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ANÁLISIS COMPARATIVO DE MODELOS DE EVAPOTRANSPIRACIÓN DE REFERENCIA CON APLICACIÓN AL ECOSISTEMA DE PÁRAMO ANDINO HÚMEDO EN EL SUR DE ECUADOR

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RESUMEN

A pesar de su importancia, la evapotranspiración es poco estudiada en los ecosistemas de páramo. Este estudio evalúa el rendimiento de 30 modelos, incluidos 21 modelos empíricos (basados en radiación, temperatura, combinación y transferencia de masa), 8 modelos de redes neuronales artificiales (RNAs) y 1 modelo splines de regresión adaptativa multivariante (MARS) para la estimación de la evapotranspiración diaria de referencia (ETo) en comparación con la ecuación estándar de Penman-Monteith (FAO 56 P-M). Un objetivo adicional fue definir para la región de estudio la mejor alternativa al método estándar. Se utilizaron datos disponibles y limitados de dos estaciones meteorológicas, respectivamente Toreadora (período 2013-2016) y Zhurucay (período 2014), ambas ubicadas en el ecosistema de páramo de la provincia de Azuay, en el sur de Ecuador. Se aplicaron métricas estadísticas simples (MBE, MAE y RMSE) para evaluar el rendimiento de los modelos. Se llevó a cabo un análisis de bosques aleatorios para definir la relevancia de las variables climáticas en el proceso de evapotranspiración. Los resultados de bosques aleatorios se usaron para ensamblar las RNAs usando diferentes combinaciones de variables climáticas. Este enfoque permitió definir la RNA con el menor número de entradas que mejor estiman ETo. El modelo MARS permitió derivar una ecuación empírica, llamada REMPE, que usa radiación solar y humedad relativa mínima como variables de entrada. Del grupo de ecuaciones empíricas, las ecuaciones basadas en combinación tienen el mejor rendimiento seguido de las ecuaciones basadas en radiación, temperatura y transferencia de masa. Se aplicó un método de calibración para mejorar el rendimiento de los modelos probados. Los resultados mostraron que las RNAs mejoradas son las más precisas para estimar la ETo diaria, mientras que la ecuación de REMPE, a pesar de haber sido desarrollada en condiciones locales, presenta un bajo rendimiento. La ETo anual se calculó para todos los modelos y se comparó con el valor anual calculado con la ecuación FAO 56 P-M. En general, los resultados permiten seleccionar el mejor modelo en función de la disponibilidad de datos meteorológicos en entornos super-húmedos, como los ecosistemas de páramo.

Palabras clave: Evapotranspiración de referencia, ecuación Penman-Monteith,

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Modelos empíricos, Redes Neuronales Artificiales (RNAs), Splines de Regresión Adaptativa Multivariante (MARS), Bosques aleatorios.

COMPARATIVE ANALYSIS OF REFERENCE EVAPOTRANSPIRATION MODELS WITH APPLICATION TO THE WET ANDEAN PÁRAMO ECOSYSTEM IN SOUTHERN ECUADOR

ABSTRACT

Despite its importance, is evapotranspiration poorly studied in páramo ecosystems. This study assesses the performance of 30 models, including 21 empirical models, (radiation-, temperature-, combination- and mass transfer-based), 8 artificial neural network models (ANNs), and 1 multivariate adaptive regression spline (MARS) model for the estimation of daily reference evapotranspiration (ETo) in comparison to the standard Penman-Monteith equation (FAO 56 P-M). An additional objective was to define for the study region the best alternative to the standard method. Available and limited data of two weather stations, respectively Toreadora (2013-2016 period) and Zhurucay (2014 period), both located in the páramo ecosystem of the Azuay province, in Southern Ecuador, were used. Simple statistical metrics (MBE, MAE and RMSE) were applied to evaluate the performance of the models. A random forests analysis was carried out to define the relevance of the weather variables in the evapotranspiration process. The random forest results were used for assembling the ANNs using different combinations of weather variables. This approach permitted to define the ANN with the smallest number of inputs that best estimate ETo. The MARS model enabled to derive an empirical equation, called REMPE, which uses solar radiation and minimum relative humidity as variable inputs. From the group of empirical equations, the combination-based equations have the best performance followed by the radiation-, temperature- and mass transfer-based equations. A calibration method was applied to improve the performance of the tested models. Results showed that the improved ANNs are the most accurate for estimating daily ETo, while the REMPE equation, despite been developed under local conditions, presents low performance. The annual ETo was calculated for all the models and compared against the annual value computed with the FAO 56 P-M equation. Overall, results permit to select the best model as a function of the availability of weather data in super-humid environments such as páramo ecosystems.
Keywords: Reference evapotranspiration, Penman-Monteith equation, Empirical models, Artificial Neural Networks (ANNs), Multivariate Adaptive Regression Spline (MARS), Random forests.

1. INTRODUCTION

Evapotranspiration (ET) is the combination of land evaporation and plant transpiration, which are crucial processes in the hydrologic cycle (Borges and Mendiondo, 2007; Khoshravesh et al., 2017). An accurate prediction of ET is essential for the estimation of the water budget and the management of water-related environmental systems (Kumar et al., 2002; Irmak et al., 2003; Chauhan and Shrivastava, 2009; Khoshravesh et al., 2017; Liu et al., 2017). The most obvious method for estimating the actual evapotranspiration (ETc) is the use of lysimeters, along with other methods such as the water balance, the eddy covariance or the imaging technique (Kumar et al., 2002; Valipour, 2015; Abdullah and Malek, 2016; Valipour, 2017); the costs of which are relative high. Because of this, field measurements of evapotranspiration are often spatially and temporally scarce, and ETc is usually calculated multiplying the reference evapotranspiration (ETo) with a crop specific coefficient (kc) (Kumar et al., 2002; Yoder et al., 2005; Chauhan and Shrivastava, 2009; Khoshravesh et al., 2017). Indirect and affordable estimates based on climatological variables are also available (Paes de Camargo and Paes de Camargo, 2000; Kumar et al., 2002; Landeras et al., 2008).

The FAO 56 Penman-Monteith (FAO 56 P-M) equation has been adopted by the scientific community as standard method for the estimation of ETo, suitable for most climate conditions (Allen et al., 2006; Gong et al., 2006; Efthimiou et al., 2013). The method requires the availability of different weather variables such as: air temperature, relative humidity, solar radiation and wind speed (Er-Raki et al., 2010). Unfortunately, weather stations that measure the full set of climatic variables needed to calculate ETo are worldwide scarce in ecosystems, particularly in highland environments, such as the Andean páramo (Córdova et al., 2015). Some authors use empirical equations to estimate ETo requiring few weather variables (e.g. Jabloun and Sahli, 2008; Er-Raki et al., 2010; Córdova et al., 2015). Those equations can be subdivided in mass transfer-, radiation-, temperature-, combination- and pan evaporation-based methods (Tabari et al., 2013; Valipour, 2015; Liu et al., 2017). In the last decades, the use of regression models (e.g. multiple linear, Bayesian regression, robust regression and multivariate adaptive regression splines (MARS)) and machine learning (e.g. artificial neural network (ANN), random forests (RF) and support vector machine (SVM)) approaches for ETo estimation has considerably increased in academic literature (e.g. Kumar et al., 2002; Trajkovic et al., 2003; Cervantes-Osornio et al., 2011; Kisi, 2013; Kisi, 2016; Khoshravesh et al., 2017). Moreover, a substantial amount of literature has been published on the performance of different models, in different climates, and with the FAO 56 P-M as standard (e.g. Borges and Mendiondo, 2007; Landeras et al., 2008; Er-Raki et al., 2010; Efthimiou et al., 2013).

