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ESTIMATION OF MONTHLY REFERENCE EVAPOTRANSPIRATION WITH SCARCE INFORMATION USING MACHINE LEARNING IN SOUTHWESTERN COLOMBIA

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ABSTRACT

This research aimed to identify an alternative method to estimate reference evapotranspiration (ETo) with scarce climatological information in southwestern Colombia between 1983-2017 by evaluating and comparing different machine learning techniques. The FAO Penman-Monteith (*FAO-PM56*) was used as the reference method and four empirical methods (*Hargreaves, Thornthwaite, Cenicafé, and Turc*) were assessed with five metrics to evaluate the method of best fit to *FAO-PM56*, root mean square error (RMSE), mean absolute error (MAE), mean bias error (MBE), Nash-Sutcliffe model efficiency coefficient (NSE), and Pearson correlation coefficient (R). Three models were designed using machine learning techniques to estimate ETo, multiple linear regression (MLR), artificial neural networks (ANN), and autoregressive integrated moving average model (ARIMA). The results showed that the ARIMA-M3 model reported the best performance metrics (RMSE = 4.13 mm month^{-1}, MAE = 3.15 mm month^{-1}, MBE = -0.08 mm month^{-1}, NSE = 0.96 and r = 0.98). However, it restricts in that it can only be used locally and cannot be extrapolated to other climatological stations, because it was calibrated with specific conditions (exogenous variables) and stations, unlike the ANN-M1 model, which only requires training the network for its application. This method will allow estimating ETo in places with scarce information, as vital for water management in places with much uncertainty regarding accessibility and availability.

Key Words: Artificial neural network; FAO-56 Penman-Monteith; Performance metrics; Southwestern Colombia; Evapotranspiration

ESTIMACIÓN DE EVAPOTRANSPIRACIÓN DE REFERENCIA CON INFORMACIÓN ESCASA UTILIZANDO MACHINE LEARNING EN EL SUROCCIDENTE COLOMBIANO

RESUMEN

Esta investigación tuvo como objetivo identificar un método alternativo para estimar la evapotranspiración de referencia (ETo) con escasa información climatológica en el suroeste de Colombia entre 1983-2017, evaluando y comparando diferentes técnicas de machine learning. Se utilizó el método de FAO Penman-Monteith (*FAO-PM56*) como método de referencia y se evaluaron 4 métodos de empíricos (*Hargreaves*, *Thornthwaite*, *Cenicafé y Turc*) con cinco métricas para evaluar el método de mejor ajuste al FAO-PM56, error cuadrático medio (RMSE), error medio absoluto (MAE), error medio de sesgo (MBE), coeficiente de eficiencia del modelo de Nash-Sutcliffe (NSE) y coeficiente de correlación de Pearson (R). Se diseñaron tres modelos utilizando técnicas de machine learning para estimar la ETo, regresión lineal múltiple (MLR), redes neuronales artificiales (ANN) y modelo de media móvil integrada autorregresiva (ARIMA). Los resultados mostraron que el modelo ARIMA-M3 presentó la mejor métrica de rendimiento (RMSE = 4,13 mm mes^{-1}, MAE = 3,15 mm mes^{-1}, MBE = -0,08 mm mes^{-1}, NSE = 0,96 y R = 0,98). Sin embargo, tiene la restricción de que sólo se puede utilizar localmente y no se puede extrapolar a otras estaciones climatológicas, porque se calibró con estaciones y condiciones específicas (variables exógenas), a diferencia del modelo RNA-M1, que sólo requiere entrenar la red para su aplicación. Este método permitirá estimar la ETo en lugares con escasa información, lo que es vital para la gestión del agua en lugares con mucha incertidumbre en cuanto a accesibilidad y disponibilidad.

Palabras clave: Redes neuronales artificiales; FAO-PM56 Penman-Monteith, Métricas de desempeño, Suroccidente Colombiano, Evapotranspiración

1) INTRODUCTION

Evapotranspiration is an aerodynamic physical process where water from the land surface evaporates, and water from plants transpires (Allen et al., 1998; Alves et al., 2017; Granata et al., 2020; Meneses et al., 2020). Correct estimation of evapotranspiration is fundamental in different research areas (Maček et al. 2018; Kumar et al., 2020), such as climate change (Cannarozo et al., 2006; Liu et al., 2008; Yao et al. 2009; Yang et al., 2011), hydroclimatology (Rivas and Caselles 2004; Castañeda and Rao, 2005), water resources planning and management (Huizhi and Jianwu, 2012; Łabędzki et al., 2014; Biggs et al., 2016) and irrigation needs (Yoder et al., 2005; Tabari, 2010).

The lysimeter is a suitable method for estimating field evapotranspiration in the field (Wang and Dickinson 2012). However, it has several limitations, such as high installation costs, complex instruments (Valipour, 2015; Goh et al., 2021), prior experimental setup, and maintenance hours to achieve reliable results (Igbadun et al., 2006; Choi and Jeon 2018; Jing et al., 2019; Ahmadi and Javanbakht 2020).

Indirect methods have been developed to estimate reference evapotranspiration (ETo) (Choi and Jeon, 2018). ETo is defined as the evapotranspiration of a grass crop with an assumed height of 0.12 m, a fixed surface resistance of 70 s m^{-1}, and an albedo of 0.23, with adequate nutrient and water availability (Allen et al., 1998). Methods that estimate ETo based on climatic factors can be classified as those based on temperature (Thornthwaite and Wilm, 1948; Blanney and Criddle, 1950; Hargreaves and Samani, 1985), radiation (Turc, 1961; Priestley and Taylor 1972), and combined methods (Allen et al., 1998).

The most recommended method for ETo estimation is the so-called FAO Penman-Monteith (*FAO-PM56*), developed by the Food and Agriculture Organization of the United Nations (FAO) (Allen et al., 1998) and the World Meteorological Organization (WMO) (Allen et al., 1998; Granata et al., 2020; Cobaner, 2010; Huo et al., 2012; Laqui et al., 2014; Ayaz et al., 2021). It can be used anywhere in the world without the need to calibrate the equation. Because of this, it has been subject to extensive validation with lysimeters in various global climatic conditions (Landeras et al., 2008; Nema et al., 2017; Quej et al., 2019; Ayaz et al., 2021; Ferreira et al., 2021).

The main drawback of using this method is the requirement of a significant number of variables for its estimation, these variables are maximum and minimum air temperature, wind speed, precipitation, and solar radiation (Valipour, 2015). This restricts its worldwide use, especially in places with a lack and insufficient availability of climatological information. For example, in protected areas and/or armed conflict countries with low budgets (Traore et al., 2008).

Numerous studies evaluate ETo models in Colombia, standing out among them the one by Barco et al. (2020), who made a macroscale estimate of evaporation in Colombia using the methods of *Turc*, *Morton, Penman, Holdridge, and Budyko*. However, they did not make comparisons with field measurements. Jaramillo (2006) developed the empirical equation of the National Coffee Research Center (Cenicafé) in several locations in the Colombian Andes, mainly in the Cauca and Magdalena River basins, and compared the relationship between the observed values of *FAO-PM56* with the Class A evaporation tank. Poveda et al. (2007) regionalized ETo in Colombia using the methods of *Turc, Morton, Coutagne, Thornthwaite, Holdridge, Meyer, Penman, Budyko, and Cenicafé.* Ramírez et al. (2011) assessed the application of the *FAO-PM56*, the Hargreaves, the Garcia and Lopez modified, and the lysimeter to estimate ETo in the coffee zone of Colombia. Toro-Trujillo et al. (2015) evaluated the reliability of evapotranspiration estimation of the *Hargreaves-Samani* and radiation methods concerning the *FAO-PM56* method in the northern banana-growing zone Urabá Antioqueño. Mendoza & Peña (2021) compared the *Blaney-Criddle, Hargreaves, Priestley-Taylor, and Camargo* methods with values of class A evaporation tanks from Colombian Sugarcane Research Center (Cenicaña) and *FAO-PM56*.

