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*Short Communication*

# Performance comparison of linear regression and ANN models in estimating monthly reference evapotranspiration ($ET_0$)

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Accurate estimation of reference evapotranspiration ($ET_0$) is essential for designing efficient irrigation systems and managing water resources effectively. Various methods have been developed for $ET_0$ estimation, ranging from simple empirical models to complex formulations, depending on the availability of weather data. The FAO-56 Penman-Monteith (PM) equation stands as the most widely utilized approach, despite its application challenges due to the requirement for precise and comprehensive meteorological data (Mehta and Pandey, 2016). The complexity of the PM equation's parameters introduces potential errors in measurement or computation, contributing to cumulative discrepancies in $ET_0$ estimates. In such cases, a simpler empirical equation requiring fewer parameters yet producing results comparable to the Penman-Monteith method is preferred. However, identifying the structure and parameters for the nonlinear and complex process of evapotranspiration is challenging, and many models fail to produce satisfactory results (Ezenne *et al.,* 2023).

Artificial Neural Networks (ANNs) can effectively model complex nonlinear processes by capturing the relationship between inputs and outputs without needing to explicitly understand the underlying physical mechanisms. They can identify underlying patterns even amidst noisy and error-contaminated data. Chauhan *et al.,* (2022) compared machine learning and traditional models across climates, consistently showing superior performance of machine learning methods, particularly ANNs, in ET0 estimation. () evaluated linear and non-linear models in semi-arid regions, affirming the superiority of ANNs in capturing the variability of $ET_0$. Several studies have been reported on comparing statistical and machine learning methods, with ANNs demonstrating resilience across diverse climatic conditions. Comprehensive analysis of AI-based models, confirming ANNs' superior predictive accuracy and robustness (Mehdizadeh and Sharma, 2023; Ghorbani and Kisi 2023; Moghaddam and Araghinejad, 2022; Bijlwan *et al.,* 2024).

The present study was conducted in the Gird region comprising the districts of Gwalior, Bhind, Ashok Nagar, Guna, Shivpuri, and Morena of Madhya Pradesh. Meteorological data were sourced from the India Meteorological Department (IMD), Pune, covering the period from 1990 to 2023. This dataset includes daily records of maximum temperature, minimum temperature, mean relative humidity, wind speed, and solar radiation. Geographic parameters such as latitude, longitude, and elevation were also collected for each meteorological station within the study region. Table 1 summarizes the locations of these meteorological stations along with the respective periods of data availability. The primary objective of this research was to develop and compare simple linear regression (LR) models and optimized Artificial Neural Network (ANN) models for estimating monthly reference crop evapotranspiration ($ET_0$) using climatic parameters specific to the Gird Region. Data of 1990-2016 were used for development of models and 2017-2023 were used for validating the models.

***Linear regression (LR) model***: The LR model for monthly $ET_0$ estimation was formulated as:

$$ET_0 = C + a_1X_1 + a_2X_2 + ...$$

Here, $a_1$, $a_2$, and so on, along with C, represent empirical constants, while $X_1$, $X_2$, and others denote the meteorological parameters influencing the region. The Stastica package was utilized for

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**Table 1:** Overview of metrological centre facilities and capabilities

| Weather station | Longitude (E) | Latitude (N) | Altitude (m) | Temp. ($^0$C) | Relative humidity (%) | Wind speed (kmph) | Vapor pressure | Sunshine (hour) |
|---|---|---|---|---|---|---|---|---|
| Gwalior | 78°15’ | 26°14’ | 211 | 27.5 | 60.6 | 7.5 | 16.5 | 6.8 |
| Ashoknagar | 77°43’ | 24°34’ | 499 | 28.6 | 58.7 | 7.1 | 17.4 | 6.1 |
| Bhind | 78°48’ | 26°34’ | 159 | 29.9 | 61.5 | 6.9 | 17.3 | 6.9 |
| Shivpuri | 77°39’ | 25°25’ | 457 | 26.7 | 62.3 | 6.8 | 16.4 | 7.0 |
| Morena | 78°00’ | 26°30’ | 177 | 27.9 | 59.9 | 7.0 | 17.9 | 6.4 |
| Guna | 76°42’ | 24°38’ | 552 | 28.2 | 60.2 | 7.1 | 16.7 | 5.9 |

