of uniform height, actively growing, and well irrigated (Allen *et al.,* 1998). Accurate estimation of reference evapotranspiration (ET_0) is essential for efficient irrigation planning, water resource management, and agrometeorological applications, especially in regions facing water scarcity and climatic variability. the critical impact of uncertainties in evapotranspiration (ET) estimation methods and data sources, emphasizing the need for improved accuracy in water resource management (Gloria *et al.,* 2023). Traditional empirical methods, while widely used, often fall short in capturing the nonlinear and dynamic nature of evapotranspiration influenced by multiple meteorological factors.

In this context, soft computing approaches like the Adaptive Neuro-Fuzzy Inference System (ANFIS) offer significant advantages by combining the learning capabilities of neural networks with the interpretability of fuzzy logic. ANFIS has proven effective in ET_0 estimation across diverse climatic zones due to its ability to model complex, nonlinear systems with limited data. Previous studies have demonstrated its superiority over traditional methods such as the Penman-Monteith equation and multiple linear regression (Dogan, 2009; Keskin and Terzi, 2009; Gavili *et al.,* 2017). The superior performance of machine learning models such as ANN, Random Forest, and LGBM in accurately estimating reference evapotranspiration using historical climatic data (Amit *et al.,* 2024). Moreover, hybridized ANFIS models integrated with optimization algorithms like PSO and PCA have shown enhanced performance in various applications (Mosavi and Mohammad, 2019; Rezaabad *et al.,* 2020). In the Indian context, Goyal *et al.,* (2014) and Adnana *et al.,* (2021) highlighted ANFIS's effectiveness in estimating pan evaporation and ET_0 in sub-tropical climates and data-scarce regions, respectively. An attempt has, therefore, been made to develop ANFIS models to predict reference evapotranspiration (ET_0) for selected stations of south India emphasizing their potential for agrometeorological decision-making and water resource optimization.

For the present study, Bangalore (13°0' N, 77°37' E, elevation 899 m), Bellary (15°09' N, 76°54' E, elevation 480m), Pattambi (10°48' N, 76°12' E, elevation 254m) and Solapur (17°04' N, 75°54' E, elevation 458m) representing four **different climatic** zones of southern India, were selected. Bangalore represents **a sub-humid** climate; Bellary is hot semi-arid; Pattambi is a humid tropical region and Solapur falls in a dry arid and semiarid region. The meteorological data comprised of maximum and minimum temperature, relative humidity, wind speed, sunshine hours and solar radiation for the period of 2001 to 2013 for Bangalore, from **1986 to 1995** for Bellary, from **1996 to 2008** for Pattambi and from 2002 to 2014 for Solapur were obtained from the Indian Meteorological Department (IMD). The variables were pre-processed cautiously and served as inputs for training and validating the ANFIS models.

Reference evapotranspiration (ET_0)

The FAO-PM equation recommended for daily reference evapotranspiration ET_0 (mm day^{-1}) estimation (Allen *et al.,* 1998) can be expressed as:

$$ETo = \frac{0.408\Delta(Rn-G)+\gamma\frac{900}{T+273}u2\,(e_s-e_a)}{\Delta+\gamma(1+0.34u2)} \quad \ldots\ldots\ldots\ldots\ldots..(1)$$

***Article info - DOI**: https://doi.org/10.54386/jam.v27i3.3008*

Received:17 April 2025; Accepted: 11 June 2025; Published online : 1 September 2025

where Rn is the net crop surface radiation (MJ m^{-2} day^{-1}), The soil heat flux density (MJ m^{-2} day^{-1}), T the air temperature at 2 m height (°C), u2 the wind speed at 2 m height (m s^{-1}), es the air vapour pressure at saturation (kPa), ea the actual vapour pressure (kPa), the slope of the vapour pressure curve (kPa $°C^{-1}$) and is the psychrometric constant (kPa $°C^{-1}$). Allen *et al.,* (1998) presented a set of complete equations for calculating the parameters of Equation (1) according to the available weather data and time step calculation, forming the P-M method. In this research, all days of month to have the ET_0 value and mean daily ET_0 computed using P-M method were taken as the measured values used to train and test the ANNs.

Adaptive neuro-fuzzy inference system (ANFIS)

Combining the learning capabilities of the neural networks with the knowledge representation of fuzzy logic results in ANFIS. An adaptive network, as its name implies, is a network structure consisting of nodes and directional links through which the nodes are connected. Moreover, parts or all of the nodes are adaptive, which means each output of these nodes depends on the parameters pertaining to this node and the learning rule specifies how these parameters should be changed to minimize a prescribed error measure. ANFIS is a multilayer feed-forward network where each node performs a particular function on incoming signals. Both square and circle node symbols are used to represent different properties of adaptive learning. To perform desired input–output characteristics, adaptive learning parameters are updated based on gradient learning rules. For simplicity, we assume the fuzzy inference system under consideration has two inputs, x and y, and one output z. suppose that the rule base contains two fuzzy if–then rules of Takagi and Sugeno's type (Fig. 1).