The different results of the authors agree that no method shows significant superiority over the other, which is attributed to the low quality of the available information. For this reason, models to estimate ETo have been developed during the last decades, using machine learning techniques such as Artificial Neural Networks (ANN) (Zanneti et al., 2008; Alves et al., 2017; Fonseca et al., 2018; Laqui et al., 2019; Meneses et al., 2020) Autoregressive Integrated Moving Average Model (ARIMA) (Jordan et al., 2008; Gautam and Sinha, Mossad and Alazba, 2016; Bouznad et al., 2020), and Multiple Linear Regression (MLR) (Yirga, 2019).

In Colombia, the spatial distribution of climatological stations is uneven due to several factors, such as complex topography (e.g., the Andean Mountain range), areas affected by the armed conflict, and low investment in technological resources, among others (Urrea et al., 2019; Canchala et al., 2022). In southwestern Colombia (Nariño), 76% of the rainfall stations are in the Andean region, with a density of one station every 470 km^2, covering 40% of the total area of Nariño. The remaining 24% of the rainfall stations are in the Pacific region, with a density of one station every 1,442 km^2, accounting the 52% of the total area of Nariño. In the case of climatological stations, the scenario is worse since, in the Andean region, there is one every 1,720 km^2 and only one in the Pacific region (Barbacoas) (Ocampo-Marulanda et al., 2022). The rainfall stations are those available Instituto de Hidrología, Meteorología y Estudios Ambientales (IDEAM). The accessibility and availability of information on climatological variables allow for a better understanding of the hydrological cycle and more efficient management for its use in agriculture.

The southwest of Colombia has the highest percentage of harvested area (7.9%); therefore, considering the problems mentioned earlier and that Nariño is one of the departments with the highest participation in the country's agricultural production (Moncayo, 2015), adequate planning of water resources must be carried out to ensure food security.

In this scenario, the objective of this research was to determine a model that allows estimating ETo in a scenario with scarce information and high spatiotemporal variability in climatic elements. A contradictory aspect of the study area is that the areas with higher rainfall have less climatological information and more missing data in their records. Knowledge of ETo would enable better management to contribute to the sustainability of food sovereignty and security by meeting the Sustainable Development Goals related to objective 2, zero hunger; objective 13, climate action; and objective 15, life on land (United Nations, 2018).

2) DATA AND METHODS

2.1) Study area

The southwest of Colombia (Nariño) is one of the most biodiverse regions of the country and the world, located between 0°21' and 2°40' north latitude and 76°50' and 79°02' west longitude, with approximately 33,268 km^2 (Canchala et al., 2020; Ocampo-Marulanda et al., 2022). The Pacific region (14,754 km^2) accounts for 52%, the Andean region (15,466 km^2) for 40% and the Amazon region (3,048 km^2) for the remaining 8% (See Figure 1) (Gobernación de Nariño, 2019). In addition, it has a privileged geostrategic position due to its proximity to the tropical Pacific Ocean, the Andes Mountains, and the Colombian-Ecuadorian border (Canchala et al., 2019).

2.2) Data

In this research, time series of maximum (TMAX), minimum (TMIN), and mean temperature (TMED) in °C, humidity (RH) in %, sunshine hours (SBH) in hours, and height in meters above sea level (COTA) were considered as regressor variables on a monthly scale from 1983 to 2017. Data from 10 climatological stations across southwestern Colombia (see Figure 1) were provided by IDEAM (see Figure 1). The missing data in the time series were less than 25%. They were estimated using Non-Linear Principal Component Analysis (NLPCA), a methodology suggested by Scholz et al. (2005), and applied in hydroclimatology by Canchala et al. (2019).

Wind speed information was only available for three stations, Aeropuerto Antonio Nariño, El Encano, and Obonuco. The imputation of missing data was performed as mentioned in the Methods.

2.3) Methods

Table 1 shows some methods for estimating ETo. FAO recommends using the *FAO-PM56* method to determine ETo without lysimeters. The estimation involves a wide range of variables, mean air temperature, relative humidity, solar radiation, and wind speed. Empirical models have been developed to estimate ETo with fewer climatic variables. For example, *Hargreaves* developed a model based on maximum, mean, minimum temperature, and solar radiation. *Turc* based his model on mean temperature, relative humidity, and net solar radiation. *Thornthwaite* proposed a model based on mean temperature and annual heat index, and Jaramillo based his model on the relationship between altitude and evapotranspiration.

The assessed performance metrics are presented in Table 2. The following metrics were used to evaluate the performance and precision of the alternative methods for estimating ETo, compared to

FAO-PM56. RMSE, which characterizes the variance of the error (Rodrigues and Braga, 2021). MAE takes the absolute value of the difference between ETo values (Choi and Jeon, 2018). MBE measures the average error magnitude of the observed and estimated data (Goh et al., 2021). NSE is used to evaluate the predictive ability of hydrological models (Nash and Sutcliffe 1980; Knoben et al., 2019; Adnan et al., 2021). Finally, R measures the linear relationship between estimated and calculated values (Laqui et al., 2019).

The Machine learning methods used in this research were:

– Multiple Linear Regression (MLR). Regression analysis is a statistical technique belonging to the class of supervised statistical learning methods that allows investigating and modelling the relationship between a response variable and one or multiple predictor variables. An advantage of multiple linear regression is that it allows to evaluation of the effect of each predictor variable in the presence of the other variables (Montgomery et al., 2002). The multiple linear regression model is presented in Equation 1.

$$y = \beta_o+\beta_1X_1+\beta_2X_2+\ldots+ \beta_kX_k + e \quad (1)$$

Where

y = Response variable

βo = Intercept with the y-axis

$\beta 1,\ldots,Bk$ = partial regression coefficients that measure the expected change in the response variable for each unit change in the predictor variable X (j=1,2,...,k), when all other regressor variables are held constant.

e = Random component of error that must comply with the assumptions of normality, zero mean, constant variance (homoscedasticity) (Goldfend and Quandt, 1965), and independence (Fox, 2016).

– Autoregressive Integrated Moving Average (ARIMA). The ARIMA model is a statistical methodology that allows describing the future behavior of a time series as a linear function of past data and errors due to chance, in addition to considering the possible inclusion of a seasonal component (Box et al., 1974). The model that allows considering regular (non-seasonal) effects in the series can be expressed as in Equation 2.

$$(1 - \Phi_1B - \Phi_2 B^2 -\ldots- \Phi_p B^p)(1-B)^d\, yt =(1 - \theta_1B - \theta_2B^2 -\ldots- \theta_qB^q) \qquad (2)$$

Where p and q indicate the order of the autoregressive (AR) and moving average (MA) components respectively, and d indicates the order of the integrated component (I) to extract the possible sources of the non-stationarity present in the series under analysis (Stellwagen and Tashman, 2013). The AR and MA terms can be identified using the simple autocorrelation functions (ACF) and partial autocorrelation functions (PACF) of the time series data. ARIMA models were used to model the temporal correlation presented in the MLR models.

– Artificial Neuronal Network (ANN). AANs are computational bio-inspired models based on biological neurons, which can store and retrieve data, classify patterns, realize input patterns to output patterns, and similar group patterns. These follow two learning processes, supervised and unsupervised (Tabari and Talaee, 2013). Multilayer perceptron (MLP) is a type of feed-forward ANN mainly used for supervised learning (Haykin, 1994) and models complex nonlinear processes in water resources and hydrology problems. The MLP is a perceptron network with more than one intermediate layer and is usually represented with an output. The perceptron uses a matrix to model a neural network and is mainly used to discriminate an input x to a single output value F(x) in that matrix (See Equation 3).

$$F(x) = \begin{cases} 1 \text{ if } w\,.\ x-u>0 \\ 0 \text{ otherwise} \end{cases} \qquad (3)$$

The function F(x) has a binary value and is used primarily for sorting, w is a vector with an associated weight, and u is a "threshold" used to offset the activation function. The sum of the inputs to the neuron must produce a value greater than u to change the neuron from state 0 to 1.