The research presented in this paper pursued the evaluation of the performance of several ETo models (21 empirical models, 8 ANN models, and 1 MARS model) in comparison to the FAO 56 P-M equation, with application to the páramo ecosystem of the Andean Highlands of southern Ecuador. A comparative study such as this has not been undertaken in those ecosystems and will provide a guide to select the most appropriate ETo equation for the super-humid conditions of páramos. Firstly, an overview of the equations of the empirical models used in the study is given, followed by the nonlinear, non-additive random forest variable selection for the identification of the most influential variables. Thirdly, we assembled ANN models with different combinations of variables following their importance after random forests analysis, and lastly, we developed for the local climate conditions an empirical equation for the estimation of the daily ETo applying the MARS method.

2. MATERIALS AND METHODS

2.1 Data collection and geographical area

The meteorological data of 2 fully automatic weather stations, both located in the high-elevation páramo of Ecuador (Fig 1), were used. The Toreadora weather station is located in the Quinuas River microcatchment on the Pacific side of the Andes mountain range, near Toreadora Lake, at 3955 m a.s.l. (79.22º W 2.78º S) for which four years of data was available (2013-2016). The Zhurucay weather station is situated in the Zhurucay river basin on the Atlantic side of the Andes mountain range, at 3780 m a.s.l. (79.24º W 3.06º S) for which one year of data was available (2014). The weather stations are equipped with the following

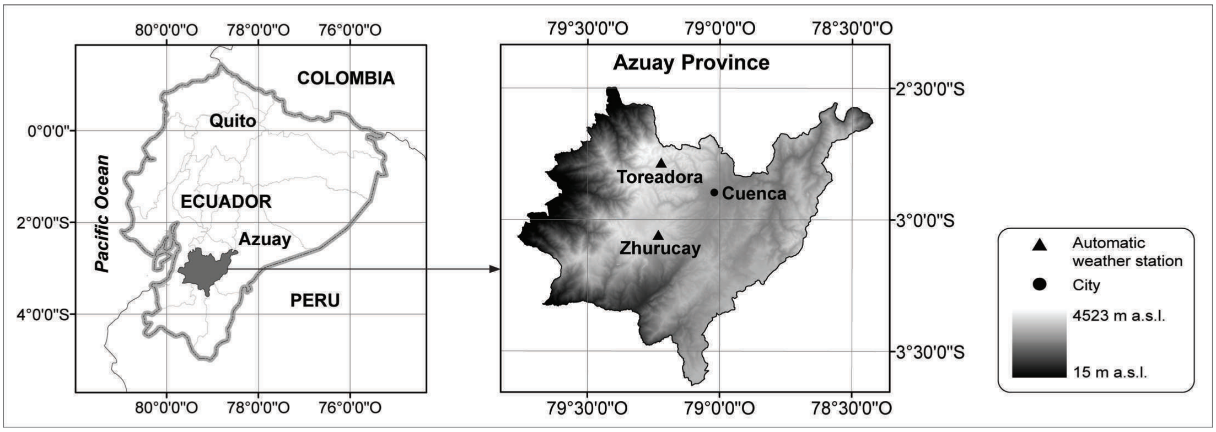

Figure 1: Location of the weather stations in the páramo ecosystem area of the Andean Highlands of southern Ecuador.

sensors positioned at 2 m above ground level: a temperature and relative humidity probe (CS2150, Campbell Scientific), an anemometer (MetOne 034B Windset, Campbell Scientific), a pyranometer (CS300, Campbell Scientific), and a barometer (VAISALA PTB110). At both sites the average value of the weather variables were recorded every 5 minutes. Both stations have excellent quality data, in accordance with the standards outlined in Allen (1996). Table 1 shows the annual average values for the meteorological variables measured in both stations, as well as the maximum and minimum values for temperature.

2.2 Reference evapotranspiration estimation methods

The equations of twenty-two empirical models for the estimation of ETo are presented in Table 2, including the FAO 56 P-M equation (standard method). Literature provides ample insight in the calculation procedure and the required parameters of the different analyzed empirical models. The equations presented in Table 2 were divided in four groups: temperature-, radiation-, combination- and mass transfer-based. The FAO 56 P-M equation was used as reference for comparison and local calibration of the ETo equations.

2.3 Calibration and validation of the empirical models

To calibrate the empirical models presented in Table 2 against the standard equation (FAO 56 P-M), the calibration method described in Fooladmand and Haghighat (2007), Tabari and Talaee (2011), and Mehdizadeh et al. (2017) was applied. The calibration radius (cr) was computed daily as:

$$cr = \frac{ET_o FAO56\text{P-M}}{ET_o\text{Model}} \tag{1}$$

Due to the limited weather data, the period 2013-2015 of Toreadora station was used for the calibration process, and it was decided not to calculate the monthly average value of the daily calibration radius but to calculate the average daily value for the period 2013-2015. This approach was applied for each of the 21 empirical ETo estimation methods using the weather data of the Toreadora station. The calibrated values for the Zhurucay station were calculated using for each estimation method the average daily calibration radius value defined for the Toreadora station for the following reasons: 1) the limited size of the weather database of the Zhurucay station, and 2) both stations are located in the same geographical area and type of ecosystem, at similar elevations. The average value of the calibration radius (cr value) for each of the empirical models are presented in Table 3. The 2016 weather data of the Toreadora station

Weather station	Temperature (°C)			Relative humidity (%)	Solar radiation (MJ m^{-2} day^{-1})	Wind speed (m s^{-1})	Precipitation (mm)
	Average	Maximum	Minimum				
Toreadora	5.44	17.2	-2.4	89.4	12.13	2.31	916
Zhurucay	5.98	15.88	-2.35	91.44	13.90	3.62	1345

Table I: Meteorological variables at the 2 weather stations.

and the 2014 data of the Zhurucay station were used for validation.

2.4 Variable importance measured with random forests

Random decision forests is a popular and efficient algorithm based on model aggregation ideas, for classification, regression and other tasks. The method was proposed by Breiman (2001), and allows measuring the importance of variables, like a sensitive analysis, by estimating the increase of the predicted error when "out-of-bag" (OOB) data for the considered variable are used while all other variables are left unchanged. Random forests for the determination of the importance of variables has been deeply studied by Sandri and Zuccolotto (2006), Strobl et al. (2007), Strobl et al. (2008), Genuer et al. (2010), Hapfelmeier and Ulm (2013), among others. The random forest decision method, using the randomForest R package (Liaw and Wiener, 2015), was applied to define the order of importance of the weather data input (solar radiation, temperature, relative humidity, wind, atmospheric pressure) of the FAO 56 P-M equation (see Table 4).

2.5 Artificial neural networks

ANNs are considered a computation tool that emulates the function of neural networks in biological systems (Landeras et al., 2008). ANNs extract the relationship of inputs and outputs of a process, without explicitly knowing the physical nature of the problem in such a way that the result is transmitted in the network until a signal output is given. The procedure of ANN-based models is, in general, divided in training, validation and testing performance (Abdullah and Malek, 2016). The architecture of an ANN has an input layer (where data are introduced to an ANN), the hidden layer(s) (where data is processed), and the output layer (where results of given inputs are provided). ANN has been widely applied for estimating ETo as a function of weather variables (Kumar et al., 2002; Trajkovic et al., 2003; González-Camacho et al., 2008; Chauhan and Shrivastava, 2009).

