

The 8th International Electronic Conference on Water Sciences



14-16 October 2024 | Online

Assessment of machine learning techniques to estimate reference evapotranspiration at Yauri meteorological station, Peru

Efrain Lujano¹, Rene Lujano², Juan Carlos Huamani³, Apolinario Lujano^{4,5} ¹Escuela Profesional de Ingeniería Agrícola, Universidad Nacional del Altiplano, Puno 21001, Peru ²Programa de Maestría en Ingeniería de Sistemas, Universidad Nacional del Altiplano, Puno 21001, Peru ³Servicio Nacional de Meteorología e Hidrología, Lima 15072, Peru ⁴Programa de Maestría en Riego y Drenaje, Universidad Nacional Agraria La Molina, Lima 15024, Peru ⁵Autoridad Nacional del Agua, Administración Local del Agua Ilave, Puno, Peru.

INTRODUCTION & AIM

Consumptive water use, or evapotranspiration (ET), is one of the fundamental components of the hydrological cycle (Jensen & Allen, 2016) and a key factor for agriculture, irrigation scheduling, and water resources (Feng & Tian, 2021).

Since determining ET for each crop is difficult, reference evapotranspiration (ETo) is calculated, and then ET is estimated using ETo (Mehdizadeh, 2018). ETo is traditionally estimated using the Penman-Monteith (PM) method, considered the standard by the FAO due to its use of multiple climatic variables, providing a solid physical basis.

RESULTS & DISCUSSION

Model 1 showed the best performance for ANN, while KNN was the least effective. In Model 2, KNN outperformed ANN despite fewer input variables. Model 3 had similar results, with ANN slightly outperforming KNN (Table 1). The Hargreaves-Samani method performed poorly compared to ANN and KNN, highlighting the effectiveness of machine learning models for estimating ETo in the study area.

Table 1. Performance results - validation period

ML MAE

This research aimed to evaluate machine learning techniques to estimate ETo at the Yauri meteorological station in Peru.

METHOD

The study was carried out at the Yauri meteorological station, located in the province of Espinar, in the Cusco region. Hydrographically it is located in the upper Apurímac river basin, at the geographic coordinates of latitude 14° 48' 5" South and longitude 71° 25' 54" West, at an altitude of 3,927 meters above sea level (Figure 1).



1) $ET_o = f(Ro, Tx, Tn, Vv, HS, HR)$ ANN0.0360.9790.9940.9910.1) $ET_o = f(Ro, Tx, Tn)$ KNN0.1710.9090.8540.8750.2) $ET_o = f(Ro, Tx, Tn)$ ANN0.1190.9430.9220.9440.3) $ET_o = f(Ro, Tx)$ ANN0.1150.9510.9360.9670.4) $ET_o = f(Ra, Tx, Tn)$ HS0.6410.6920.4200.5000.	Model	algorithm/HS	[mm/day]	ACC	NSE	KGE'	SA
$ \begin{array}{c} \text{KNN} & 0.171 & 0.909 & 0.854 & 0.875 & 0. \\ \text{ANN} & 0.119 & 0.943 & 0.922 & 0.944 & 0. \\ \text{KNN} & 0.115 & 0.951 & 0.936 & 0.967 & 0. \\ \text{ANN} & 0.115 & 0.944 & 0.925 & 0.939 & 0. \\ \text{ANN} & 0.115 & 0.944 & 0.925 & 0.939 & 0. \\ \text{ANN} & 0.129 & 0.939 & 0.913 & 0.911 & 0. \\ \end{array} $	1) $ET_o = f(Ro, Tx, Tn, Vv, HS, HR)$	ANN	0.036	0.979	0.994	0.991	0.014
2) $ET_o = f(Ro, Tx, Tn)$ 3) $ET_o = f(Ro, Tx)$ KNN 0.115 0.951 0.936 0.967 0. ANN 0.115 0.944 0.925 0.939 0. KNN 0.129 0.939 0.913 0.911 0.		KNN	0.171	0.909	0.854	0.875	0.068
KNN = 0.115 = 0.951 = 0.936 = 0.967 = 0. $ANN = 0.115 = 0.944 = 0.925 = 0.939 = 0.$ $KNN = 0.129 = 0.939 = 0.913 = 0.911 = 0.$	2) $ET_o = f(Ro, Tx, Tn)$	ANN	0.119	0.943	0.922	0.944	0.050
3) $ET_o = f(Ro, Tx)$ KNN 0.129 0.939 0.913 0.911 0.		KNN	0.115	0.951	0.936	0.967	0.045
KNN 0.129 0.939 0.913 0.911 0.	3) $ET_o = f(Ro, Tx)$	ANN	0.115	0.944	0.925	0.939	0.050
A) $FT = f(P_{\alpha} T_{x} T_{y})$ HS 0.641 0.602 0.420 0.500 0		KNN	0.129	0.939	0.913	0.911	0.053
$-1/2I_0 - f(Ru, IX, IR)$ IIS 0.041 0.092 0.420 0.300 0.	$4) ET_o = f(Ra, Tx, Tn)$	HS	0.641	0.692	0.420	0.500	0.260

The box plots in Figure 3 illustrate the residual distribution for the models compared to PM values, confirming the precision of the ML models. Model 1 (ANN) has residuals within ± 0.1 mm/day, Model 2 (KNN) ranges from -0.4 to 0.5 mm/day, and Model 3 (ANN) shows residuals around ± 0.4 mm/day.



Figure 3. Box diagram of the residuals, a) model 1, b) model 2 and c) model 3.

It is possible to obtain reliable ETo values using machine learning algorithms based on extraterrestrial solar radiation and temperature data. Models 2 and 3 align with the approach proposed by Hargreaves and Samani (1985); however, the results suggest that fewer combinations of meteorological variables can be a suitable alternative when complete weather data is unavailable.

Figure 1. Location of the study area.



Figure 2. Methodological flowchart.

CONCLUSION

The evaluated algorithms presented a better performance to estimate ETo in relation to the HS model and can be used as an alternative in cases of limited meteorological data.

REFERENCES

•Feng, K., & Tian, J. (2021). Forecasting reference evapotranspiration using data mining and limited climatic data. *European Journal of Remote Sensing*, *54*(2), 363-371.

•Hargreaves, G.H., & Samani, Z.A. (1985). Reference Crop Evapotranspiration from Temperature. *Applied Engineering in Agriculture, 1*(2), 96-99.

•Jensen, M. E., & Allen, R. G. (2016). Evaporation, Evapotranspiration, and Irrigation Water Requirements, ASCE Manuals and reports on Engineering Practice: no 70. *Am. Soc. Civ. Eng., Reston, VA*.

•Mehdizadeh, S. (2018). Estimation of daily reference evapotranspiration (ETo) using artificial intelligence methods: Offering a new approach for lagged ETo data-based modeling. *Journal of Hydrology, 559*, 794-812.

https://sciforum.net/event/ECWS-8