A successful development for an ANN depends on several parameters, e.g., hidden layers, neurons in the hidden layer, learning rate, and activation function, among others. However, there is no guideline on how to build an ANN or how many neurons should be placed in the hidden layer to estimate the output (Murat and Serhat, 2018). Therefore, through trial-and-error tests, the parameters were varied until the combination with the lowest error and the highest possible R^2 was found. In this research multiple architectures were built, combining activation functions, such as: identity, tanh, logistic and relu with the optimizers lbgfs, adam and sgd. Furthermore, given the complexity and the requirements one hidden layer with three neurons and a learning rate of 0.01 was enough. Through trial-and-error test, the best performance model with 1000 iterations was determined, and the best model was: tanh function activation, lbgfs optimizer, one hidden layer, three neurons and a learning rate of 0.01. The training algorithm of the ANN was 80% of the data and 20% to validate.

In selecting regressor variables for the ARIMA and MLR models, the VIF was used to avoid multicollinearity among the variables (Montgomery et al., 2002). In the case of ANNs, this technique performs nonlinear computational procedures which are not affected by multicollinearity because they tend to be overparameterized, i.e., the same algorithm updates the weights associated with redundant variables to have no impact on the final solution (De Veaux and Ungar, 1994).

Linear Principal Component Analysis (PCA) was applied to formulate one of the ARIMA models. PCA is one of the most widely used statistical techniques to reduce dimensionality and preserve the most significant amount of information in a data set (Jolliffe, 2002), allowing the elimination of possible multicollinearity between regressor variables. The principal components between TMAX, TMED, and TMIN were estimated in this case.

Lee et al. (2012) mentioned that ETo is affected by topographic factors such as altitude because as altitude increases, there is a decrease in solar radiation and wind speed. Therefore, to represent the monthly ETo, an interpolation process was performed using the cokriging technique using altitude as an exogenous variable and with a spherical semivariogram. Basconcillo et al. (2017) and Cerón et al. (2021) suggest that with this technique, better correlations are obtained with monthly temperature and precipitation; considering that the former is one of the variables most correlated with ETo, it will be possible to spatialize ETo in southwestern Colombia.

The general methodology is presented in Figure 2. Initially, the information provided by IDEAM was compiled, then the exploratory data analysis was carried out, and the missing data were estimated. Subsequently, the ETo of the three stations was estimated using the *Hargreaves, Thornthwaite, Cenicafé*, and *Turc* methods. Then, the ETo methods were evaluated using five performance metrics, Nash-Sutcliffe model efficiency coefficient (NSE), Pearson correlation coefficient I, root mean square error (RMSE), mean absolute error (MAE) and mean bias error (MBE), to select the best-fit method concerning for *FAO-PM56*. Next, Spearman's correlation coefficient was applied to find the variables with the highest correlation with ETo and the variance inflation factor (VIF) to reduce multicollinearity among the regressor variables of the proposed statistical models. Finally, three models were built for each machine learning technique (Artificial Neural Networks – ANN, Multiple Linear Regression – RLM, and Autoregressive Integrated Moving Average Model – ARIMA), i.e., nine models, which were evaluated by five performance metrics (NSE, R, RMSE, MAE and MBE) to estimate *FAO-PM56* with scarce information.

Then, multi-year monthly averages of all variables were estimated, and the annual value of precipitation was reported. Subsequently, the Jarque-Bera normality test was performed, which tests whether a data set presents the skewness and kurtosis of a normal distribution (Jarque and Bera, 1982). The test was used to determine parametric or non-parametric statistical tests to calculate the correlation between climatic variables. Empirical models have been developed to estimate Eto with fewer climatic variables.

3) RESULTS AND DISCUSSION

The descriptive statistics of the climatic variables were estimated and presented in Table 3. It can be observed that the altitude of the stations is in the mountainous zone, except for Barbacoas, which is in the Pacific plain, and Monopamba, located in the Amazon jungle (see Figure 1). The precipitation values ranged between 888 and 6,927 mm/year, consistent results considering that the department includes the Andean, Amazon, and Pacific regions, the latter being one of the rainiest regions in the world. The TMAX ranges between 32.5 °C and 18.8 °C, the TMED between 11.7 °C and 26.2 °C, and the TMIN between 4.8 °C and 20 °C. The RH presented values above 75%, with 89.5% being the highest reported at the Barbacoas station. Finally, the SBH reported values between 2.1 and 5.4 hours. The indicators shown in Table 3 were calculated with the complete time series, with a previous estimation of missing data using NLPCA.

The reconstruction errors were, 7 mm month^{-1} for precipitation, 0.16 °C month^{-1} for maximum temperature, 0.07 °C month^{-1} for mean temperature, 0.16 °C month^{-1} for minimum temperature, 0.55 % month^{-1} for relative humidity and 0.10 hours month^{-1} for sunshine hours. These results show very low error variance in magnitude, demonstrating that the imputation method accurately estimated the missing data in the time series.

Figure 3 shows a graphical comparison of ETo methods with *FAO-PM56* for the time series of the Aeropuerto Antonio Nariño, El Encano and Obonuco stations to find the method with the most well-adjustment to *FAO-PM56*. *Hargreaves* method was the only one that overestimated ETo, since the others tended to underestimate it. The *Turc* method was similar in shape and magnitude to the *FAO-PM56* method at El Encano station, while at Obonuco, the most well-adjusted method was *Hargreaves*. At the Aeropuerto Antonio Nariño station, it was observed that both methods were adjusted in shape and magnitude.

In this sense, the performance metrics were estimated to validate the most adjusted method concerning *FAO-PM56*, and the results are presented in Table 4. The average RMSE performance metrics ranged from 16.9 to 50.4 mm month^{-1}, MAE from 14.2 to 48.7 mm month^{-1}, MBE from 10.3 to 48.7 mm month^{-1}, R from 0.80 to 0.90 and NSE from 0.64 to 0.81. The results of the *Turc* method show that it was the most well-adjusted concerning *FAO-PM56* by the reported metrics (MAE= 14.2 mm month^{-1}, MBE=10.3 mm month^{-1} and RMSE= 16.9 mm month^{-1}). However, the R and NSE metrics (0.90 and 0.81) show *Hargreaves* as the best. Trajkovic and Kolakovic (2009a) state that *Turc* method overestimates ETo at windless locations and underestimates at windy locations; for example, Figure 3 shows underestimation in Aeropuerto Antonio Nariño, Obonuco and El Encano stations located at heights above 1700 m. These results agree with Poveda et al. (2007), who regionalized evapotranspiration in Colombia and observed that the *Turc* and *Morton* methods are the most appropriate; and Fisher & Pringle (2013), who used three alternative methods in a humid region in the United States (Mississippi) and concluded that Turc consistently underestimates ETo.

Other research reports that the *Turc* method has historically performed well under humid (Jensen et al., 1990; Trajkovic and Kolakovic, 2009b; Fisher & Pringle, 2013; Birara et al., 2020) and tropic conditions (Tukimat et al., 2012; Lima et al., 2019; Santos et al., 2019; Monteiro et al., 2021). One of the possible reasons is that the method was initially developed under wet conditions (southern France) (Tabari, 2010; Ahmadi and Javanbakht 2020; Diouf et al., 2016). In a semiarid region in Senegal Diouf et al. (2016) concluded that the *Turc* method showed similar high accuracy (R^2>0.80) reported in this research. Similar findings were observed in Malaysia, where Goh et al. (2021) concluded that the *Turc* method provides the closest results to *FAO-PM56* in subhumid and humid climate conditions in the absence of data, as the R^2 and the MBE reported one of the highest R^2 (0.81) and the MBE results were closer to zero for the monthly ETo estimation concerning *FAO-PM56*. The Same happened in Brazil, where Santos et al. (2019) concluded that the best option when meteorological data is unavailable is the *Turc* method given the R results (0.90) concerning *FAO-PM56*. In contrast, Monteiro et al. (2021) suggest that the ETo estimation should give priority to *Turc* Method regardless of the season and climatic conditions. From these results, it can be concluded that in the absence of information to estimate *FAO-PM56*, the *Turc* method is the best alternative to estimate ETo in southwestern Colombia.