The ANN models were applied using the software NeuralTools v7.5 (Palisade Corporation). The ANN type was the Multi-Layer Feedforward Network (MLFN) or Multi-Layer Perceptron Network (MLPN). A sigmoidal function was used as activation in the hidden neuron layers. Specifically, NeuralTools uses a hyperbolic tangent function. Training consists in finding a set of connection weights and bias terms that direct the network to the right answer. During the training process, the Conjugate Gradient Descent method, together with the Simulated Annealing method, were used according to Bishop (1995) and Masters (1995). To avoid over-learning of ANN models, the available training data (Toreadora weather station, period 2013-2015) were divided in two subsets: 80 % of patterns for training and 20 % for cross validation. The 2016 weather data of the Toreadora station and the 2014 data of the Zhurucay station were used for independent validation of the models. According to Koleyni (2010), the performance of a neural network is very often related to its architecture. This performance is usually

Model	Reference	Formula
Temperature-based		
Schendel (SCH)	Schendel (1967)	$ET_o = 16 \cdot \frac{T}{RH}$
Hargreaves-Samani (H-S)	Hargreaves and Samani (1985)	$ET_o = 0.0023 \cdot (T_{max} - T_{min})^{0.5} \cdot (T + 17.8) \cdot R_a$
Baier-Robertson (B-R)	Baier and Robertson (1965)	$ET_o = 0.157 \cdot T_{max} + 0.158(T_{max} - T_{min}) + 0.109 \cdot R_a - 5.39$
McCloud (MC)	McCloud (1955)	$ET_o = 0.254 \cdot 1.07^{1.8T}$
Radiation-based		
Jones-Ritchie (J-R)	Jones and Ritchie (1990)	$ET_o = \alpha \cdot (0.00387 \cdot R_s(0.6 \cdot T_{max} + 0.4 \cdot T_{min} + 29)$ $5°C < T_{max} < 35°C \quad \alpha = 1.1$ $T_{max} > 35°C \quad \alpha = 1.1 + 0.05 \cdot (T_{max} - 35)$ $T_{max} < 5°C \quad \alpha = 0.1 \cdot \exp[0.18 \cdot (T_{max} + 35)]$
Irmak (IR)	Irmak et al. (2003)	$ET_o = -0.611 + 0.149 \cdot R_s + 0.079 \cdot T$
Makkink (MK)	Makkink (1957)	$ET_o = 0.61 \cdot \frac{\Delta}{\Delta + \gamma} \cdot \frac{R_s}{\lambda} - 0.12$
Turc (TR)	Turc (1961)	$ET_o = a_T\, 0.013 \cdot \frac{T}{T + 15} \cdot \frac{23.8856 \cdot R_s + 50}{\lambda}$ $RH \geq 50\% \quad a_T = 1$ $RH < 50\% \quad a_T = 1 + (50 - RH)/70$
Jensen-Haise (J-H)	Jensen and Haise (1963)	$ET_o = 0.0102 \cdot (T + 3) \cdot R_s$
Priestley-Taylor (P-T)	Priestley and Taylor (1972)	$ET_o = 1.26 \cdot \frac{\Delta}{\Delta + \gamma} \cdot \frac{R_n - G}{\lambda}$
Tabari (TB)	Tabari et al. (2013)	$ET_o = -0.642 + 0.174 \cdot R_s + 0.0353 \cdot T$
Copais (CP)	Alexandris et al. (2006)	$ET_o = 0.057 + 0.227 \cdot C_2 + 0.643 \cdot C_1 + 0.0124 \cdot C_1 \cdot C_2$ $C_1 = 0.6416 - 0.00784 \cdot RH + 0.372 \cdot R_s - 0.00264 \cdot RH \cdot R_s$ $C_2 = -0.0033 + 0.00812 \cdot T + 0.101 \cdot R_s + 0.00584 \cdot T \cdot R_s$
Combination-based		
Valiantzas (VT1)	Valiantzas (2013)	$ET_o = 0.051 \cdot (1 - \alpha) \cdot R_s \cdot \sqrt{T + 9.5} - 0.188 \cdot (T + 13) \cdot \left(\frac{R_s}{R_a} - 0.194\right) \cdot \left[1 - 0.00015 \cdot (T + 45)^2 \cdot \sqrt{RH/100}\right] - 0.0165 \cdot R_s \cdot u^{0.7} + 0.0585 \cdot (T + 17) \cdot u^{0.75} \cdot \frac{[(1 + 0.00043 \cdot (T_{max} - T_{\min})^2)^2 - HR/100]}{[1 + 0.00043 \cdot (T_{max} - T_{\min})^2]} + 0.0001z$

Table II: Selected models and reference equation to estimate the potential daily evapotranspiration with their reference, formula, and parameterization.

Valiantzas (VT2)	Valiantzas (2013)	$ET_o = 0.00668 \cdot R_a \cdot \sqrt{(T+9.5)\cdot(T_{max}-T_{dew})} - 0.0696 \cdot (T_{max}-T_{dew}) - 0.024 \cdot (T+20) \cdot \left(1-\frac{RH}{100}\right) - 0.0455 \cdot R_a \cdot (T_{max}-T_{\mathrm{dew}})^{0.5} + 0.0984 \cdot (T+17) \cdot [1.03 + 0.00055 \cdot (T_{max}-T_{\mathrm{min}})^2 - (RH/100)]$
Rijtema (RI)	Rijtema (1966)	$ET_o = \frac{\left(\frac{\Delta \cdot Rn}{\lambda}\right) + \gamma \cdot r \cdot u^{0.75} \cdot (e_s - e_a)}{(\Delta + \gamma)}$
Mass transfer-based		
Mahringer (MA)	Mahringer (1970)	$ET_o = 2.86 \cdot u^{0.5} \cdot (e_s - e_a)$
Trabert (TR)	Trabert (1896)	$ET_o = 3.075 \cdot u^{0.5} \cdot (e_s - e_a)$
WMO	WMO (1966)	$ET_o = (1.298 + 0.934 \cdot u) \cdot (e_s - e_a)$
Brockamp-Wenner (B-W)	Brockamp and Wenner (1963)	$ET_o = 5.43 \cdot u^{0.456} \cdot (e_s - e_a)$
Rohwer (RO)	Rohwer (1931)	$ET_o = (3.3 + 0.891 \cdot u) \cdot (e_s - e_a)$
Penman (PE)	Penman (1948)	$ET_o = (2.625 + 0.713 \cdot u) \cdot (e_s - e_a)$
FAO standard equation		
Penman-Monteith (FAO 56 P-M)	Allen et al. (2006)	$ET_o = \frac{0.408 \cdot \Delta \cdot (R_n - G) + \gamma \cdot [900/(T+273)] \cdot u \cdot (e_s - e_a)}{\Delta + \gamma \cdot (1 + 0.34 \cdot u)}$

Table II: Selected models and reference equation to estimate the potential daily evapotranspiration with their reference, formula, and parameterization.
ET_o is the reference crop evapotranspiration (mm day^{-1}), R_n the net radiation (MJ m^{-2} day^{-1}), G the soil heat flux (MJ m^{-2} day^{-1}), γ the psychrometric constant (kPa °C^{-1}), δ the latent heat of vaporization (MJ kg^{-1}), e_s the saturation vapour pressure (kPa), e_a the actual vapour pressure (kPa), Δ the slope of the saturation vapour pressure-temperature curve (kPa °C^{-1}), T the average daily air temperature (°C), u the mean daily wind speed at 2 m (m s^{-1}), r the roughness coefficient, z the site elevation (m), T_{min} the minimum air temperature (°C), T_{max} the maximum air temperature (°C), T_{dew} the dew point temperature (°C), RH the average relative humidity (%), R_a the extraterrestrial radiation (MJ m^{-2} day^{-1}), R_s the solar radiation (MJ m^{-2} day^{-1}), and α is equal to 0.23. For the calculation of T and T_{dew}, the reader is referred to Allen et al. (2006), and for the definition of the roughness coefficient value (r) for páramo ecosystem to Poulenard et al. (2001).