A hybrid algorithm combining a combination of the least squares approach and gradient descent approach is utilized to solve this problem. The hybrid algorithm consists of a forward pass and a backward pass. The least squares approach (forward pass) is employed to optimize the consequent parameters with fixed premise parameters. As soon as the optimal consequent parameters are determined, the backward pass commences. The gradient descent technique (backward pass) is applied to adjust the premise parameters that correspond to the fuzzy sets of the input space optimally. The output of the ANFIS is determined by using the consequent parameters obtained in the forward pass. The output error is utilized to adapt the premise parameters through a normal back-propagation algorithm. This hybrid algorithm has been proved to be quite efficient in ANFIS training.

Two sets of ANFIS models were developed. Model 1 includes a full set of climatic variables viz. maximum temperature (Tmax), minimum temperature (Tmin), maximum relative humidity (RHmax), minimum relative humidity (RHmin), wind speed (U2) and sunshine shine hour (SSH) while Model 2 uses fewer inputs (maximum, minimum temperature and wind speed) to simulate conditions where limited data are available. This comparison helps assess model performance under varying input scenarios. The model performance was evaluated using statistical parameters coefficient of determination (R^2) and the root mean square error (RMSE).

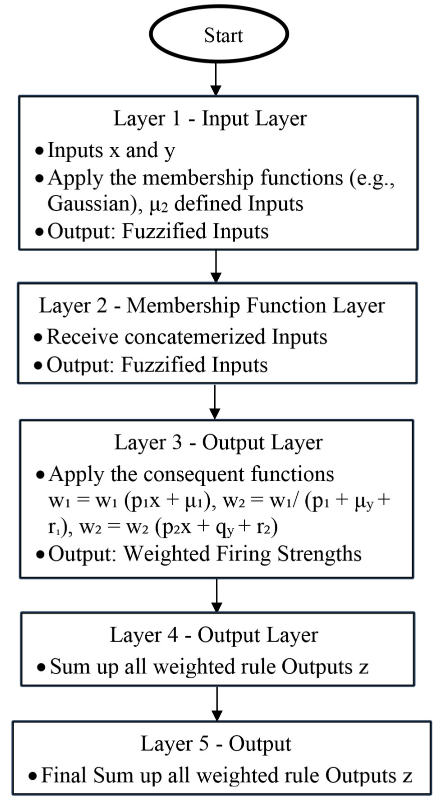

Fig. 1: Layered flowchart representing the ANFIS architecture with Two-Rule Sugeno-Type model for ET_0 prediction

Performance of ANFIS models

ANFIS Model-1 employed six meteorological input variables and was structured with 149 nodes, 10 fuzzy rules, and 190 parameters (70 linear and 120 nonlinear). It was trained using subtractive clustering and a hybrid learning approach over 30 epochs. ANFIS Model-2, built with a compact structure of 62 nodes and 7 to 8 fuzzy rules, utilized only three meteorological inputs. The performance results of both models are presented in Table 1.

At Bangalore, Model-1 achieved outstanding performance with an RMSE of 0.035 and R^2 = 0.987 during training, and 0.051 RMSE with R^2 = 0.973 during testing. These results reflect high precision and generalization capability, indicating that Model-1 is highly effective in capturing complex interactions influencing ET_0 under Bangalore's climatic conditions. Despite the reduced complexity in Model-2, it yielded a training and testing RMSE of 0.123, with an R^2 of 0.944 for both sets (Table 1). This consistency demonstrates reliable performance, making Model-2 a suitable option where computational resources or input data availability are limited.

At Bellary, ANFIS Model-1 also showed strong accuracy with a training RMSE of 0.059 and R^2 = 0.960, and testing RMSE of 0.060 and R^2 = 0.950. The model's consistent performance across both sets confirms its robustness in semi-arid zones and suitability for tasks requiring precision in ET_0 prediction. ANFIS Model-2 presented a noticeable drop in performance, with training

Table 1: Performance comparison of ANFIS models at different stations

Stations	ANFIS model-1				ANFIS model-2			
	Training		Testing		Training		Testing	
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
Bangalore	0.035	0.987	0.051	0.973	0.123	0.944	0.123	0.944
Bellary	0.059	0.960	0.060	0.950	0.152	0.890	0.160	0.870
Pattambi	0.052	0.950	0.062	0.943	0.150	0.850	0.154	0.840
Solapur	0.040	0.980	0.045	0.970	0.045	0.920	0.235	0.900

and testing RMSEs of 0.152 and 0.160, and R^2 values of 0.890 and 0.870, respectively (Table 1). While still usable, the reduced accuracy suggests that Bellary's climatic dynamics benefit more from the richer input structure of Model-1.