When the normality test (Jarque-Bera) was applied to the regressor variables, a p-value of 0.00 was obtained, which means that the data did not follow a normal distribution. Therefore, the nonparametric Spearman correlation coefficient was applied between the climatic variables and *FAO-PM56*. The results were, COTA -0.84, RH -0.69, SBH 0.87, TMAX 0.88, TMED 0.84 and TMIN 0.66, which suggest the highest positive correlation concerning *FAO-PM56* are TMAX, SBH and TMED, and the highest negative correlation was COTA. However, SBH is a complex variable to obtain due to its high costs and technical complexities (Laidi, 2018). TMED results in a lower saturation pressure, hence a lower vapour pressure deficit, which results in a lower estimate of ETo (Allen et al., 1998). Hence, TMAX and COTA were considered the most crucial regressor variables for constructing the ARIMA and MLR models, as shown in Table 5, where the VIF results are also presented to identify any possible multicollinearity.

The TMIN and RH presented the lowest correlation coefficients (0.66 and -0.69), which indicates that they are not the best choice as regressor variables. Multicollinearity was evidenced for TMAX, TMED and COTA due to the high values (> 5) in the VIF. These results are congruent, considering that both temperatures are correlated and have an inversely proportional relationship with altitude. Therefore, the TMAX variable was prioritized for the construction of the models since it was the one that reported the highest correlation coefficient (0.88).

Figure 4 presents the graphical comparison between the best machine learning models, MLR-M2, ANN-M1 and ARIMA-M3, during 1983-2017, reported in Table 6. The ARIMA-M3 method was the closest in magnitude and shape for the Aeropuerto Antonio Nariño station. The MLR-M2 model was the one that reported the highest accuracy in the extreme values for the three stations, evidencing it in the maximum and minimum peaks. However, these methods cannot be extrapolated to other climatological stations because they were calibrated with specific COTA and TMAX conditions, and stations. The ANN-M1 model underestimates ETo at Aeropuerto Antonio Nariño, although it reported higher accuracy at El Encano and Obonuco stations. However, it is necessary to perform a quantitative evaluation to validate the graphical results. Therefore, Table 6 presents the performance metrics results for the nine proposed machine learning models.

The performance metrics showed that the average of 9 models ranged in RMSE from 4.1 to 8.2 mm month^{-1}, MAE from 3.2 to 6.6 mm month^{-1}, MBE from -0.1 to 0.3 mm month^{-1}, NSE from 0.84 to 0.96 and r from 0.92 to 0.98. Of the 9 models constructed, the ARIMA-M3 model reported the best results in terms of error (RMSE=4.1 mm month^{-1}, MAE=3.2 mm month^{-1}, MBE= -0.1 mm month^{-1}, NSE=0.96 and R=0.98). This result suggests that using this model would allow estimating ETo more accurately in error and correlation. However, these can only be used if there is prior information on the response variable (*FAO-PM56*) due to its autoregressive component, making it difficult to use in places with scarce information. Although the ANNs did not report the best metrics, they can be used as an alternative for estimating *FAO-PM56* in places with scarce information since it is not necessary to know the response variable for its estimation.

These results agree with what has been reported in other research (Zanetti et al., 2008; Alves et al., 2017; Nema et al., 2017; Laqui et al., 2019; Granata et al., 2020; Meneses et al., 2020), where it is shown that the application of ANNs using MLP with few regressor variables allows estimating ETo more accurately. Moreover, Feng et al. (2018) and Shiri (2017) suggest that machine learning models outperformed empirical equations, which is evident in the results of the performance metrics, as the *Turc* method goes from having RMSE from 16.9 to 7.3 mm month^{-1}, MAE from 14.2 to 5.9 mm month^{-1}, MBE from 10.3 to 0.1 mm month^{-1}, R from 0.81 to 0.87 and NSE from 0.65 to 0.94. It is crucial select TMAX, SBH, and COTA to achieve efficient ANN models in regions with scarce information. To improve the error and efficiency of the ANN, we recommend adding wind speed, given that Maček et al. (2018) suggest that it accounts for a significant contribution to the aerodynamic component. However, unfortunately, this is the most complex variable to get data due to the lack of stations in the country.

Even though there are no previous monthly scale studies on this methodology in Colombia, Laqui et al. (2019) investigated in a similar context (Peruvian highlands), i.e., climatological stations with scarce information located at high altitudes (3819 and 4660 masl). Although the scale was a daily scale, the results showed that ANNs allow estimating with reasonable accuracy at high altitude stations with scarce information. Pinos et al. (2020) assesses 30 models for the estimation of daily ETo in two weather stations with limited data in a wet Andean paramo ecosystem (southern Ecuador). Their results suggest that the ANNs outperformed the empirical models and accurately estimated ETo in super-humid conditions. It is agreed with different studies developed in humid (Ayaz et al., 2021), subhumid (Nema et al., 2017), arid (Tabari and Talaee, 2013), semiarid (Ayaz et al., 2021) and wetland areas (Granata et al., 2020) around the world where ANN were used to estimate ETo with few input variables.

In northern Greece, Antonopoulos & Antonopoulos (2017) build 3 ANNs models and concluded that any model that uses temperature and radiation as inputs should be able to estimate the ETo sufficiently. Mohawesh (2013) proved several ANNs in 3 stations across the Jordan valley and concluded that the overall results suggest that temperature based ANNs can be used when there is insufficient data. In Serbia, Petković et al. (2015) developed an adaptive neuro-fuzzy inference system and concluded that the maximum relative humidity and maximum air temperature are the most influential optimal. The same happened in Brazil, where Ferreira (2019) concluded that the relative humidity and temperature increased the capacity of the ANNs to estimate ETo adequately. Thereby, the results shown in this research represent an option to substitute the *FAO-PM56* method in regions with scarce information; since the amount of information required by this method could be a limiting factor for its application.

Figure 5 shows the results of the ETo estimation with the ANN-M1 model for the seven stations for which *FAO-PM56* could not be estimated. It shows that most results present the same shape and magnitude except for Barbacoas, which is congruent considering that it is in the Pacific region with marked differences concerning the Andean region, where most other stations are located.

Interpolation with ordinary cokriging with the spherical semivariogram from the stations of this

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research to know the annual ETo in southwestern Colombia was performed. The results in Figure 6 show that the highest values are found in the Pacific region. Lower values are observed as one approaches the Andean region and reaches the Amazon region. A noteworthy result is that the reported values of ETo in the Andean region in comparison with precipitation could indicate a water deficit.

4) CONCLUSIONS

The results show that this proposed machine learning models allow a precise estimation of ETo in southwestern Colombia with scarce information since the performance metrics were better than those reported by the best-fitted empirical method (*Turc*). However, as these were far from the ideal value, it was decided to build machine learning techniques to reduce the error associated with ETo estimation. Initially, four regressor variables were considered for estimation, and given the high correlation with *FAO-PM56* (Spearman correlation coefficient) with TMAX (0.88) and COTA (-0.84) and easiness of obtaining these variables, the machine learning model was built prioritizing TMAX and COTA over the others. More input variables give accurate information about ETo estimation, as many researchers suggest (Rivas and Caselles, 2004; Nema et al., 2017; Choi and Jeon, 2018); yet one of the purposes of this research is to develop an alternative model with few inputs variables to ease application to adequately estimate ETo in the absence of data as in southwestern Colombia.