Model	Type	cr
SCH	Temperature-based	1.62
H-S		0.80
B-R		0.46
MC		1.01
J-R	Radiation-based	1.08
IR		1.23
MK		1.22
TR		3.69
J-H		1.73
P-T		0.79
TB		1.32
CP		1.42
VT1	Combination-based	0.95
VT2		0.93
RI		0.94
MA	Mass transfer-based	2.60
TR		2.42
WMO		3.23
B-W		1.42
RO		2.05
PE		2.57

Table III: Average calibration radius of each of the 21 ETo estimation methods using the Toreadora station weather data period 2013-2015.

determined through test-error experiments due to lack of theory (Laaboudi et al., 2012). To avoid this time-consuming task, NeuralTools software allows to choose the option “Best Net search” to obtain the best neural network configuration and architecture across test-error performance. The advantage of the neural method relies in the possibility of improving the performance criteria by modifying the network architecture (Laaboudi et al., 2012).

The combination of inputs (daily values of weather parameters) for each ANN was defined after the variable selection with random forests. The three most important parameters were solar radiation, minimum relative humidity and maximum air temperature (see Table 4). Combination of input variables were chosen to

Variable	Score
R_s	100
RH_{min}	46.84
T_{max}	19.94
RH_{max}	2.40
u	1.85
T_{min}	1.06
P	1.02

Table IV: Importance of the input variables of the FAO 56 P-M equation according to random forests method.
T_{max} (maximum air temperature in °C), T_{min} (minimum air temperature in °C), R_s (solar radiation in W m^{-2}), RH_{min} (minimum relative humidity in %), RH_{max} (maximum relative humidity in %), u (wind speed at 2 m height in m s^{-1}), P (atmosphere pressure in mbar).

derive ANN models with the least number of weather variables. A summary of tested inputs is listed in Table 5.

2.6 Multivariate adaptive regression splines (MARS)

MARS is a non-parametric model of nonlinear regression that allows explaining the dependence of the response variable on one or more explanatory variables (Friedman, 1991). Non-parametric modeling does not approximate one single function, but adjusts it to several other functions for simple metrics, usually low-order polynomials, defined on a sub-region of the domain (parametric adjustment per section), or sets a simple function for each value of the variable (global setting) (Sánchez-Molina and Poveda-Jaramillo, 2006). MARS is preferred because it allows to approximate complex nonlinear relationships from the data, without postulating a hypothesis about the type of nonlinearity present. The construction of the algorithm model incorporates mechanisms that allows the selection of relevant explanatory variables. The resulting model is easier to interpret as opposed to black box models such as artificial neural networks. Finally, the

Variable inputs	ANN1	ANN2	ANN3	ANN4	ANN5	ANN6	ANN7	ANN8
R_s	•	•	•	•	•	•	•	
RH_{min}	•	•	•	•	•	•		•
T_{max}	•	•	•	•	•		•	•
RH_{max}	•	•	•	•				
u	•	•	•					
T_{min}	•	•						
P	•							

Units are the same as in Table 4.

Table V: Summary of the set of inputs for each of the used ANN's.

estimation of its parameters is computationally efficient and rapid (Velásquez-Henao et al., 2014). Friedman (1991) fully presented the MARS algorithm related to non-metric modeling and adaptive computing. The MARS method has been widely applied for the forecasting of nonlinear time series (e.g. Sánchez-Molina and Poveda-Jaramillo, 2006; Velásquez-Henao et al., 2014), and for its implementation we used the earth R package (Milborrow, 2017).

MARS was applied using the weather inputs for the FAO 56 P-M equation. Local páramo conditions were analyzed by a non-parametric regression, resulting to a model that in this research is considered as the Reference Evapotranspiration Model for Páramo Ecosystems (REMPE equation). Data from the Toreadora weather station, 2013-2015 period, were used for the regression analysis, and data of the periods 2016 (Toreadora) and 2014 (Zhurucay) were used for independent validation of the equation.

The REMPE equation is shown below (R_s is in W m^{-2}, and RH_{min} in %):
BF1 = max(0, R_s − 151,949);
BF2 = max(0, 151,949 − R_s);
BF3 = max(0, RH_{min} − 82,5);
BF4 = max(0, 82,5 − RH_{min});
BF5 = max(0, R_s − 234,782);
BF6 = max(0, R_s − 114,839);
REMPE ETo= 1.77954 + 0.0064776 * BF1 - 0.00793659 * BF2 - 0.0256779 * BF3 + 0.0188508 * BF4 - 0.00135548 * BF5 + 0.001299 * BF6

2.7 Model comparison analysis

To define similarities and differences among models, the following statistical metrics were applied: the mean bias error (MBE), the mean absolute error (MAE) and the root mean square error (RMSE):

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - O_i|$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2}$$

where O_i represents observed values, P_i simulated values, and n is the number of considered data.

3. RESULTS AND DISCUSSION

3.1 Analysis of influential weather variables and model performance

According to the random forest analysis solar radiation (see Table 4) is the dominant variable influencing ETo. The importance level of solar radiation was also found by Córdova et al. (2015) and referred as key factor in the ETo FAO 56 P-M equation for páramo ecosystems. The second dominant variable is the minimum relative humidity which is clearly visible analyzing the 2015 (example year) pattern of the maximum and minimum daily relative humidity for the Toreadora station as shown in Fig 2. For the analyzed 4 year period fluctuates the maximum value of the relative humidity around 100 %, and the minimum value fluctuates between 20 and 95 %; this pattern is a key factor controlling the evapotranspiration dynamics. As stated by Gong et al. (2006) evapotranspiration increases when humidity decrease, and evapotranspiration decrease when humidity increase. As revealed by the random forest analysis minimum relative humidity seems to have a strong influence on ETo because of its high intra-daily variation.

Results from the random forest analysis also highlighted that the least dominant variables for ETo estimation are wind and atmospheric pressure. This is corroborated by Córdova et al. (2015) who determined that wind is the least important variable for ETo estimation in páramo environment. Similar results were found by Contreras (2015) who, based on a sensitive analysis, stated that in páramo ETo is more susceptible to changes in relative humidity, followed by solar radiation, temperature and to a lesser degree by wind speed. To define the minimum number of input variables needed to estimate ETo, eight ANN models were assembled (see Table 5), while the MARS method resulted into the derivation of the REMPE equation, which incorporated solar radiation and minimum relative humidity as the dominant input variables. As such, results showed that the variable discrimination procedure performed by MARS is in conformity with the variable order of importance classified by the random forest analysis.

3.2 Comparison of ETo estimation methods

The performance of the ETo empirical equations, ANN models, and the MARS equation for both weather stations is given in Fig 3 and Fig 4. Simple statistical metrics (MBE, MAE and RMSE) were used to assess the performance of the models versus the FAO 56 P-M model.

3.3 Empirical models

The statistical analysis revealed that of the 21 empirical equations the combination-based group of equations yield the best fitting with the standard FAO 56 P-M equation. The following best group of empirical estimation methods are the radiation-based group, followed by the temperature-based and mass transfer-based group. The same tendency, although for a different environment, was found by Liu et al. (2017). This is explained by the fact that the combination-based equations incorporate all, or most, of the weather variables. The VT1 model perform better in terms of precision that VT2 and RI models, and this for both weather stations. In fact, the VT1 and VT2 equations are derived from the FAO 56 P-M equation (Valiantzas, 2013), and whereas the VT1 equation requires the whole data set of weather data, the VT2 equation does not include the wind speed parameter. Notwithstanding, the VT2 equation yield great performance, the equation indicates that for the study region wind speed is not a very important variable. On the other hand, the RI equation needs a precise roughness value to obtain high performance, for which the roughness values provided by Poulenard et al. (2001) for three páramo sites were used.

