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Modelling of Reference Evapotranspiration Parameters in South Africa Using Fuzzy Inference Systems

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Abstract

Effective planning, design and management of irrigation water resources requires the estimation of reference evapotranspiration (ET_0). Standard Penman - Monteith (PM) equation, also called FAO – 56 method, was approved by the United Nations for estimating ET_0. However, in many developing countries, such as South Africa, a major limitation to the successful use of this FAO – 56 method, is the non-availability or limited data sets of the required input variables. It is imperative to develop alternative methods for estimating ET_o. This study models weather and meteorological parameters considered in the estimation of ET_o by performing multivariate analysis of the correlated variables, using adaptive neuro-fuzzy inference systems (ANFIS). Weather and Meteorological data between 2001 and 2020 for Winterton irrigation scheme (WIS) in South Africa were used in this study. Average monthly data of minimum and maximum temperature (°C), rainfall (mm), relative humidity (%), and wind-speed (m/s) were inputs to the ANFIS model, with ET_o as output. ANFIS indicated that temperature gradients and wind-speed have the highest impact on ET_o while rainfall and relative humidity have lower significance on ET_o. The correlation of temperature and wind speed with ET_o was presented using input-output surface viewer. This study improves ET_o estimation.

Keywords

Fuzzy inference system, Irrigation, Reference evapotranspiration, South Africa, Winterton

1. Introduction

Evapotranspiration (ET) is a physical process that refers both to evaporation from soil and transpiration from plants [1]. In the hydrologic cycle, ET plays a huge role because it aids the continuity of rainfall within the cycle [2]. The ET rate from a reference surface is called the reference ET and denoted by ET_o [3, 4]. Estimation of ET_o is vital for effective planning, design and management of irrigation water resources at the farm level [5].

There are many computer-based methods and techniques adopted for estimating ET_o. These techniques can be categorized as combination-type, pan evaporation based, radiation based and temperature-based [6]. Specific models used for this purpose includes artificial neural networks [7-10], genetic algorithms [8, 11], fuzzy logic [12-14] and support vector machines methods [14, 6, 15].

Paramount among the combination-type category is the Penman - Monteith (PM) equation, also called FAO – 56 method and approved by the Food and Agriculture Organisation (FAO) [4]. This method requires some weather and meteorological parameters such as sunshine hours, relative humidity, wind-speed, average temperature, and solar radiation as inputs in order to estimate ET_o at different time steps [16]. Numerous studies worldwide have shown that the FAO-56 PM model is the most accurate method under various climatic conditions [11, 17-21].

However, in many developing countries such as South Africa, a major limitation to the successful use of this FAO-56 PM method is non-availability or limited data sets of the required parameters. Therefore, the application of ETo equations and models that require fewer weather and meteorological parameters is recommended under certain situations where complete datasets are lacking [22]. In order to establish the dominant climatic and meteorological parameters involved in the estimation of ET_o, adaptive neuro-fuzzy inference system (ANFIS) technique is adopted.

ANFIS is a type of artificial neural network which is dependent on fuzzy set and fuzzy relation. Ref [1] stated that it was introduced by Takagi–Sugeno in 1985. It comprises of inputs, outputs and a set of inference rules. Each input and output can have multiple numbers of membership functions (MFs). A curve which shows how each point in the input space is mapped to a membership value between 0 and 1 is called a MF [23]. The general name for a system that uses fuzzy reasoning to map an input space to an output space is called Fuzzy Inference System (FIS). It combines the principles of both neural networks and fuzzy logic to capture the information of both input and output in a single framework [24].The fuzzy inference process is as explained in [25, 26].

ANFIS is an effective mathematical tool used for dealing with uncertainty, handling imprecision of real-world problems and an effective technique for data modelling and analysis without using complex analytical equations [27]. In general, FIS has a rule base, a database and also a reasoning mechanism. These three forms the basic conceptual components of a fuzzy inference system [1].

The two main parts of FIS are the input (antecedence) and the output (consequence) part. Furthermore, the antecedence part is divided into rule - based or cluster - based [28]. The rule - based approach forms some subsets using the input and output variables. These subsets may be linear or non-linear functions and they are represented by linguistic constructs such as "many", "low", "medium", "often", and "few" [28]. In the cluster-based approach, the fuzziness of each data point is measured by its distance from the cluster centers. The cluster center is the point located at the shortest distance from the remaining dataset and this distance is defined as the cluster potential [23]. Clustering techniques include prior knowledge dependent and non-prior knowledge dependent approach. The dataset of the non-prior knowledge dependent approach does not require prior analysis hence, it is more preferred [27].