At Pattambi, ANFIS Model-1 demonstrated high performance with a training RMSE of 0.052 and R^2 = 0.950 and testing RMSE of 0.062 with R^2 = 0.943. This indicates strong learning and generalization, making Model-1 ideal for ET_0 estimation in humid or coastal regions like Pattambi. ANFIS Model-2, however, showed comparatively lower performance, with a training RMSE of 0.150 and R^2 = 0.850, and testing RMSE of 0.154 and R^2 = 0.840 (Table 1). Despite using fewer inputs, it maintained logical consistency and moderate accuracy, which may still support real-time applications with constrained data availability.

At Solapur, ANFIS Model-1 stood out with an RMSE of 0.040 and R^2 = 0.980 during training, and 0.045 RMSE with R^2 = 0.970 during testing. These metrics underscore the model's strength in capturing ET_0 variations in arid zones with high precision and stability. ANFIS Model-2 showed a more pronounced decrease in testing performance, with RMSE increasing to 0.235 and R^2 dropping to 0.900, despite achieving 0.045 RMSE and R^2 = 0.920 in training (Table 1). The disparity suggests a risk of overfitting or reduced generalizability under Solapur's more variable climate, warranting caution for operational use.

ANFIS Model-1 consistently outperformed Model-2 across all stations. The improved accuracy can be attributed to the use of six meteorological inputs and a more complex fuzzy rule base, which enabled better learning of nonlinear climatic interactions. In contrast, Model-2, although computationally efficient, displayed variability in generalization—especially under arid conditions. While Model-1 is recommended for high-precision applications, such as precision irrigation or climate modelling, Model-2 is preferable in real-time or resource-constrained environments where a trade-off between accuracy and computational efficiency is acceptable. Both models hold strong potential for supporting irrigation planning and sustainable water resource management, with future scope for integration with remote sensing and decision-support systems.

ACKNOWLEDGEMENT

The authors are grateful to the Department of Agrometeorology, GKVK, Bengaluru and India Meteorological Department, Pune for providing meteorological data in carrying out this research.

Funding: The research work was conducted without external funding; however, it benefitted from the support of a university resources.

Conflict of Interest Statement: The author(s) declare (s)that there is no conflict of interest.

Data availability: Data will be available through corresponding author on reasonable ground.

Author's contribution: **Mahadeva M:** Investigation, Methodology, Writing and editing, **Sriram A V:** review, editing and Supervision.

Disclaimer: The contents, opinions, and views expressed in the research article published in the Journal of Agrometeorology are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

Publisher's Note: The periodical remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

REFERENCES

Adnana, N., Hamid, A. T. A. and Wahab, A. F. (2021). ANFIS-WCAMFO hybrid model for monthly ET_0 estimation in data-scarce environments. *Water Resour. Manage.,* 35(2): 543-558.

Allen, R. K., Pereira, L. S., Raes, D. and Smith, M. (1998). Crop evapotranspiration guideline for computing crop water requirements. FAO Irrigation and Drainage Paper No. 56. United Nations Food and Agricultural Organization, Rome

Amit Bijlwan, Shweta Pokhariyal, Rajeev Ranjan, R.K Singh and Ankita Jha (2024). Machine learning methods for estimating reference evapotranspiration, *J. Agrometeorol.,* 26(1): 63-68. https://doi.org/10.54386/jam.v26i1.2462

Dogan, E. (2009). Daily grass crop reference evapotranspiration estimation using ANFIS. *J. Irrig. Drain. Engg.,* 135(3): 330-337.

Gavili, A., Mousavi, S. J. and Alizadeh, A. (2017). Comparison of ANFIS and multiple linear regression models for estimation of daily reference evapotranspiration in a semi-arid climate. *J. Irrig. Drain. Engg.,* 143(6): 04017014.

Gloria I. Ezenne, Nkpouto U. Eyibio, Jane L. Tanner, Felix U. Asoiro and Sunday E. Obalum (2023). An overview of uncertainties in evapotranspiration estimation techniques, *J. Agrometeorol.,* 25 (1): 173-182. https://doi.org/10.54386/jam.v25i1.2014

Goyal, M. K., Ojha, C. S. P. and Singh, R. D. (2014). Modeling of pan evaporation using ANN, ANFIS, and GEP models. *J. Hydrol. Sci.,* 59(1): 116-130.

Keskin, M. E. and Terzi, O. (2009). Artificial neural network and adaptive neuro-fuzzy inference system for predicting daily pan evaporation. *J. Hydrol.,* 372(1-4): 104-112.

Mosavi, A. and Mohammad, R. (2019). A hybrid ANFIS–PSO–PCA model for ET_0 prediction: Enhancing accuracy through optimization and feature reduction. *Environ. Earth Sci.,* 78(1): 1-14.

Rezaabad, M. A., Moosavi, V. and Kisi, O. (2020). Hybrid ANFIS models for estimation of ET_0 using optimization algorithms. *Agric. Water Manag.,* 231: 106003.