The radiation-based equations also showed high performance. J-R is within this group the best model for data from the Toreadora weather station followed by IR, TB and MK; whereas for data from the Zhurucay weather station IR was the best model, followed by MK, J-R and TB. This might be explained by the stronger influence of the solar radiation variable on the ETo estimation, as confirmed by the random forest analysis. Xu and Singh (2002) and Lu et al. (2005) also suggested that radiation-based approaches perform better than temperature-based methods, all of which corroborate the findings in this study. J-H, P-T and CP models showed moderate performance, whereas the TR model depicted the poorest performance for both weather stations. In the case of the TR model, results in this study are in agreement with those from Trajkovic and Kolakovic (2009), who stated that the Turc equation is suited for ETo estimations in humid

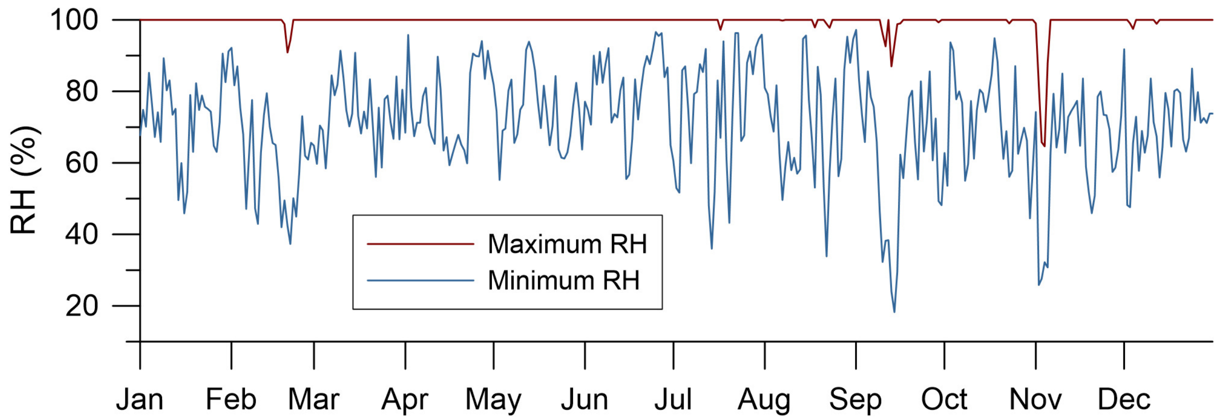

Figure 2: Daily variation of the maximum and minimum relative humidity in 2015 for the Toreadora weather station.

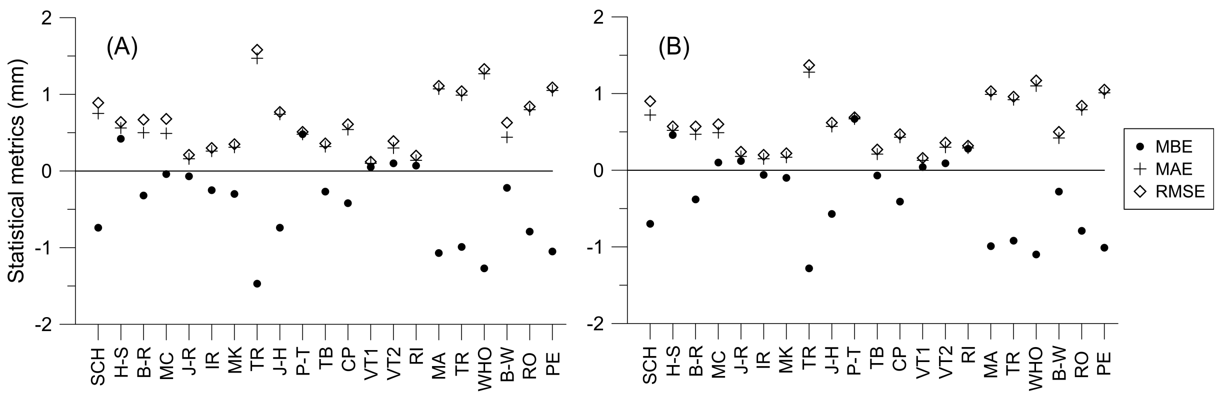

Figure 3: Graphical representation of the statistical performance of the 21 ETo estimation methods versus the FAO 56 P-M model using the A) Toreadora weather station data of 2016; and B) Zhurucay weather station data of 2014.

areas.

The results from the temperature-based group of equations were very similar to those from the radiation-based group. According to the random forest analysis possess the maximum and minimum temperature variables an acceptable power to explain ETo estimates. For both weather stations MC was the best model; B-R and H-S were intermediate and SCH was the least. According to Almorox et al. (2015) temperature-based models in tropical climates showed important variations upon fluctuations of specific local weather, since temperature alone may not be enough to allow a correct estimation of ETo. In this study, most of the temperature-based models do not account for solar radiation, vapor pressure deficit, or sunlight duration.

The mass transfer-based group of equations presented the poorest performance. This might be explained by the fact that the hygrometric deficit $(e_s - e_a)$ in páramos is small, and so it may not have a significant effect on the ETo estimation. Also, the incorporation of wind speed seems to have a negative effect on this method's performance, as it was showed by the random forest analysis. As mentioned in the study of Singh and Xu (1997) and Gong et al. (2006) wind speed is not a significant factor in ETo estimation models in humid conditions. Valipour (2017) stated that the precision of mass transfer-based models is sensitive to the