FIS consists of four major parts: fuzzification interface, fuzzy rule base, fuzzy inference engine and defuzzification interface. The function of fuzzification is to change classical data into fuzzy data using a set of input MFs. The IF-(antecedent part)–THEN-(consequence part) rule statements are used to formulate the conditional statements that comprise fuzzy logic [29]. Defuzzification transforms a fuzzy output into a crisp [30]. FIS can be achieved using the graphical user interface tool "Fuzzy Inference System (FIS) Editor" in MATLAB fuzzy logic toolbox [31].

ANFIS method is widely used in several areas of engineering and technology. This includes water resources planning, reservoir operations, signal processing, system identification, pattern recognition, time series prediction and data mining [32]. It’s use in water resources and evapotranspiration modelling have recorded a huge success.

Ref [28] developed a daily streamflow model for Letaba River in South Africa using ANFIS. The model is applied in a semi-distributed manner to three river reaches. The result of the study shows that ANFIS technique is suitable for modellingstreamflow. In addition, [13] adopted ANFIS to estimate reference evapotranspiration based on two sets of weather data from Spain and Iran. The obtained results showed the capabilities of generalized ANFIS model in estimating ET_o in different climatic zones. Furthermore, Ref [1], conducted a study to study the most influential weather parameter on ET_o in Serbia. A 30 - year data for twelve weather stations were considered in the study. The effects of seven meteorological and weather parameters on ET_o were analysed using ANFIS technique. From the study, it was concluded that ANFIS is a good and robust modelling technique to understand the non-linear behaviour of ET variables. Ref [33], successfully adopted ANFIS to forecast water supply system demand for Hogenakkal Water Supply in India. The technique gave a very good forecasting result after statistical evaluations.The aim of this study is to determine how weather parameters affect the estimation of ET_o at WIS, in other to identify the most influential variables for the estimation of ET_o at WIS.

2. Materials and Methods

2.1. Study Area and Collected Data

The study area is Winterton irrigation scheme (WIS). The WIS is located at the Okhahlamba local municipality which is located in uThukela district municipality on the western boundary of KwaZulu-Natal province, South Africa. It is situated on the banks of the Tugela River in the foothills of the Drakensberg Mountains, it is on the R-74 Road network between Bergville and the N3 as well as the R-600 Road network between Ladysmith and central Drakensberg. The scheme covers the total area of 0.86 km^2 with the coordinates: 28°48′48″ S and 29°32′10″ E; Fig. 1. The WIS was founded in 1905 where it was given the name Springfield during the time the Natal government built a weir across the little Tugela River and in 1910 the town was renamed Winterton irrigation scheme [34].

The WIS has a mean annual rainfall of 790 mm, mean annual temperatures of 17°C and high irrigation demand [35]. Summer rainfall occurs during the month of August to May while in winter server frosts occur occasionally. The scheme has about 3692 hectares of the total farmland which is under irrigation while maize, wheat and soybeans are the major irrigated crops grown throughout the year [35]. WIS is currently supplying irrigation water to 55 commercial farmers and other small-scale farms and the annual net irrigation requirements ranges between 500 and 1200 mm per annum [35]. Figure 1 shows the geographical location of the study area.

Meteorological and weather data which covers a 20-year period (2001-2020) and has 240 dataset records per variable were used for this study. Average monthly data of minimum and maximum temperature (°C), rainfall (mm), relative humidity (%), wind speed (m/s) and ET_o (mm/day) were collected from the South African Weather Service (SAWS) and Agricultural Research Council. This data was extracted from three meteorological stations at WIS. Figure 2 shows the mean monthly data of the six ET_o variables collected (2001-2020) for this study.