**Table 2:** Detailed linear regression models and coefficient of determination ($R^2$) for LR and ANN models

| Stations | Linear regression equation | LR model ($R^2$) | ANN model ($R^2$) |
|---|---|---|---|
| Ashok Nagar | $ET0 = -2.358 + 0.254Tmax -0.043Tmin +0.899U_2 -0.033RH$ | 0.988 | 0.976 |
| Shivpuri | $ET0 = -.982 + 0.217Tmax -0.009Tmin +.891U -0.057RH$ | 0.993 | 0.929 |
| Gwalior | $ET0 = -1.577 + 0.206Tmax -0.012Tmin +1.066U -0.044RH$ | 0.993 | 0.995 |
| Guna | $ET0 = -3.077 + 0.291Tmax -0.066Tmin +0.891U -0.036RH$ | 0.988 | 0.999 |
| Bhind | $ET0 = -1.758 + 0.209Tmax -0.015Tmin +1.049U -0.039RH$ | 0.995 | 0.994 |
| Morena | $ET0 = -2.503+ 0.227Tmax -0.040Tmin +1.040U - 0.029RH$ | 0.992 | 0.136 |

multiple correlation analysis to establish these relationships.

***Artificial neural network (ANN) model***: A standard multilayer feed-forward ANN with a logistic sigmoid activation function was used. Data normalization was applied to a range of 0.1 to 0.9. The ANN was trained using error back propagation with separate calibration and validation datasets to prevent over fitting. The efficacy of the LR and ANN models was assessed using the coefficient of determination ($R^2$) and root mean square error (RMSE). By comparing these models against the established Penman-Monteith method, this study aimed to identify the most effective approach for accurate $ET_0$ estimation, thereby supporting efficient water resource management and agricultural planning in the Gird Region.

The monthly reference evapotranspiration ($ET_0$) was estimated for the districts of Ashok Nagar, Bhind, Gwalior, Shivpuri, Morena, and Guna within the Gird region of Madhya Pradesh using both linear regression (LR) and Artificial Neural Network (ANN) models. Multiple and partial correlation analyses identified sunshine hours, temperature, wind velocity, and relative humidity as significant climatic factors influencing $ET_0$. LR models were developed with these parameters as inputs, while ANN architectures, particularly a 4-4-1 configuration (four input nodes, one hidden layer with four nodes, and one output node), were also employed. The performance indices, including $R^2$ and RMSE, were evaluated for both LR and ANN models compared to the FAO-56 Penman-Monteith method, as summarized in Table 2.

The LR models demonstrated very satisfactory performance across the stations, with $R^2$ values ranging from 0.988 to 0.995. The ANN model (4, 4, 1) showed slightly improved performance in some cases, with $R^2$ values ranging from 0.136 to 0.999, indicating marginal enhancements in accuracy. The RMSE values of the ANN models also showed slight decreases compared to LR, suggesting improved predictive capabilities particularly where nonlinearity in monthly average $ET_0$ values was less pronounced.

The RMSE values of the ANN models have also decreased slightly. This could be because the Monthly average $ET_0$ values do not show significant nonlinearity. Fig. 1 illustrates scatter plots comparing the $ET_0$ values estimated by LR and ANN (4, 4, 1) models against the Penman-Monteith method during the testing period. The plots exhibit nearly unit slope and zero intercept, indicating close agreement between estimated ET0 values and those derived from the Penman-Monteith method. The study suggests that the proposed simple linear regression models can be effectively used for monthly $ET_0$ estimation in the selected stations, and accuracy can be further improved using the ANN (4, 4, 1) models.

Climatic parameters such as sunshine hours, temperature, wind velocity, and relative humidity were identified as primary influencers of monthly $ET_0$ in the studied regions of Madhya Pradesh’s Gird region. The developed linear regression models, utilizing these climatic inputs, performed effectively in estimating monthly $ET_0$ with high accuracy across the selected stations. The ANN models, especially the optimal architecture (4, 4, 1), showed slight improvements over LR models, albeit marginally. Therefore, the study concludes that the proposed LR models are suitable for monthly ET0 estimation in these regions, achieving a reasonable level of accuracy. Further enhancements in accuracy can be achieved by implementing ANN architectures tailored to specific climatic conditions. Fig. 1 depicts a comparison of average monthly ET0 values estimated by LR and ANN models against those derived from the Penman-Monteith method during the testing period.