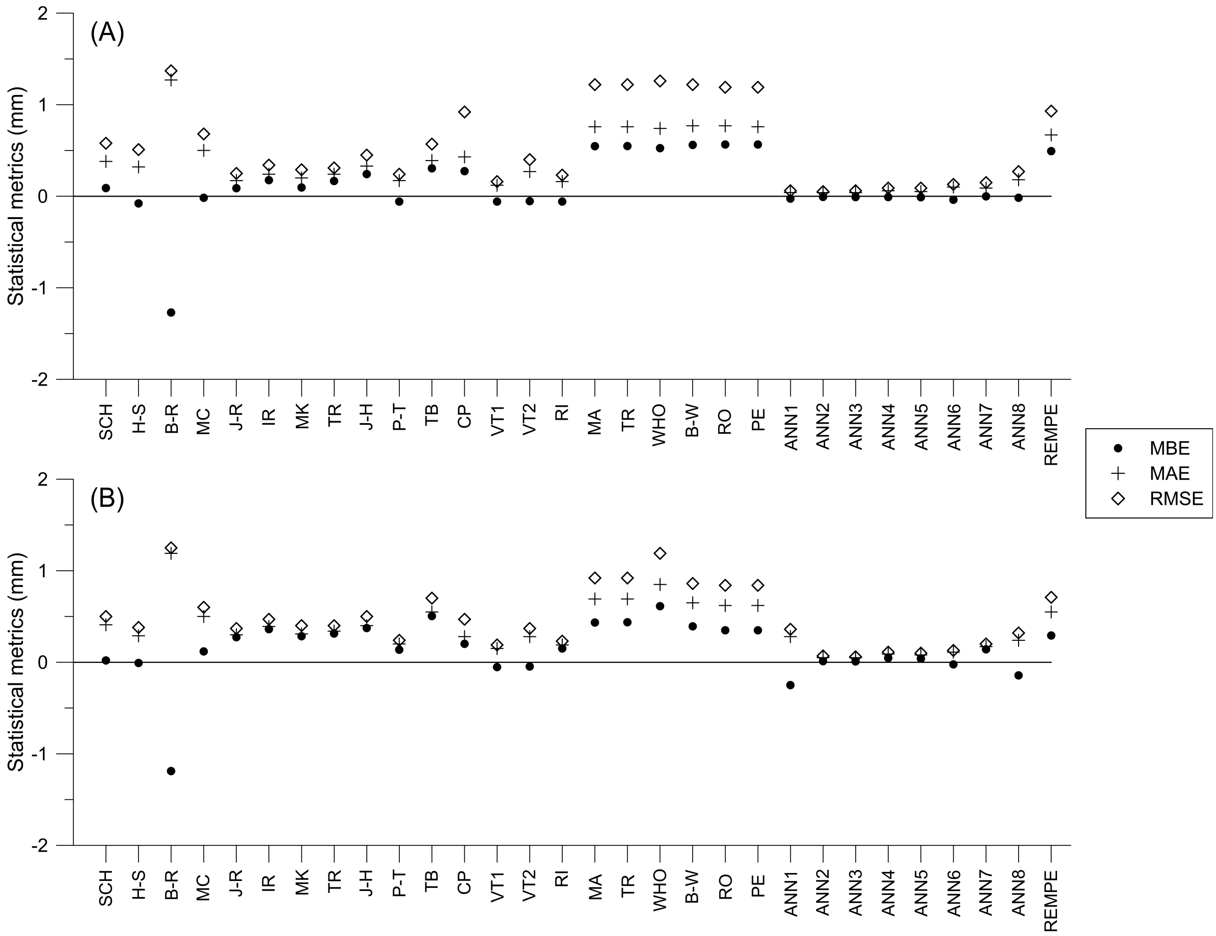

Figure 4: Graphical representation of the statistical performance of the 30 calibrated ETo estimation methods versus the FAO 56 P-M model using the A) Toreadora weather station data of 2016; and B) Zhurucay weather station data of 2014.

parameter variation in each model. The B-W equation in the mass-transfer group appears to be an acceptable estimation model for both stations. No other model in this group showed appropriate estimates. Similar results were found in Tabari et al. (2013). These authors showed that the mass transfer-based equations had the worst performances, while the radiation-based and temperature-based models were the best-suited equations for ETo estimations.

3.4 Calibration of empirical models

Models with an average cr value close to 1 (MC, J-R, VT1, VT2 and RI) denote that the estimated values of those models are almost equal to those obtained with the standard FAO 56 P-M equation (see Table 3). The variation in cr value of the 21 empirical equations, using the weather data of the Toreadora station, are shown in Fig 5A. This Box-Whisker plot depicts for the period 2013-2015 the variation of the cr value for each of the 21 empirical equations prior to calibration, respectively the median (center line), the interquartile range (25 to 75 %) (box) and the lower and upper quartile range (0-25 % and 75-100 %) multiple to a factor 1.5 (whiskers). The H-S, J-R, IR, MK, P-T, VT1, VT2 and RI show the smallest variation in cr value, followed by the SCH, B-R, J-H, TB and CP equations. The TR and the equations in the mass-transfer group show the largest variation in cr value. Fig 5B shows the variation in cr value after model calibration for the 2016 validation period

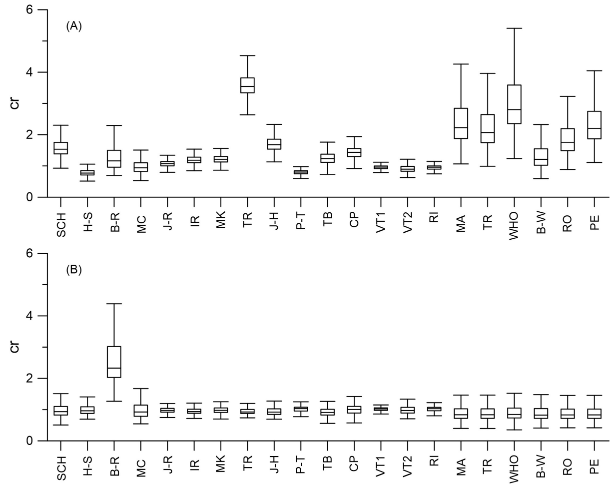

Figure 5: (A) Box-Whisker plot of the variation of the cr values for the 21 empirical models, and (B) the Box-Whisker plot of the variation of cr values for the models after calibration.

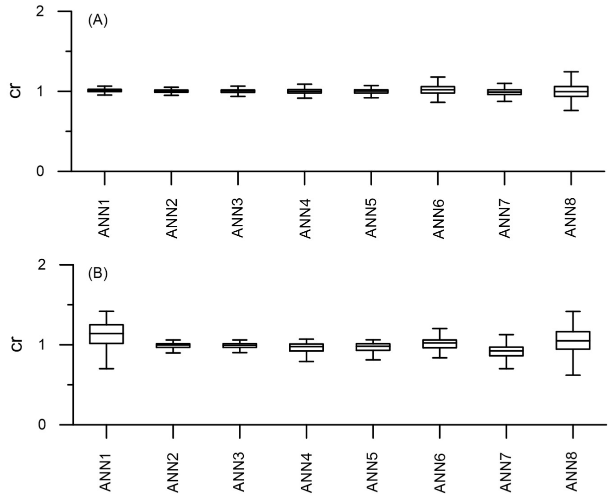

Figure 6: Box-Whisker plot of the variation of the cr values for the 8 artificial neural network models. (A) Toreadora station (2016), and (B) Zhurucay station (2014).

of Toreadora station.

Several ETo equations improved their performance after calibration, more precisely the SCH, IR, CP, MK, J-H, TB and P-T models for the Toreadora weather station and the SCH, H-S, J-H, P-T and CP models for the Zhurucay weather station. For both weather stations, the TR model increased its performance considerably, whilst the B-R model decreased significantly its performance. No significant improvement was observed for the remaining models.

The results obtained after calibration for the temperature-based group of equations are in line with the recommendation by Bautista et al. (2009) and Contreras (2015) not to use in tropical sub-humid climate temperature-based models without preliminary local calibration. Model calibration is also recommended for the radiation-based group; e.g. Sentelhas et al. (2010) concludes that the application of the P-T model is only recommended after local calibration. All mass transfer-based models, with exception of the B-W equation, improve their performance after calibration, but these equations remain poor estimating methods. On the contrary, some models (e.g. B-R, TB, IR, B-W) according to MAE and RMSE values present better performance in the original form than after calibration (see Figs 3 and 4). Such unpredictability could be explained by the high variability in the distribution of cr values. Despite this, several of the models with low variability in cr value improved after calibration their performances yielding more accurate results. Based on the analysis it is not recommended for the given study region to use, even after calibration, the mass transfer-based models to estimate ETo.

3.5 Artificial neural network models

ANN models showed high performance in estimating daily ETo for both weather stations surpassing to a large extent most of the empirical models. Based on the cr values it can be observed that ANN2 present higher accuracy for the Toreadora station (2016) (Fig 6A), and ANN3 for the Zhurucay station (2014) (Fig 6B).

As was expected, the ANN models showed less error using the weather data of the Toreadora station than of the Zhurucay station. This is explained by the fact that the calibration was done with data belonging to the Toreadora station. Despite, the ANN models were calibrated with Toreadora station data (2013-2015), the models adjusted very well to the validation period of the Zhurucay station (2014). Nevertheless, better results could have been obtained if there were complete climate databases for the Zhurucay station.

The ANN1 model for the Zhurucay weather station is the least accurate in estimating the daily ETo, due to the atmospheric pressure variable that probably introduced noise in the ANN model negatively affecting its performance. The ANN8 model did not incorporate the solar radiation variable (the most important variable for ETo estimation according to random forests analysis), and consequently its performance was lower compared to the other ANN models (Figs 6A and 6B). Despite of that, this model revealed to be much better than most of the empirical models used for ETo estimation. It's highlighted, that ANN6 to ANN8 models were assembled in different combinations of two or three main climate parameters, to anticipate the risk a sensor failed. The configuration and performance of each ANN model during calibration are shown in Table 6.