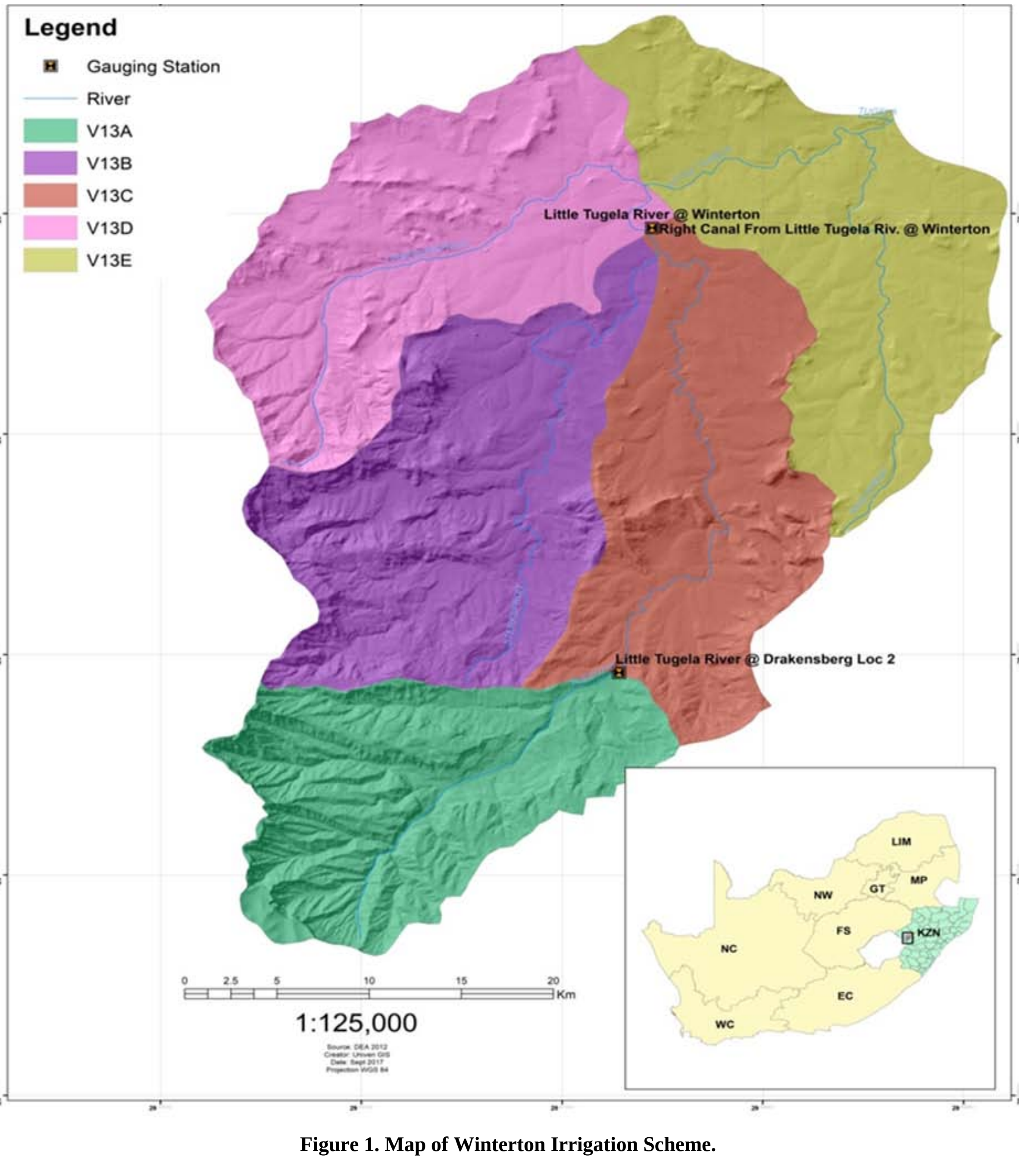

Figure 1. Map of Winterton Irrigation Scheme.

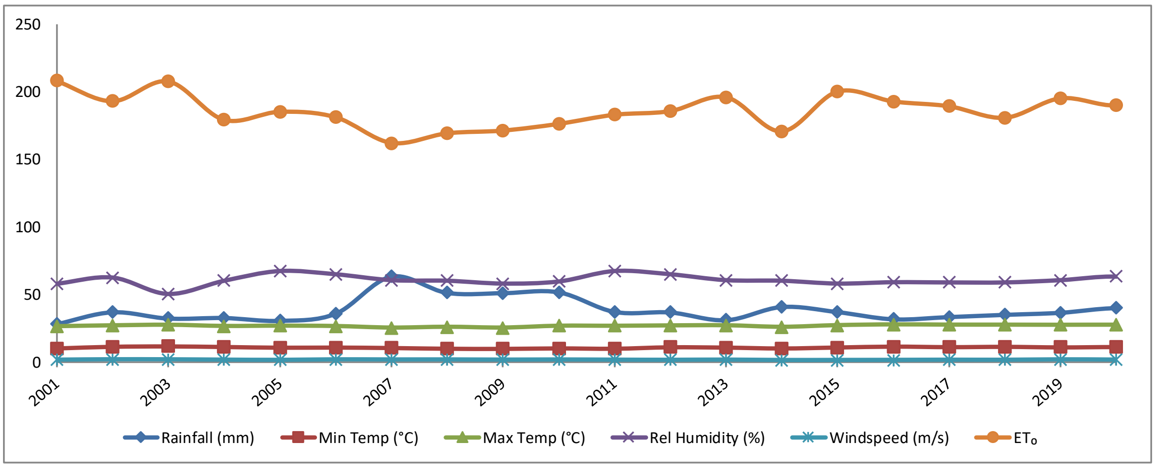

Figure 2. Mean monthly values of the ETo variables collected at WIS (2001-2020).