Hence, ETo was calculated with nine machine learning models, and it was determined that the ARIMA-M3 and MLR-M2 models presented the best performance, because it was calibrated with specific conditions like COTA, TMAX (exogenous variables), and stations. However, there are restrictions on their use since they cannot be extrapolated outside the study area. Therefore, the ANN-M1 model was used as an alternative method to estimate ETo in southwestern Colombia with scarce information, considering previous successful studies, their unrestricted application, and good performance metrics, and that does not require knowing the response variable for its estimation since it works as a black-box model.

Metrics performance of the ANN-M1 model concerning those calculated by the *Turc* method is better, as it goes from having an RMSE of 16.9 to 7.3 mm month^{-1}, an MAE of 14.2 to 5.9 mm month^{-1}, an MBE of 10.3 to 0.1 mm month^{-1}, an R of 0.81 to 0.87 and an NSE of 0.65 to 0.94. These results suggest that using the ANN-M1 model allows a more accurate estimation of ETo in places with little information at high altitudes, which allows considering it as a methodology to be used in forecasts or to improve the understanding of future hydroclimatic events to reduce the uncertainty generated.

The ANNs tend to underestimate the ETo results slightly; this may be because the developed network did not adequately assimilate the spatial variation with the current information. Considering that the results obtained are reasonable, it is suggested to improve the data source by installing new climatological stations to better train the ANNs. It is also necessary to better understand the spatial-temporal variation of the climatic variables and, thus, to have better planning and management in managing the water resources of the southwestern part of Colombia.

The results presented here contributed to validating the idea of the application of machine learning techniques to estimate ETo in places with scarce information. This fact provides, easy and accurate information to agriculturists and stakeholders to develop programs that provide and enhance water resources management to achieve the proposed sustainable development goals and ensure food security and sovereignty. Future studies could emphasize developing machine learning models (ANN) to estimate and forecast the ETo in different climate conditions, e.g., arid and humid, on a monthly scale.

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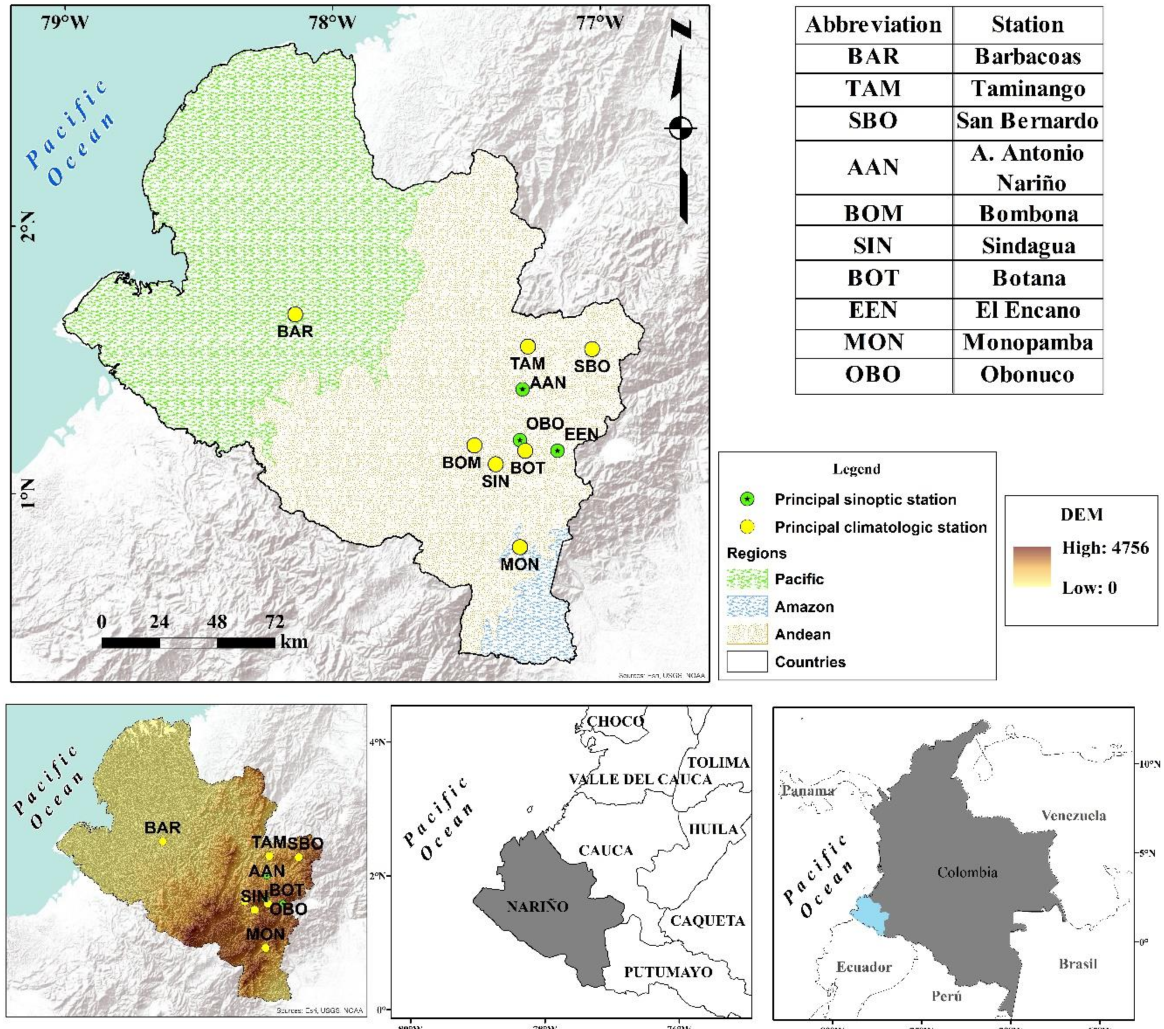

Abbreviation	Station
BAR	Barbacoas
TAM	Taminango
SBO	San Bernardo
AAN	A. Antonio Nariño
BOM	Bombona
SIN	Sindagua
BOT	Botana
EEN	El Encano
MON	Monopamba
OBO	Obonuco

Figure 1. The geographical location of the study area and distribution of climatological stations, principal sinoptic station includes wind velocity data

