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Modeling of daily pan evaporation in sub tropical climates using ANN, LS-SVR, Fuzzy Logic, and ANFIS

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ABSTRACT

This paper investigates the abilities of Artificial Neural Networks (ANN), Least Squares – Support Vector Regression (LS-SVR), Fuzzy Logic, and Adaptive Neuro-Fuzzy Inference System (ANFIS) techniques to improve the accuracy of daily pan evaporation estimation in sub-tropical climates. Meteorological data from the Karso watershed in India (consisting of 3801 daily records from the year 2000 to 2010) were used to develop and test the models for daily pan evaporation estimation. The measured meteorological variables include daily observations of rainfall, minimum and maximum air temperatures, minimum and maximum humidity, and sunshine hours. Prior to model development, the Gamma Test (GT) was used to derive estimates of the noise variance for each input–output set in order to identify the most useful predictors for use in the machine learning approaches used in this study. The ANN models consisted of feed forward backpropagation (FFBP) models with Bayesian Regularization (BR), along with the Levenberg–Marquardt (LM) algorithm. A comparison was made between the estimates provided by the ANN, LS-SVR, Fuzzy Logic, and ANFIS models. The empirical Hargreaves and Samani method (HGS), as well as the Stephens–Stewart (SS) method, were also considered for comparison with the newer machine learning methods. The Root Mean Square Error (RMSE) and Correlation Coefficient (CORR) were the statistical performance indices that were used to evaluate the accuracy of the various models. Based on the comparison, it was found that the Fuzzy Logic and LS-SVR approaches can be employed successfully in modeling the daily evaporation process from the available climatic data. In addition, results showed that the machine learning models outperform the traditional HGS and SS empirical methods.

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1. Introduction

Evaporation, as a major component of the hydrologic cycle, is important in water resources development and management since it affects the yield of river basins, the capacity of reservoirs, the consumptive use of water by crops and the yield of underground supplies. In many parts of the world, where availability of water resources is scarce, the estimation of this evaporation loss is very important in the planning and management of irrigation practices, and these losses should be considered in the design of various water resources and irrigation systems (Tabari, Marofi, & Sabziparvar, 2009). In areas with little rainfall, evaporation losses can represent a significant part of the water budget for a lake or reservoir, and may contribute significantly to the lowering of the water surface elevation (McCuen, 1998). Despite this significance, evaporation is one of the least understood components of the hydrologic cycle (Brutsaert, 1982; Jackson, 1985). Empirical and semi-empirical models reported in the literature are based on relationships between evapotranspiration and a limited number of meteorological variables. A number of researchers have attempted to estimate evaporation values from various climatic variables (Burman, 1976; Coulomb, Legesse, Gasse, Travi, & Chernet, 2001; Gavin & Agnew, 2004; Linarce, 1967; Reis & Dias, 1998; Stephens & Stewart, 1963), and most of these methods require data that are not easily available. Furthermore, some of these methods are valid only under specific climatic and agronomic conditions, and they cannot be applied under conditions which are different from those they were originally developed for. Simple methods that have been reported (e.g., Stephens & Stewart, 1963) try to fit a linear relationship zbetween the explanatory variables. However, the process of evaporation is highly non-linear in nature, as evidenced by many of the estimation procedures (Sudheer, Gosain, Rangan, & Saheb, 2002).

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Several studies have emphasized the need for accurate estimates of evaporation in hydrologic modeling studies (e.g., Sudheer et al., 2002; Szilagyi & Jozsa, 2009). This requirement could be addressed through better models that address the inherent non-linearity in the process. Recently, machine learning approaches such as Artificial Neural Networks (ANN), Least-Squares – Support Vector Regression (LS-SVR), Fuzzy Logic, and Adaptive Neuro-Fuzzy Inference System (ANFIS) have been successfully applied in a number of diverse fields, including water resources. Most of the applications reported in the literature are related to estimation, prediction, and classification problems. In the hydrological context, recent studies have reported that ANN, LS-SVR, Fuzzy Logic, and ANFIS approaches may offer a promising alternative to traditional hydrological forecasting approaches, including evaporation (Cancelliere, Giusiano, Ancarani, & Rossi, 2002; Chang, Chang, Kao, & Wu, 2010; Cigizoglu & Kisi, 2005, 2006; Ismail, Shabri, & Samsudin, 2012; Kalra, Li, & Ahmad, 2013; Kisi, 2004a, 2004b, 2005a, 2005b; Kisi & Yildirim, 2005a, 2005b; Kumar, Raju, & Sathish, 2004; Minnes & Hall, 1996; Sudheer et al., 2002; Supharatid, 2003; Tayfur, 2002; Twarakavi, Misra, & Bandopadhyay, 2006).