2.2. ANFIS

The Fuzzy Logic Toolbox component in [31] was used for designing the system based on fuzzy logic. Initially, the relationship between the input and output variables were modeled by clustering the data. After that, fuzzy logic was implemented to capture the broad categories identified during clustering into a FIS. The following steps were followed in designing the ANFIS system.

2.2.1. Clustering the Data

Clustering is normally used to identify natural groupings of data from a large data set so that the system's performance can be concisely represented. The function subclust in [31] was chosen to implement a clustering technique, called subtractive clustering. Subtractive clustering is a fast and one-pass algorithm used for estimating the number of clusters and the cluster centers in a dataset. The results from clustering were further used to build a fuzzy inference system.

2.2.2. Generating the FIS

The function genfis2 was applied for creating the FIS using subtractive clustering (subclust). The function genfis2 uses subclust in the background, to cluster the data and uses the cluster centers and their range of influences to build a FIS. The fuzzy inference was modeled by the Sugeno integral as an aggregation operator. The AND method was prod (product), which scales the output fuzzy set. The function genfis2 constructs the FIS in an attempt to capture the position and influence of each cluster in the input space. The simulation procedure was established by creating m-file/ MATLAB software.

2.2.3. Defuzzification

In defuzzification, the fuzzy output set is converted to a crisp number. For Sugeno-style inference, the commonly used techniques for defuzzification are wtaver (weighted average) or wtsum (weighted sum). In the study, the wtaver method was chosen. Suppose, there are M rules fired and the fuzzified output is represented by w1, w2, ... wM and crisp output is represented by z1, z2, ...,zM, then final crisp output wtaver is given by the expression in equation (1):

$$z = \frac{\sum_{i=1}^{M} w_i z_i}{\sum_{i=1}^{M} w_i} \tag{1}$$

2.3. Pre-screening using ANFIS

The environmental conditions affecting ET_o is a nonlinear regression problem, where several inputs are used to predict an output. The five input attributes were rainfall, minimum temperature, maximum temperature, relative humidity and wind speed, whereas the output variable to be predicted was ET_o. The function exhsrch in [31] performs an exhaustive search within the available data to determine the one most influential input attribute in predicting the output. Essentially, the function exhsrch builds an ANFIS model for each combination, trains it for one epoch and reports the performance achieved. The exhaustive search operates by searching for the minimum training error for different permutations of inputs to the ANFIS. ANFIS uses a hybrid-learning algorithm to identify parameters of Sugeno-type fuzzy inference systems. It applies a combination of the least-squares method and the back-propagation gradient descent method for training ANFIS membership function parameters to emulate a given training data set. For building the ANFIS model, 70% of data is used for training process and 30% for the evaluation set. The training argument stops if the designated epoch number is reached or the error goal is achieved, whichever comes first. The checking data are used for testing the generalization capability of the FIS and monitor how well the model predicts the corresponding data set output values.

2.4. Post-screening using surface FIS

In this post-screening step, the effect of minimum temperature, maximum temperature and wind speed on ET_o were investigated using FIS. The number of observations (samples) was 228. The model first clustered the data and the cluster centers were then used to define the FIS.

3. Results and Discussion

3.1. Pre-screening results

The current ANFIS model selected one input from five candidates, so that the total number of ANFIS models is C (5, 1) = 5. As displayed in Figure 3, the left-most input variable had the least training and checking errors, i.e., the most relevant with respect to the output (ET_o). The inputs maximum temperature, wind speed, minimum temperature, relative humidity and rainfall had training errors of 26.9, 36.6, 43.8, 59.0 and 67.3, as well as checking errors of 24.6, 36.7, 47.4, 62.8 and 77.5, respectively. These results indicate that the three most significant environmental inputs affecting the ET_o are in the order of maximum temperature > wind speed > minimum temperature. Thus, rainfall and humidity were removed from the post-screening step.

3.1.1. Results from clustering the data

The variable C (Table 1) held all the centers of the clusters that had been identified by subclust. Each row of C contained the position of a cluster. In this case, C had five rows accounting for five clusters. Additionally, the subclust had identified four columns that represented the positions of the clusters in each dimension.