Our results suggest that the ANNs are a powerful and accurate tool for modeling ETo in super-humid conditions. This is corroborated by several ETo estimation studies that highlighted the high accuracy of ANNs in relation to other methods (e.g. Kumar et al., 2002; Abdullah and Malek, 2016).

3.6 MARS model

The REMPE equation showed an unexpected poor performance for both weather stations, respectively RMSE = 0.93 and 0.71, MBE = 0.49 and 0.29 in Toreadora and Zhurucay stations. Notwithstanding the fact that the equation was calibrated with data from the Toreadora weather station, REMPE surprisingly performed better with data from the Zhurucay weather station. For both stations, the results of the REMPE model surpassed those from the mass transfer-based group with exception of the B-W model, which presented better performance in its original form. Nevertheless, the REMPE model scored better in comparison to the original form of the SCH, J-H and TR equations for the Toreadora station and the SCH, H-S, B-R, TR, J-H, P-T and CP equations for the Zhurucay station. However, after model calibration of the empiric equations performed the REMPE method only better than the B-R equation using the Toreadora data, and better than the IR, B-R, TR, J-H and TB equations using the data of the Zhurucay station. Comparison of daily estimates of the standard FAO 56 P-M equation and the REMPE model for the validation period of both weather stations are shown in Fig 7.

The REMPE model produced a higher error with respect to the best results between the original and calibrated empirical models. The mass transfer-based models were the only exception. These findings were unanticipated and probably the result of the enormous number of factors involved in climate, even in specific locations. This sensitivity makes it rather difficult to show that a simple equation, especially a nonlinear, can produce accurate predictions (Traore et al., 2010). The short time series of data used for the calibration of the empirical models, might also negative affect the performance. Further, the results obtained in this study are contradictory to the Aghajanloo et al. (2013) findings, in which their results showed that multiple nonlinear regression (MNLR) models can be an acceptable approach to predict daily ETo in semi-arid ecosystems. Aghajanloo et al. (2013) showed that increasing the number of input variables in the MNLR models leads to an improvement of the accuracy of ETo estimates. The difference in climate and seasonal patterns between super-humid and semi-arid ecosystems could be crucial factors partially explaining this contradiction.

Model	Structure	RMSE Training (mm day^{-1})	RMSE Testing (mm day^{-1})	Inputs
ANN1	7-5-1	0.048	0.046	R_s, $HR_{min,max}$, $T_{min,max}$, u, P
ANN2	6-3-1	0.051	0.056	R_s, $HR_{min,max}$, $T_{min,max}$, u
ANN3	5-5-1	0.054	0.049	R_s, $HR_{min,max}$, T_{max}, u
ANN4	4-5-1	0.062	0.064	R_s, $HR_{min,max}$, T_{max}
ANN5	3-4-1	0.065	0.083	R_s, HR_{min}, T_{max}
ANN6	2-3-1	0.104	0.104	R_s, HR_{min}
ANN7	2-4-1	0.094	0.146	R_s, T_{max}
ANN8	2-3-1	0.221	0.202	HR_{min}, T_{max}

Table VI: Summary of the training and cross validation processes of the evaluated ANNs using the Toreadora weather data of the 2013-2015 calibration period. Structure: number of inputs-number of neurons/nodes in the hidden layer-number of outputs.

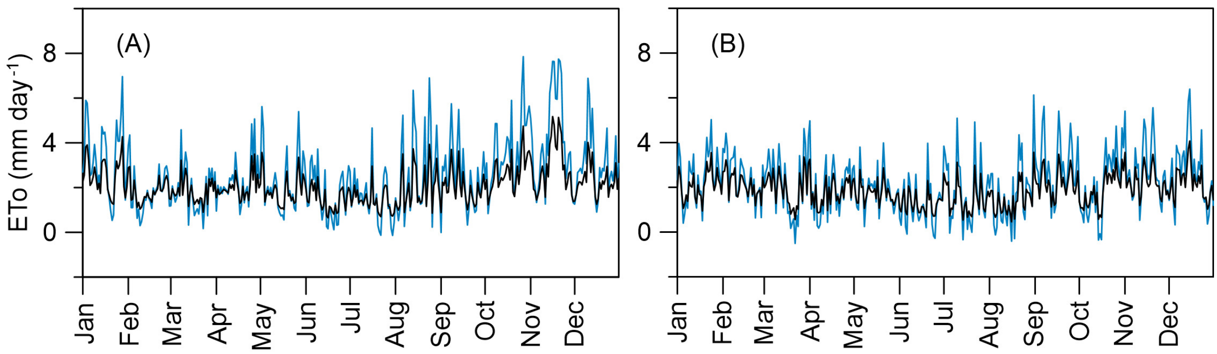

Figure 7: Daily REMPE ETo estimates versus estimates of the standard model (FAO 56 P-M) for: (A) Toreadora station (2016), and (B) Zhurucay station (2014). Light blue and black line depict REMPE and FAO 56 P-M model respectively.

3.7 Annual reference evapotranspiration

Annual values of ETo were obtained by making the sum of daily ETo values. Fig 8 shows for each of the 21 non-calibrated empirical equations the annual ETo value, respectively for the stations Toreadora (Fig 8A) and Zhurucay (Fig 8B), and the years 2016 and 2014. The full horizontal line in the vertical bar graphs depict the annual value of ETo calculated with the FAO 56 P-M standard method. As depicted in Fig 8 yielded the MC and J-R models (Fig 8A) and the VT1, VT2, MK, J-R, IR and TB models (Fig 8B) an annual value for ETo very close to the standard in their original or non-calibrated form. The other models respectively under- or overestimated the standard annual ETo value. This result shows that estimating the annual ETo without carrying out this previous analysis can have consequences in terms of water management, which can introduce water supply problems for agriculture and human consumption.

Application of the calibration procedure improved for some of the empirical models the estimate of ETo. Consequently, annual estimations of ETo improved as well. This is clearly visible in Figs 9A and 9B. Fig 9A depicts the annual ETo value generated with the calibrated 21 empirical models, the ANNs

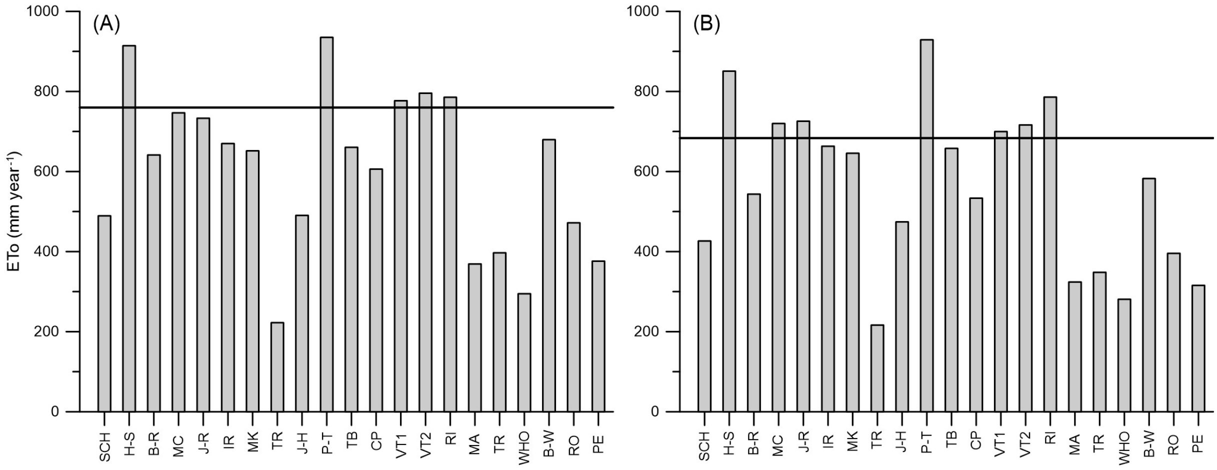

Figure 8: Annual estimate of the ETo value for the 21 original empirical models, using respectively the 2016 data of the Toreadora weather station (A) and the 2014 weather data of the Zhurucay weather station (B). The horizontal line presents the annual ETo value using the FAO 56 P-M standard method.