Eslamiam, Gohari, and Malekian (2008) estimated monthly pan evaporation using ANNs and support vector machines with climatic variables such as air temperature, solar radiation, wind speed, relative humidity and precipitation as input data for the models. The results showed that both ANN and support vector machines provided accurate pan evaporation estimates. Kim and Kim (2008) applied ANN and genetic algorithm models for modeling pan evaporation and evapotranspiration. The study further confirmed the capabilities of ANN and genetic algorithm models as effective tools for estimation of pan evaporation and evapotranspiration. Tabari et al. (2009) estimated daily pan evaporation using artificial neural network (ANN) and multivariate non-linear regression (MNLR) methods in a semi-arid region of Iran. The results indicated that the ANN method provided the best estimates of daily pan evaporation in comparison to MNLR. Recently, Guo, Sun, and Ma (2011) studied the applicability of LS-SVR models for real-time prediction of daily reference crop evapotranspiration. The authors considered public weather forecast variables such as: minimum and maximum air temperature, average relative humidity, wind scale, and weather conditions. The authors compared the forecast of their LS-SVR model against Penman–Monteith estimated daily crop reference evapotranspiration. It was found that the LS-SVR model provided a 90% model efficiency score; it was concluded that the LS-SVR approach was a successful tool that can be used to measure daily crop reference evapotranspiration using public weather forecasts. The authors also recommended that future research be carried out in other catchments to further explore the applicability of the LS-SVR method as a crop reference evapotranspiration estimation tool. Similarly to Guo et al. (2011), Kisi (2013) investigated the applicability of LS-SVR for daily reference crop evapotranspiration estimation at two sites in Southern California. This study included empirical methods (Priestley-Taylor, Hargreaves, and Ritchie methods) and also considered feed forward ANNs as comparison methods to the LS-SVR model. The following variables were considered in developing the models: daily weather data, solar radiation, air temperature, relative humidity, and wind speed. The LS-SVR method outperformed all empirical methods as well as the ANN models, with coefficients of determination in excess of 0.96 for the best LS-SVR models at both sites. The most useful sets of predictors were solar radiation, air temperature, relative humidity, and wind speed.

Keskin, Özlem, and Dilek (2004) applied the Fuzzy Logic method to estimate daily pan evaporation based on meteorological data for Lake Eğirdiris and compared this with the Penman method. It was concluded that the Fuzzy Logic approach can be used to estimate daily pan evaporations effectively. Atiaa Alaa and Abdul-Qadir Amal (2012) used Fuzzy Logic for estimating monthly pan evaporation from meteorological data from Emara meteorological station in southern Iraq, and found that the method was useful. Kisi (2006) investigated the abilities of the ANFIS technique against ANN and SS methods for daily evaporation estimation and found that the ANFIS computing technique could be employed successfully in modeling evaporation processes from the available climatic data as it outperformed both techniques. Kumar, Kumar Jaipaul, and Tiwari (2012) developed ANN and ANFIS models to forecast monthly potential evaporation in Pantagar, India and found that the ANFIS model outperformed the ANN model. To the best knowledge of the authors, no studies have compared the ANN, LS-SVR, Fuzzy Logic, and ANFIS machine learning methods, and no studies have compared these newer machine learning methods with the traditional HGS and SS empirical methods for evaporation modeling/forecasting.

In this study, the potential of four new machine learning techniques (i.e., ANN, LS-SVR, Fuzzy Logic, and ANFIS) for the estimation of pan evaporation using climatic variables was investigated. Multiple input variable combinations were assessed using the Gamma Test (GT) before model development to provide insight to regarding the most useful sets of predictors to model pan evaporation. The performance of these models was compared with that of the traditional Hargreaves and Samani (HGS) and Stephens–Stewart (SS) empirical methods. The Hargreaves-Samani method is a well-known method to estimate daily incoming solar radiation values by using available data. The SS method was chosen following the suggestion of Al-Shalan and Salih (1987), who evaluated 23 well-known climatic methods of evaporation estimation and concluded that the Stephens–Stewart model performed the best of all the methods tested.