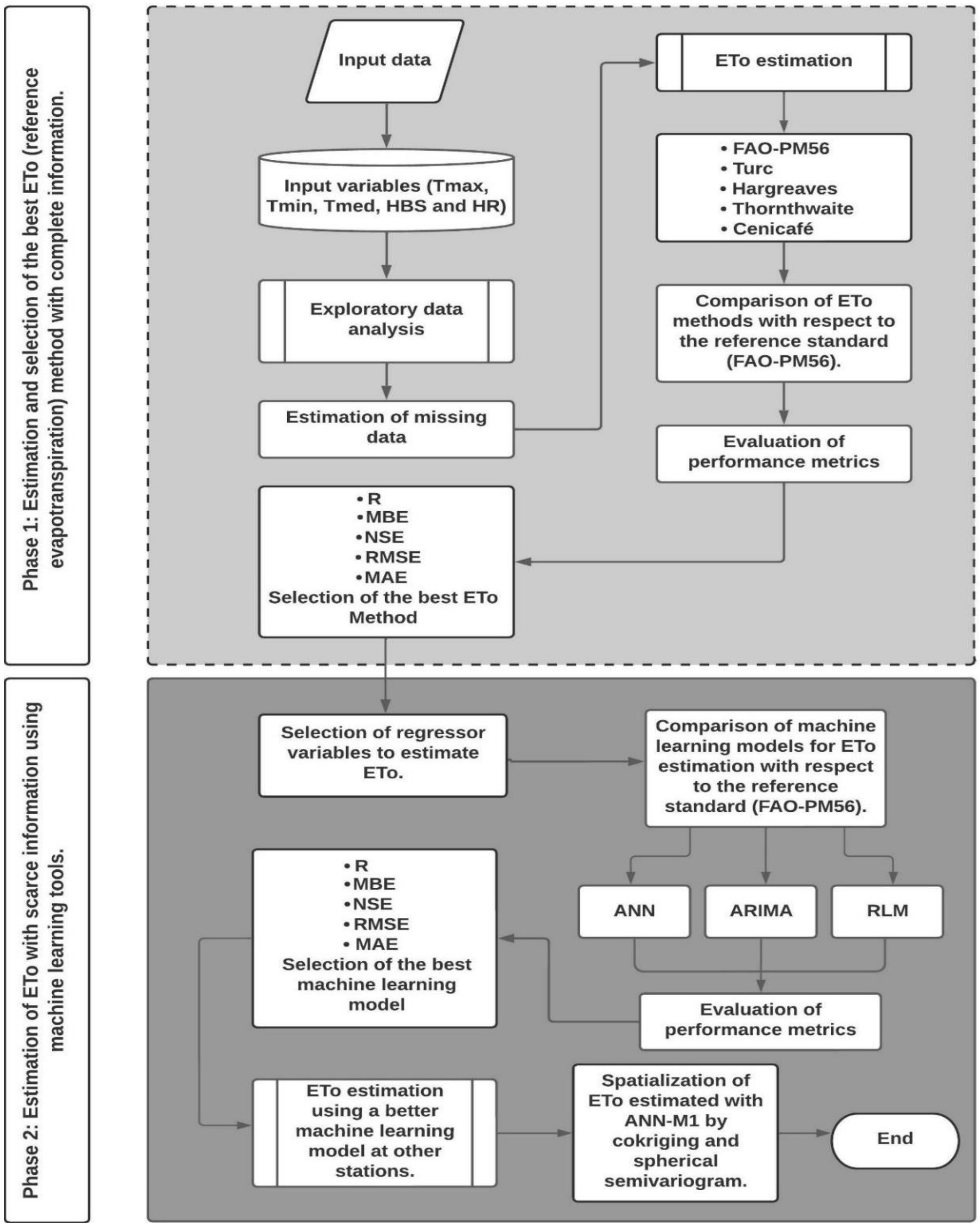

Figure 2. Methodological diagram of the research

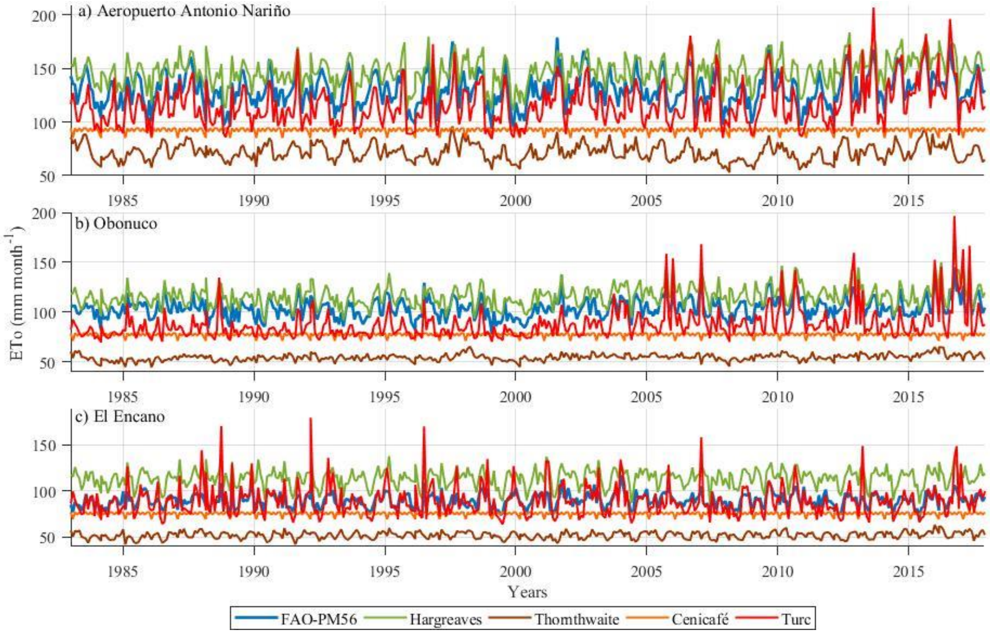

Figure 3. Graphical comparison of evapotranspiration by different methods: a) Aeropuerto Antonio Nariño 1983-2017, b) Obonuco 1983-2017, and c) El Encano 1983-2017

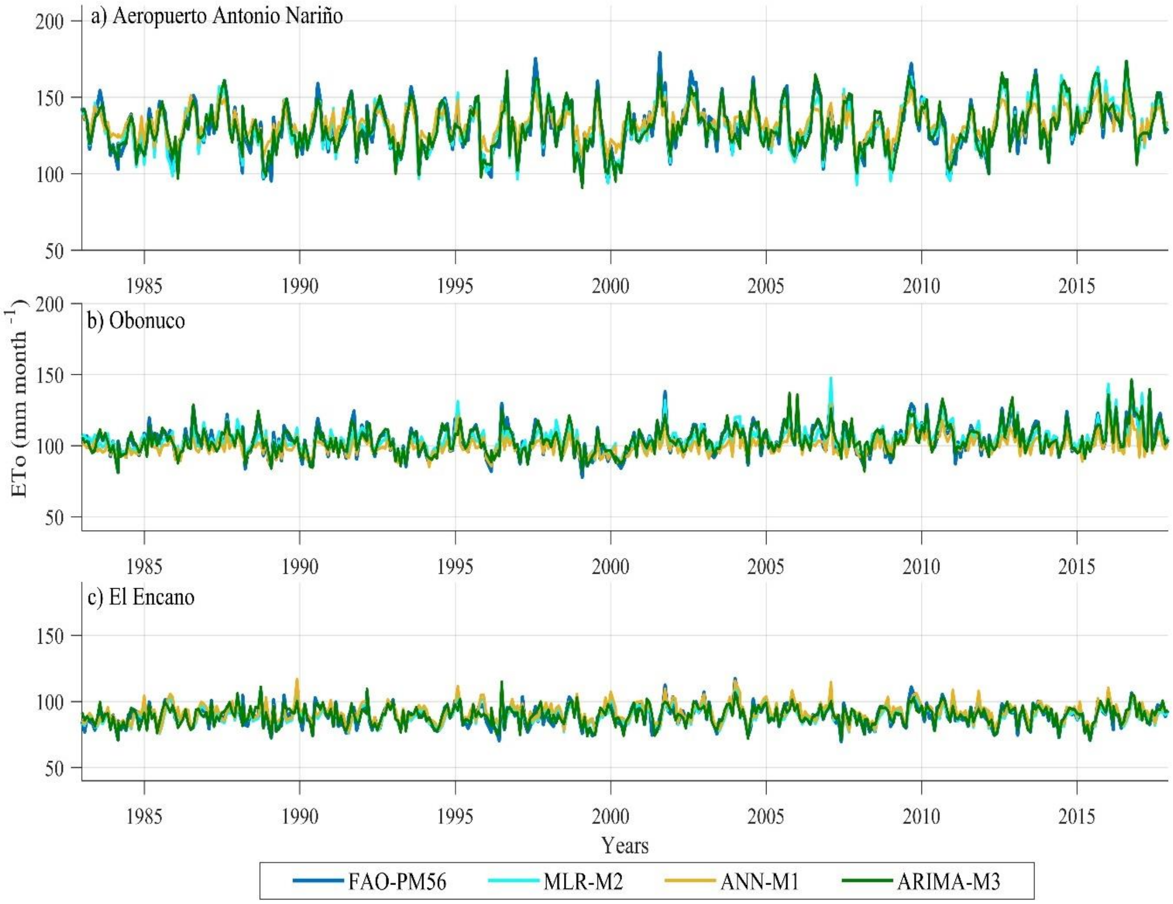

Figure 4. Graphical comparison of machine learning models: a) Aeropuerto Antonio Nariño, b) Obonuco and c) El Encano