and the REMPE model using the 2016 data of the Toreadora station, while Fig 9B presents the same information using the 2014 weather data collected in the Zhurucay station. The radiation-based models are the equations that improved most, specially when using the Toreadora data (Fig 9A). The annual value of ETo fit well with the reference annual value of ETo for all ANN models using respectively the 2016 and 2014 data from the Toreadora and Zhurucay station, with the exemption of the ANN1 and ANN8 models when using the data from the Zhurucay weather station (Fig 9B). The mass transfer-based models overestimated annual ETo values for data from both stations (Figs 9A and 9B). As opposed to the pattern described in previous paragraph, after calibration most of the models overestimated the reference annual ETo value, and only a few underestimated the annual ETo value derived with the FAO 56 P-M equation.

4. CONCLUSIONS

The need to correctly estimate the reference evapotranspiration is not new and resulted in many climate regions to the testing of existing and the development of new methods. In line herewith, a comparative analysis was conducted of the performance of existing empirical equations, ANN models, and a newly developed MARS-based model for the estimation of ETo of wet páramo ecosystems in Southern Ecuador. The performance of the daily ETo estimates was defined versus the standard FAO 56 P-M model. The main reason of the search for prediction models that require a small number of weather parameters as input is the lack of complete data sets in the high Andean páramo region. Altogether, the combination-based models performed well, followed by the radiation-based and temperature-based models. The mass transfer-based models had poor performances, with exception of the B-W model; however, results indicate that these models should not be recommended for ETo estimations in páramo regions because of the super-humid environmental conditions. The calibration method significantly improved the performances of several of the tested models. The latter should be further explored in view of the development of more advanced calibration methods.

The ANN models showed to accurately estimate ETo although specific patterns, difficult to explain, are observed most probably due to complex nonlinear phenomena. The fact

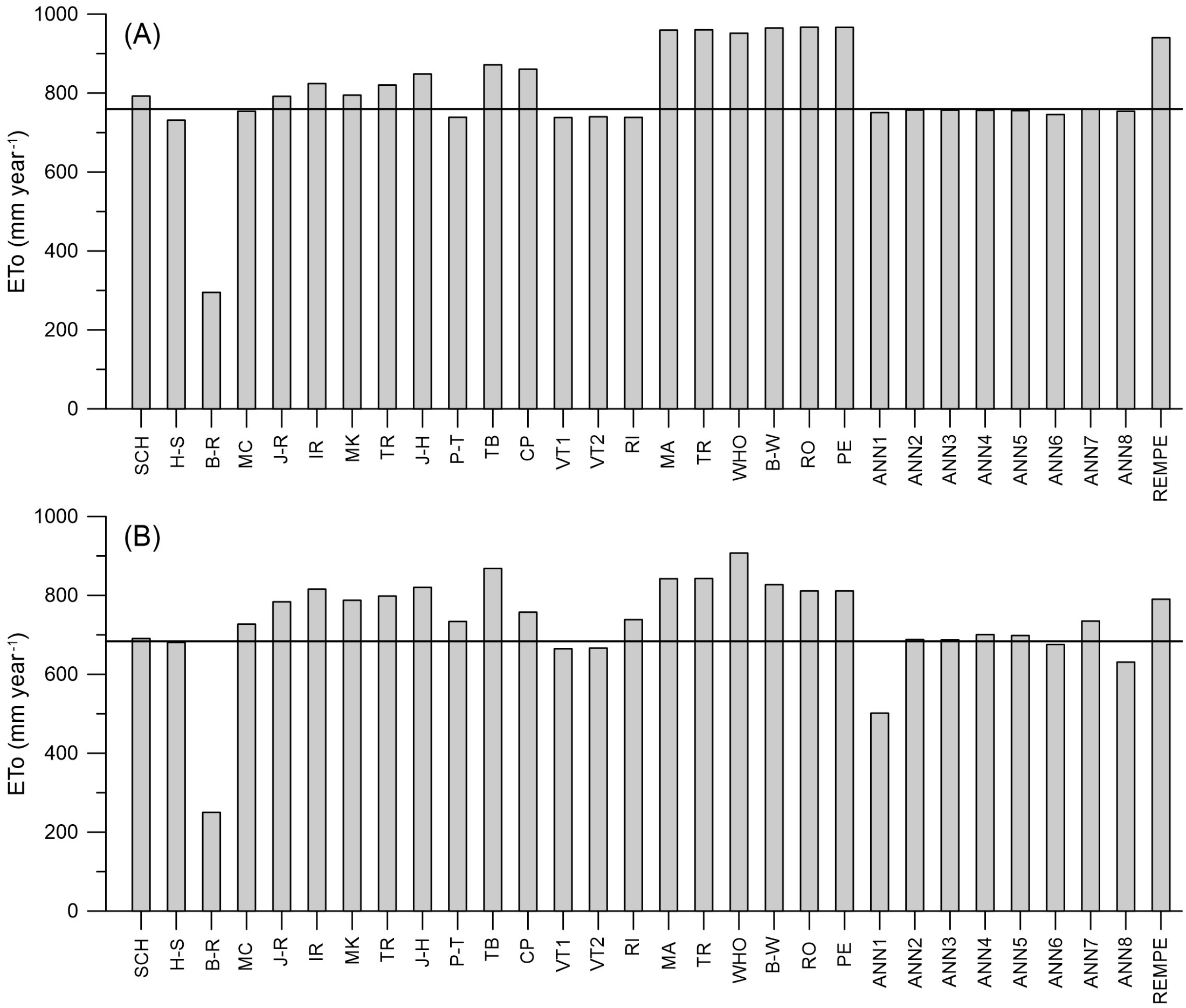

Figure 9: Estimate of the annual ETo value for the 30 calibrated methods, using respectively the 2016 data of the Toreadora weather station (A) and the 2014 weather data of the Zhurucay weather station (B). The horizontal line presents the annual ETo value using the FAO 56 P-M standard method.

that ANN models permit to include different combinations of weather variables enabled to define the ANN model with the smallest possible number of weather variables as input, without decreasing modeling performance. The ANN models are the first approach to be applied for estimating the ETo of páramo ecosystems when only few weather data are monitored. The REMPE model, using only solar radiation and minimum relative humidity as input variables, showed unsatisfactory performance. The question if the performance of the REMPE equation can be improved by adding more input variables, is important and open for further studies.

The FAO 56 P-M equation served as reference in the absence of lysimeter measurements. It is generally accepted that lysimeter measurements are free of random or systematic error making the method useful for validating empirical and model-based methods. However, for the given study area by the absence of lysimeter data the question rises whether the FAO 56 P-M method is a valid reference to be used under super-humid conditions. Therefore, it is suggested that in future studies the FAO 56 P-M equation is calibrated to lysimeter data. Notwithstanding this limitation, the research presented an interesting comparison between 30 methods, requiring varying weather variables as input, to estimate ETo in the páramo ecosystem of Andes mountain range in Southern Ecuador. The combination-based models and the artificial neural network methods seems to outperform all other tested approaches. In terms of software, the study showed that NeuralTools v7.5 and R Package are user friendly, easy to implement, and therefor highly recommended for data modeling in similar studies.

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