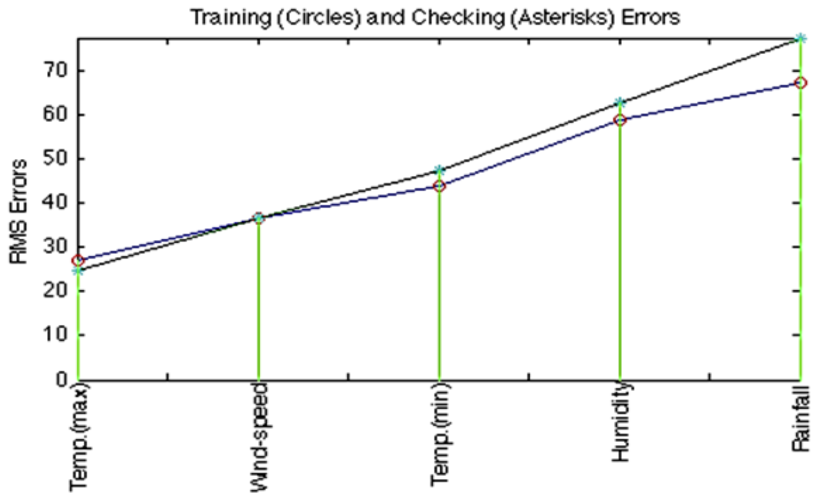

Figure 3. Influence of individual variables on ET_o.

Table 1. C (clustering matrix results)

Maximum Temperature	Windspeed	Minimum Temperature	ET_o
3.8	21.0	0.6	109.7
15.8	31.1	2.0	238.2
13.3	26.8	1.2	156.8
7.5	25.5	2.2	213.8
14.9	32.3	3.4	298.0

The variable S (Table 2) containing the sigma values, had four columns representing the influence of the cluster centers on each of the four dimensions. All cluster centers shared the same set of sigma values.

3.1.2. Clusters-FIS Relationship

The function genfis2 constructs the FIS in an attempt to capture the position and influence of each cluster in the input space. Since the dataset had three input variables and one output variable, genfis2 constructed a FIS with three inputs and one output. The function subclust identified five clusters in the current dataset. Therefore, each input and output were characterized by five MFs. Also, the number of rules is equivalent to the number of clusters and hence five rules were created.

As listed in Table 3, the first MF of the first input (in1cluster1) is "gaussmf" (Gaussian type membership function). It has Gaussian curve spread coefficient of 3.465 and the center of the Gaussian curve is 3.8, in1cluster1 captures the position and influence of the first cluster for the input variable population, C (1,1) = 3.8 and S (1) = 3.465.

Similarly, the position and influence of the other four clusters for the input variable "minimum temperature" are captured by the other four MFs in1cluster2, in1cluster3, in1cluster4 and in1cluster5. The other two input variables (maximum temperature and wind speed) follow the exact pattern mimicking the position and influence of the five clusters along their respective dimensions in the dataset.

The output of the FIS has five linear MFs representing the five clusters. The coefficients of the linear MFs are estimated from the dataset using least squares estimation technique. Those coefficients are listed in Table 3. All the five MFs are in the form a × Temp. (min) + b × Temp. (max) + c × wind speed + d

Table 2. S (Sigma values)

Maximum Temperature	Windspeed	Minimum Temperature	ET_o
3.5	3.6	0.7	64.0

Table 3. Fuzzy linguistic set of input variables

Fuzzy linguistic sets of input variable "Minimum temperature" with universes of discourse [-0.2 19.4]					
MF name	in1cluster1	in1cluster2	in1cluster3	in1cluster4	in1cluster5
MF type	gaussmf	gaussmf	gaussmf	gaussmf	gaussmf
MF parameters	[3.465 3.8]	[3.465 15.8]	[3.465 13.3]	[3.465 7.5]	[3.465 14.9]
Fuzzy linguistic sets of input variable "Maximum temperature" with universes of discourse [15.5 35.7]					
MF name	in2cluster1	in2cluster2	in2cluster3	in2cluster4	in2cluster5
MF type	gaussmf	gaussmf	gaussmf	gaussmf	gaussmf
MF parameters	[3.571 21]	[3.571 31.1]	[3.571 26.8]	[3.571 25.5]	[3.571 32.3]
Fuzzy linguistic sets of input variable "Wind speed" with universes of discourse [0.2 3.9]					
MF name	in3cluster1	in3cluster2	in3cluster3	in3cluster4	in3cluster5
MF type	gaussmf	gaussmf	gaussmf	gaussmf	Gaussmf
MF parameters	[0.6541 0.6]	[0.6541 2]	[0.6541 1.2]	[0.6541 2.2]	[0.6541 3.4]
Fuzzy linguistic sets of input variable "ETo" with universes of discourse [0 361.9]					
MF name	out1cluster1	out1cluster2	out1cluster3	out1cluster4	out1cluster5
MF type	Linear	Linear	Linear	Linear	Linear
MF parameters	[-1.076 10.46 23.57 -112.8]	[-17.28 29.8 9.014 -429.7]	[1.363 13.72 40.71 -291.5]	[-5.127 21.82 -0.381 -318.2]	[-3.218 13.23 11.21 -131.4]