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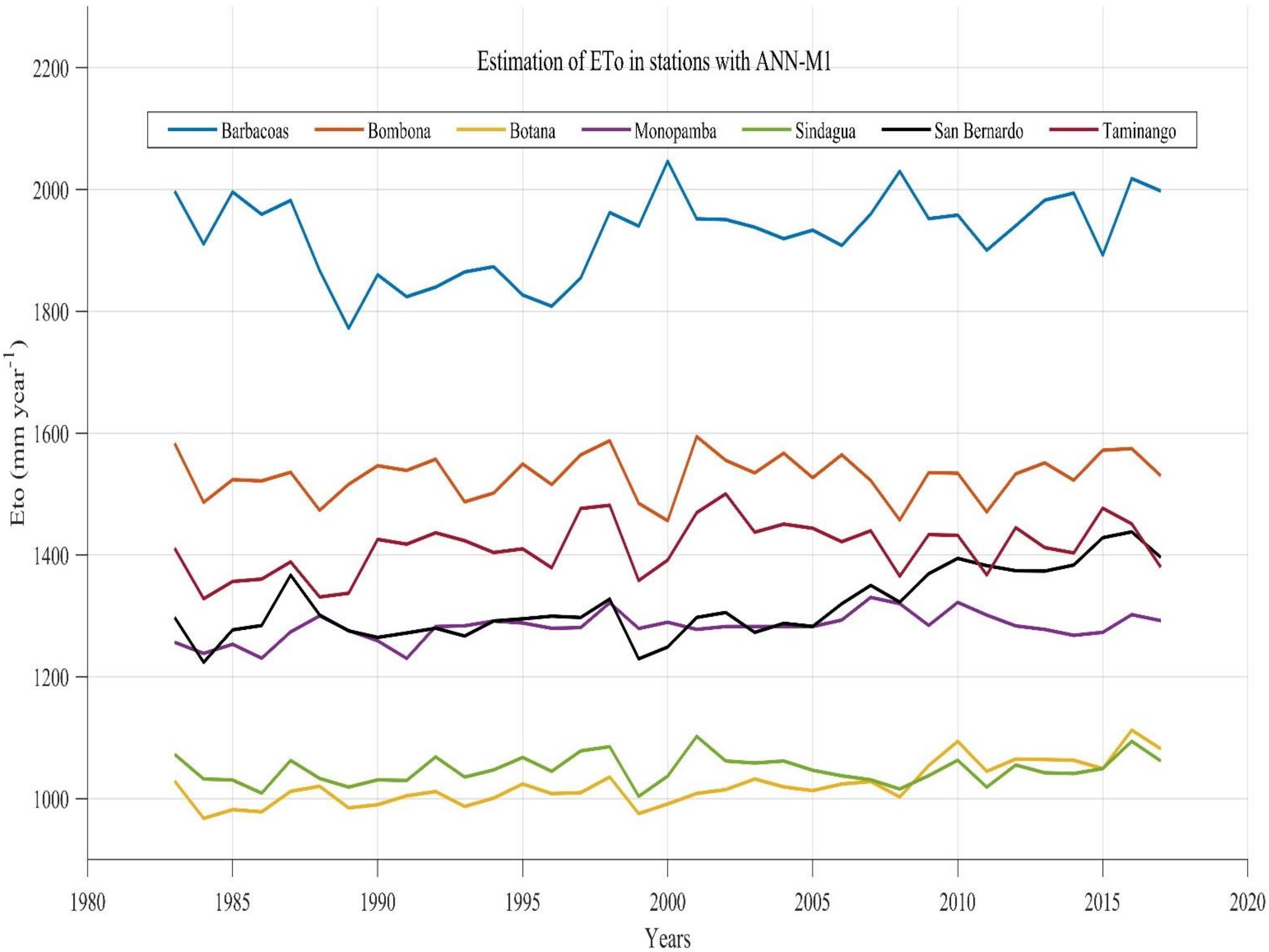

Figure 5 Estimation of ETo by ANN-M1 at stations with scarce information

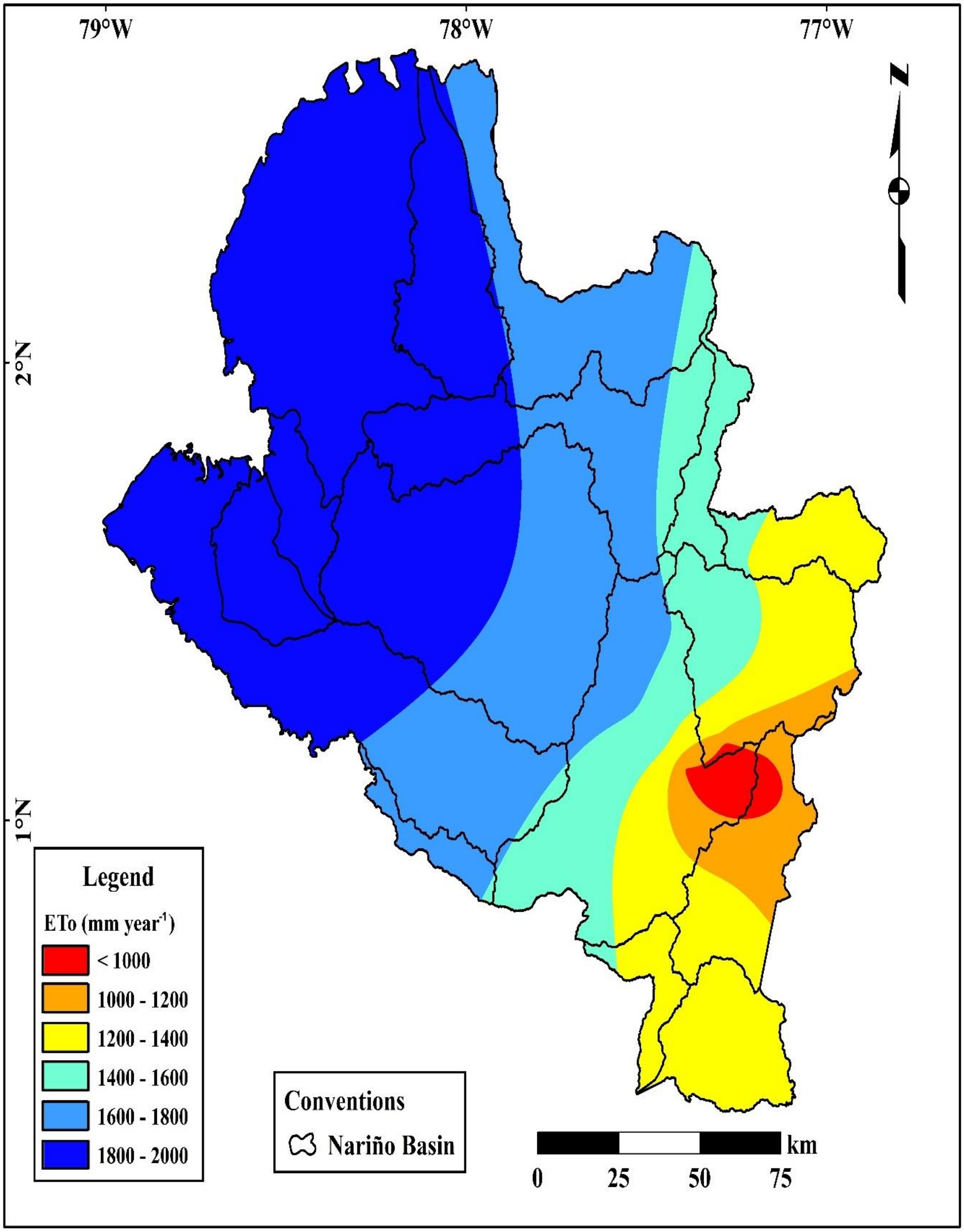

Figure 6 Spatialization of ETo in southwestern Colombia

Table 1. Reference evapotranspiration models were used in this research. The input variables for this model are: Ra = extraterrestrial solar radiation (MJ m^{-2}), Tmax = maximum temperature (°C) at 2 meters, Tmin = minimum temperature (°C) at 2 meters, Tmean = mean temperature (°C) at 2 meters, Ra = incident solar radiation on the atmosphere (MJ m^{-2} d^{-1}), Rn = net radiation (MJ m^{-2} d^{-1}) , Rs = net radiation (MJ m^{-2}), h= masl, RH = relative humidity (%), Δ the slope of the vapor pressure curve [kPa $°C^{-1}$], G = ground heat flux density [MJ m^{-2} day^{-1}], γ = psychrometric constant [kPa $°C^{-1}$] and U2 the wind speed at 2 m height [m s^{-1}]