1.1. Study area

The study area, the Karso watershed in India, is a part of the Damodar Barakar catchment, and is situated between 85° 23′ 30″E to 85° 28′E longitude and 24° 12′N to 24° 18′N latitude with an elevation ranging from 390–650 m above MSL (Mean Sea Level) (Fig. 1). The geographical area of the watershed is approximately 27.93 km^2. The watershed receives an average annual rainfall of 1300 mm, and 75 percent of the rainfall occurs during the monsoon season (June to October). The minimum and maximum temperature varies in the range of 3–42 °C. The mean relative humidity varies from a minimum of 40 percent in April to a maximum of 85 percent in the month of July. The overall climate of the area can be classified as sub humid tropical. The soil is mainly sandy loam type and the soil depth ranges from 0 to 45 cm. The average land slope of the watershed varies from 0 to 8%, and the maximum slope of some hilly sections of the watershed is close to 22%. The dominant crop in the study area is paddy. Erosion problems are prevalent in the study area due to the rolling topography and improper agricultural management practices. Daily rainfall data of the watershed was collected from the automatic rain gauge station located at the outlet of the study watershed by the Soil Conservation Department, Damodar Valley Corporation (DVC), Hazaribag, Jharkhand, India. The datasets used in this study are discussed in the Input Variable Determination section and descriptive statistics of this dataset can be found in Table 1.

2. Methodology

This section provides a short introduction to the Gamma Test for identifying the most useful input variable set combinations, as well as descriptions of the ANN, LS-SVR, Fuzzy Logic, and ANFIS methods.