There exist five rules and each rule attempts to map a cluster in the input space to a cluster in the output space. The firing strengths of the rules were then used to generate the output of the FIS, through the output MFs. The (1) at the end of the rule is to indicate that the rule has a weight or an importance of "1". The rules were:

1) If (Temp. (min) is in1cluster1) and (Temp. (max) is in2cluster1) and (Wind speed is in3cluster1) then (ETo is out1cluster1) (1)

2) If (Temp. (min) is in1cluster2) and (Temp. (max) is in2cluster2) and (Wind speed is in3cluster2) then (ETo is out1cluster2) (1)

3) If (Temp. (min) is in1cluster3) and (Temp. (max) is in2cluster3) and (Wind speed is in3cluster3) then (ETo is out1cluster3) (1)

4) If (Temp. (min) is in1cluster4) and (Temp. (max) is in2cluster4) and (Wind speed is in3cluster4) then (ETo is out1cluster4) (1)

5) If (Temp. (min) is in1cluster5) and (Temp. (max) is in2cluster5) and (Wind speed is in3cluster5) then (ETo is out1cluster5) (1)

The response of the FIS is plotted against the inputs as a surface (Figure 4). This visualization is very helpful to understand how the system behaves for the entire range of values in the input space.

Figure 5 shows a snapshot of the entire fuzzy inference process, right from how the MFs are being arranged in every rule to how the final output is being generated through defuzzification.

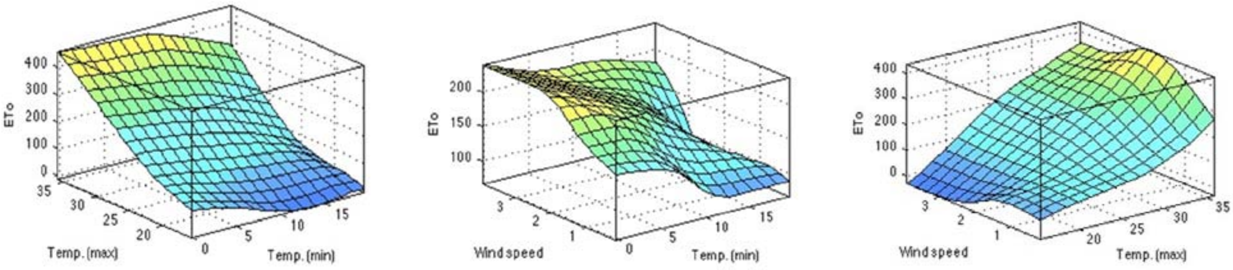

Figure 4. Input – Output Surface viewer of the dataset.

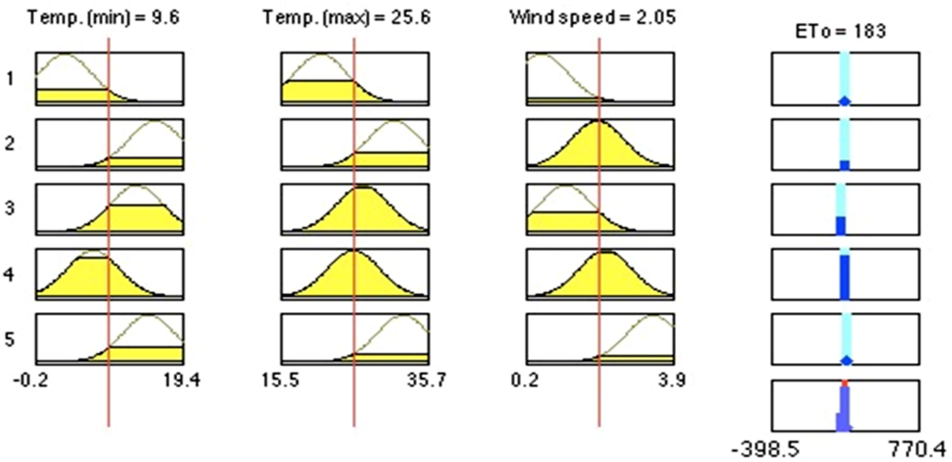

Figure 5. Rule viewer that simulates the entire fuzzy inference process.