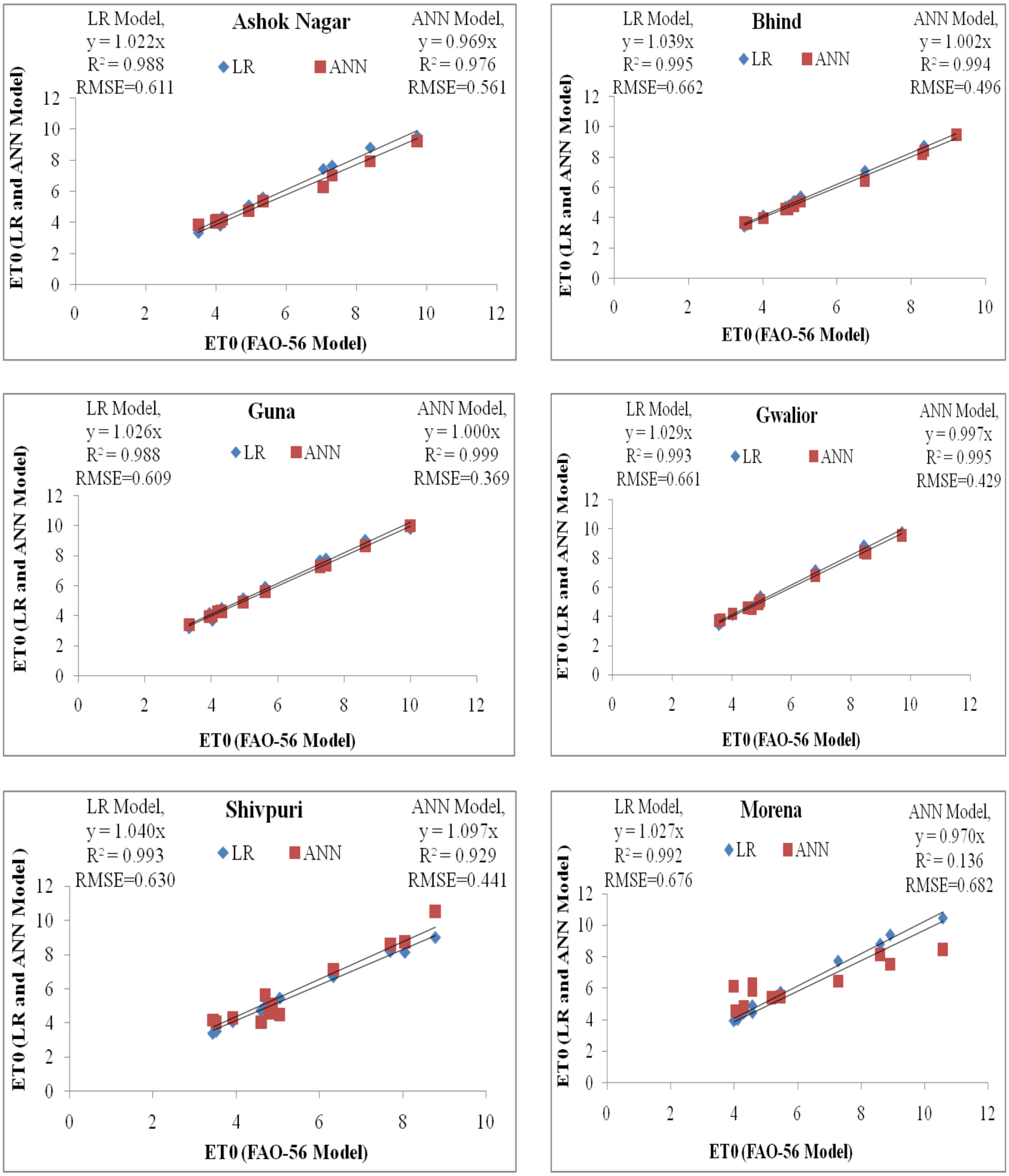


**Fig. 1:** Comparison of average monthly $ET_0$ values estimated using LR and ANN models with those estimated by Penman-Monteith method during testing period


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