Name	ETo estimation methods	Reference	Model Type
FAO-PM56	$ETo = \frac{0.408\,\Delta(Rn - G) + (\gamma\,\frac{900}{Tmean+273})U2\,(es - ea)}{\Delta + \gamma(1+0.34U2)}$	(Allen et al., 1998)	Combined
Hargreaves	$ETo = 0.0023\,(Tmean + 17.8)\,(Tmax - Tmin)^{0.5}\,Ra$	(Hargreaves and Samani, 1985)	Temperature
Turc	$ETo = 0.013\,(\frac{Tmean}{Tmean+15})(23.8846xRs + 50)(1+\frac{50-HR}{70})$ if RH< 50 $ETo = 0.013\,(\frac{Tmean}{Tmean+15})(23.8846Rs + 50)$ if RH > 50	(Turc, 1961)	Radiation
Thornthwaite	$ETo = 16\ x\ (\frac{10*Tmean}{I})^{\alpha}$ $\alpha = 6.75 \times 10^{-7} \times I^3 - 7.71 \times 10^{-5} \times I^2 + 1.79 \times 10^{-2} \times I + 0.49$ $I = \sum_{i=1}^{12}(\frac{Tmean^{1.514}}{5})$	(Thornthwaite and Wilm, 1948)	Temperature
Cenicafé	$ETo = 4.37^{-0,0002*h}$	(Jaramillo , 2006)	Temperature

Table 2. Validation performance metrics used: N = Number of data, ETo = observed value *FAO-PM56*, ETo' = predicted ETo, $\overline{ET_0}$= average estimated ETo *FAO-PM56*, $\overline{ET_0}'$ = average predicted ETo

Name	Equation	Purpose of metrics	Perfect score
RMSE (Root mean squared error)	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(ETo - ETo')^2}$	Goodness-of-fit for high values	0
MAE (Mean Absolute Error)	$MAE = \frac{1}{N}\ \sum_{i=1}^{N}\lvert ETo - ETo'\rvert$	Goodness-of-fit for mean values	0
MBE (Mean Bias Error)	$MBE = \frac{1}{N}\ \sum_{i=1}^{N}(ETo - ETo')$	Determine the average model bias	0
NSE (Nash–Sutcliffe efficacy coefficient)	$SE\ =\ 1 - \frac{\sum_{i=1}^{N}(ETo - \overline{ET_0})^2}{\sum_{i=1}^{N}(ETo' - \overline{ET_0})^2}$	Evaluate the predictive capability of hydrological models.	1
R (Pearson correlation coefficient)	$r = \frac{\sum_{i=1}^{N}(ETo - \overline{ET_0})\left(ETo' - \overline{ET_0}'\right)}{\sqrt{\sum_{i=1}^{N}(ETo - \overline{ET_0})^2 * \sum_{i=1}^{N}\left(ETo' - \overline{ET_0}'\right)^2}}$	Statistical correlation between two variables	1

Table 3. Characteristics of weather stations in the study area: Tmax, Tmed, Tmin, RH, and SBH

Name	Height	Multiyear monthly averages of climatological variables					Annual precipitation
Station	masl	Tmax (°C)	Tmed (°C)	Tmin (°C)	RH (%)	SBH (h)	mm year^{-1}
Aeropuerto Antonio Nariño	1796	27.3	19.2	12.9	76.5	5.4	1216
Barbacoas	32	32.5	26.2	20	89.5	2.9	6927
Bombona	1493	28.9	20.1	13.9	77.9	4.7	1071
Monopamba	1776	23.6	17.0	11.6	88.8	2.1	3214
Obonuco	2710	20.0	13.0	6.9	79.9	3.3	888
Sindagua	2800	20.4	13.1	7.5	80.2	3.9	988
Botana	2820	19.8	12.6	5.9	78.6	3.2	964
El Encano	2830	18.8	11.7	4.8	86.4	2.5	1402
Taminango	1875	26.2	18.0	13.2	83.9	-	1715

Table 4. Performance metrics for ETo estimation methods concerning *FAO-PM56*

Performance metrics	*Cenicafé*	*Hargreaves*	*Thornthwaite*	*Turc*
RMSE (mm month^{-1})	30.4	20.0	50.4	16.9
MAE (mm month^{-1})	26.4	18.0	48.7	14.2
MBE (mm month^{-1})	26.4	-17.9	48.7	10.3
R	0.80	0.90	0.86	0.81
NSE	0.64	0.81	0.74	0.65

Table 5. VIF for climatic variables

Model	Inputs variables	VIF					
		TMAX	TMIN	TMED	RH	SBH	COTA
1	TMAX + TMED	12.59	-	12.59	-	-	-
2	TMAX + SBH	3.07	-	-	-	3.07	-
3	TMAX + SBH + COTA	8.67	-	-	-	3.18	7.93
4	TMAX + SBH + COTA + TMED	12.70	-	32.01	-	3.52	17.89
5	TMAX + SBH + COTA + TMED + RH	12.71	-	41.1	2.63	4.32	25.58
6	TMAX + SBH + COTA + TMED + RH + TMIN	13.29	10.59	51.7	2.64	4.64	26.76

Table 6. Performance metrics of machine learning models compared to *FAO-PM56*; the models selected in bold are the best

Combination	Input parameters	RMSE (mm month^{-1})	MAE (mm month^{-1})	MBE (mm month^{-1})	NSE	R	Observations
MLR-M1	TMAX, SBH, and COTA	7.7	6.1	0.3	0.86	0.93	All models comply with the error assumptions, and COTA was added as a categorical variable; for MLR-M1, a natural root transformation was applied, and for MLR-M2 and MLR-M3, a square root transformation was applied.
MLR-M2	**TMAX, SBH, and COTA**	**5.5**	**4.4**	**0.1**	**0.93**	**0.93**	
MLR-M3	TMAX, HUMREL, and COTA	6.5	5.2	0.1	0.90	0.95	
ANN-M1	**TMAX and COTA**	**7.3**	**5.9**	**0.1**	**0.87**	**0.94**	In the development of these models, multiple architectures were built. The tanh activation function, the lbgfs optimizer, and a hidden layer with three neurons, a learning rate of 0.01 and 1000 iterations were performed for each model. The weights of the COTA with the first, second and third neuron was: 0.010, 0.19 and 0.46 respectively. The weights of the TMAX with the first, second and third neuron was: -0.15, 0.29 and -6.16 respectively. The weights of the hidden layer to the output neuron were: -6.52, 7.62 and -0.30.
ANN-M2	TMAX and TMED	8.2	6.6	0.1	0.84	0.92	
ANN-M3	TMAX, TMED, and TMIN	7.6	6.1	0.1	0.87	0.93	
ARIMA-M1	TMAX and COTA	5.2	4.0	-0.1	0.94	0.97	The different combinations between the autoregressive and moving average components with their respective lags were tested. It was obtained that the best combination involved an autoregressive coefficient in the regular and seasonal phases with a seasonality of 12 months. ARIMA(1,0,0)(1,0,0)$_{12}$
ARIMA-M2	TMAX, TMED, and COTA	5.0	3.9	0.1	0.94	0.97	
ARIMA-M3	**PCA1*COTA + PCA2*COTA**	**4.1**	**3.2**	**-0.1**	**0.96**	**0.98**	