4. Conclusions

The aim of this study was to determine the multivariate analysis of correlated variables involved in the estimation of ET_o at Winterton irrigation scheme (WIS) in South Africa using adaptive neuro-fuzzy inference systems (ANFIS). The objective was to determine the most influential set of variables in the estimation of ET_o. This is a novel study of this kind conducted in the study area. The average monthly dataset of six meteorological and weather variables between 2001 and 2020, which are paramount to the estimation of ET_o were analyzed. From the ANFIS analysis, it was discovered that temperature (min and max) and wind speed are the most important variables in the estimation of ET_o at WIS. Other variables, such as rainfall and relative humidity had less significance on the value of ET_o.

Therefore, it can be concluded that ANFIS is a robust tool for reducing input variable dimensionality into the most significant ones before adequate and further simulation modeling operations takes place in order to predict$_o$EThe limitation of the study is that the dataset only included data from 2001 until 2020, collected for the WIS. Future research will develop novel methods and techniques that can estimate reference evapotranspiration using the most important variables (minimum temperature, maximum temperature, and wind speed) discovered from this study.

References

[1] Petković, D., Gocic, M., Trajkovic, S., Shamshirband, S., Motamedi, S., Hashim, R. and Bonakdari, H. (2015). Determination of the most influential weather parameters on reference evapotranspiration by adaptive neuro-fuzzy methodology. Computers and Electronics in Agriculture, 114: 277-284.

[2] Ramoelo, A., Majozi , N., Mathieu , R., Jovanovic , N., Nickless , A. and Dzikiti , S. (2014). Validation of Global Evapotranspiration Product (MOD16) using Flux Tower Data in the African Savanna, South Africa. Remote Sensing, 6: 7406-7423.

[3] Allen, R. G., Jensen, M. E., Wright, J. L. and Burman, R. D. (1989). Operational Estimates of Reference Evapotranspiration. Agronomy Journal, 81: 650-662.

[4] Allen, R. G., Pereira, L. S., Raes, D. and Smith, M. (1998). Crop Evapotranspiration - Guidelines for Computing Crop Water Requirements. Food and Agriculture Organisation. Available: http://www.fao.org/docrep/x0490e/x0490e0b.htm. (Accessed 16/8/2015).

[5] Ikudayisi, A., Adeyemo, J., Odiyo, J. and Enitan, A. (2018). Optimum irrigation water allocation and crop distribution using combined Pareto multi-objective differential evolution. Cogent Engineering, 5 (1): 1-16.

[6] Gocic, M. and Trajkovic, S. (2010). Software for estimating reference evapotranspiration using limited weather data. Computers and Electronics in Agriculture, 71 (2): 158-162.

[7] Kisi, O. (2006). Evapotranspiration estimation using feed-forward neural networks. Nord. Hydrology, 37 (3): 247-260.

[8] Kisi, O. (2008). The potential of different ANN techniques in evapotranspiration modelling. Hydrological Processes, 22: 1449–2460.

[9] Kumar, M., Raghuwanshi, N. and Singh, R. (2009). Development and validation of GANN model for evapotranspiration estimation. Journal of Hydrological Engineering, 14 (2): 131-140.

[10] Kisi, O. (2011). Modeling Reference Evapotranspiration Using Evolutionary Neural Networks. Journal of Irrigation and Drainage Engineering - ASCE, 137 (10): 636-643.

[11] Gocić, M., Motamedi, S., Shamshirband, S., Petković, D., Ch, S., Hashim, R. and Arif, M. (2015). Soft computing approaches for forecasting reference evapotranspiration. Computers and Electronics in Agriculture, 113: 164-173.

[12] Kisi, O. (2013). Applicability of Mamdani and Sugeno fuzzy genetic approaches for modeling reference evapotranspiration. Journal of Hydrology, 504: 160-170.

[13] Shiri, J., Nazemi, A. H., Sadraddini, A. A., Landeras, G., Kisi, O., Fard, A. F. and Marti, P. (2013). Global cross-station assessment of neuro-fuzzy models for estimating daily reference evapotranspiration. Journal of Hydrology, 480: 46-57.

[14] Shiri, J., Nazemi, A. H., Sadraddini, A. A., Landeras, G., Kisi, O., Fakheri Fard, A. and Marti, P. (2014). Comparison of heuristic and empirical approaches for estimating reference evapotranspiration from limited inputs in Iran. Computers and Electronics in Agriculture, 108: 230-241.

[15] Kisi, O. (2016). Modeling reference evapotranspiration using three different heuristic regression approaches. Agricultural Water Management, 169: 162-172.

[16] Kamble, B., Irmak, A., Hubbard, K. and Gowda, P. (2013). Irrigation Scheduling using Remote sensing data assimilation approach. Advances in Remote Sensing, 2: 258-268.

[17] Raziei, T. and Pereira, L. S. (2013). Estimation of ETo with Hargreaves–Samani and FAO-PM temperature methods for a wide range of climates in Iran. Agricultural Water Management, 121: 1-18.

[18] Todorovic, M., Karic, B. and Pereira, L. S. (2013). Reference evapotranspiration estimate with limited weather data across a range of Mediterranean climates. Journal of Hydrology, 481: 166-176.

[19] Pereira, L. S., Allen, R. G., Smith, M. and Raes, D. (2015). Crop evapotranspiration estimation with FAO56: Past and future. Agricultural Water Management, 147: 4-20.

[20] Gocic, M., Petković, D., Shamshirband, S. and Kamsin, A. (2016). Comparative analysis of reference evapotranspiration equations modelling by extreme learning machine. Computers and Electronics in Agriculture, 127: 56-63.

[21] Yassin, M. A., Alazba, A. A. and Mattar, M. A. (2016). Artificial neural networks versus gene expression programming for estimating reference evapotranspiration in arid climate. Agricultural Water Management, 163: 110-124.

[22] Xing, X., Liu, Y., Zhao, W. g., Kang, D. g., Yu, M. and Ma, X. (2016). Determination of dominant weather parameters on reference evapotranspiration by path analysis theory. Computers and Electronics in Agriculture, 120: 10-16.

[23] Lu, H., Huang, G. and He, L. (2011). An inexact rough-interval fuzzy linear programming method for generating conjunctive water-allocation strategies to agricultural irrigation systems. Applied Mathematical Modelling, 35 (9): 4330-4340.

[24] Tahmasebi, P. and Hezarkhani, A. (2012). A hybrid neural networks-fuzzy logic-genetic algorithm for grade estimation. Computers & Geosciences, 42 (Supplement C): 18-27.

[25] Jha, G. K. (2007). Artificial neural networks and its applications. http://www.iasri.res.in/ebook/ebadat/5-Modeling%20and%20Forecasting%20Techniques%20in%20Agriculture/5-ANN_GKJHA_2007.pdf: Accessed (15th May 2015).

[26] Abdulkadir, T. S., Sule, B. F. and Salami, A. W. (2012). Application of Artificial Neural Network Model to the Management of Hydropower Reservoirs along River Niger, Nigeria. International Journal of Engineering, 3 (3): 123-127.

[27] Nasr, M., Moustafa, M., Seif, H. and El-Kobrosy, G. (2014). Application of fuzzy logic control for Benchmark simulation model.1. Sustainable Environment Research, 24 (4): 235-243.

[28] Katambara, Z. and Ndiritu, J. (2009). A fuzzy inference system for modelling streamflow: Case of Letaba River, South Africa. Physics and Chemistry of the Earth, Parts A/B/C, 34 (10–12): 688-700.

[29] Nasr, M., Mahmoud, A., Fawzy, M. and Radwan, A. (2015). Artificial intelligence modeling of cadmium(II) biosorption using rice straw. Applied Water Science, 10: 295-394.

[30] Sanchez, E., Celikovsky, S., Gonzalez, J. and Ramirez, E. (2001). Wastewater treatment plant control by combining fuzzy logic and nonlinear estimation. In: Proceedings of 2001 IEEE. International Symposium on Intelligent Control. Mexico City, September, 2001.

[31] MATLAB. (2002). Fuzzy Logic Toolbox for use with MATLAB. MA, USA: The Mathworks, Natick.

[32] Fiter, M., Güell, D., Comas, J., Colprim, J., Poch, M. and Rodríguez-Rodal, I. (2005). Energy saving in a wastewater treatment process: an application of fuzzy logic control. Environmental Technology, 26 (11): 1263-1270.

[33] Vijayalaksmi, D. P. and Babu, K. S. J. (2015). Water Supply System Demand Forecasting Using Adaptive Neuro-fuzzy Inference System. Aquatic Procedia, 4: 950-956.

[34] Whelan, D. (2019). Water, settlement and food provision in Natal Colony: The Winterton Irrigation Settlement, 1902-1904. Historia, 64 (1): 42-64.

[35] De Jager, J. W. and Mottram, R. (2018). Research on Maximising Irrigation project efficiency in different soil-climate-irrigation situations. Pretoria: Water Research Council. Available: www.wrc.org.za (Accessed 15 February 2021).