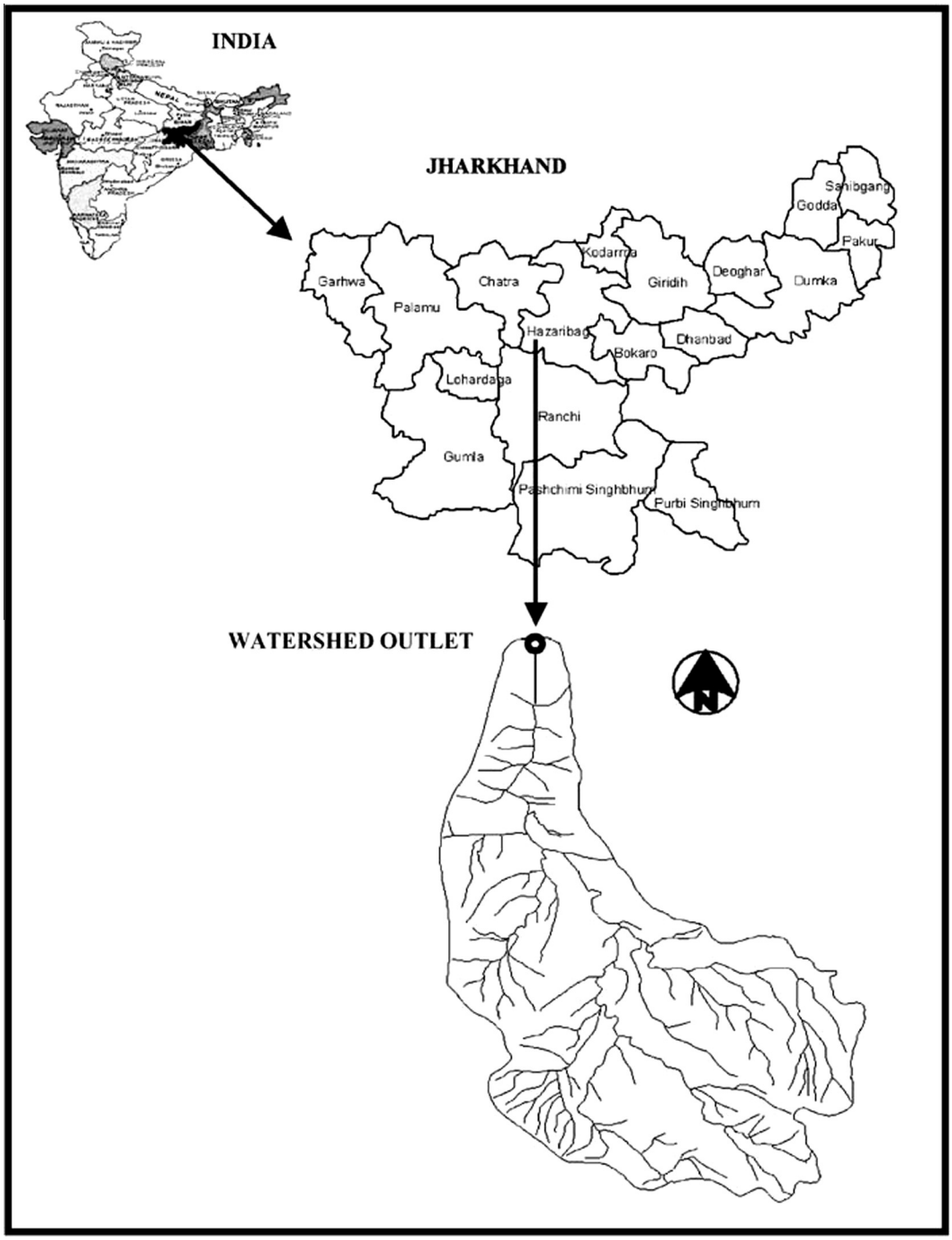

Fig. 1. Location of Karso watershed, India.

Table 1
Descriptive statistics for each input variable used in the various machine learning methods.

Descriptive statistics							
Variable	Evaporation (mm)	Tmax (°C)	Tmin (°C)	Hmax (%)	Hmin (%)	Shours (h)	Rainfall (mm)
Mean	3.63	29.09	16.56	74.87	55.36	7.14	3.18
Standard deviation	2.65	5.12	6.40	17.10	22.96	3.19	10.60
Mode	2.00	30.00	22.00	91.00	77.00	9.50	0.00
Median	3.00	29.00	18.50	80.00	58.00	8.50	0.00

2.1. Gamma Test (GT)

An important aspect of developing non-linear machine learning models is the determination of useful predictors from a database of potential input variables that may improve the model's output function. In order to assess the usefulness of different input variable combinations and their effect on the desired model output, an effective approach is to use a recent technique named the Gamma Test (GT) (Koncar, 1997; Stefansson, Koncar, & Jones, 1997) to estimate the mean squared error (MSE) of the noise variance that cannot be modeled by the smoothest possible model. The Gamma Test statistic gives an indication of the unexplainable variance that exists between an input–output dataset and is a very useful statistic to use when comparing multiple input variable datasets against a desired output. The GT method has been used in other hydrological studies to assess the usefulness of various input–output data sets for the input variable selection problem (Noori & et al., 2011; Wan Jaafar, Liu, & Han, 2011). In particular, (Moghaddamnia & et al., 2009) used the GT as a method to identify the most useful sets of predictors for evaporation estimation using ANN and ANFIS approaches.

Since the study outlined in this present paper explored a variety of machine learning methods that determine the output function based on internal mechanisms that differ from one learning machine to another, the GT was determined to be a versatile and impartial method to determine the potential of each input variable combination. The GT is a non-parametric approach that avoids relying on information related to a specific machine learning model for addressing the usefulness of a particular variable/input variable combination and as such is well suited to address the input variable determination problem for this study.

For any input–output data set the Gamma Test provides an estimate of the MSE of the residual series that cannot be modeled by the smoothest possible model using a k-nearest neighbor (k-NN) approach (Evans & Jones, 2002). The use of the GT for identifying useful input variables is straightforward to apply as a pre-calibration step for non-linear modeling of water resources variables. In order to calculate the GT statistics for the various input variable combinations in this study, the MATLAB Toolbox referenced in (Evans, Kemp, Singh, & Jones, 2006) was used.

2.2. Artificial Neural Networks (ANN)

ANNs are a form of computing inspired by the functioning of the brain and nervous system, and are discussed in detail in a number of hydrologic papers (e.g., Maier & Dandy, 2000; Minns & Hall, 1996; Sudheer et al., 2002; Senthil kumar, Goyal, Ojha, Singh, & Swamee, 2013; Senthil Kumar, Sudheer, Jain, & Agarwal, 2005; Srinivasulu & Jain, 2009). The feed forward ANN has been adopted in many hydrological modeling studies because of its applicability to a variety of different problems (Hsu, Gupta, & Sorooshian, 1995; Rumelhart, Hinton, & Williams, 1986). Maier and Dandy (2000) report that not more than one hidden layer is required in feed forward networks because a three-layer network can generate arbitrarily complex decision regions. Also, the appropriate input vector to the ANN model can be identified according to the procedure of Sudheer et al. (2002). Back propagation is the most popular algorithm used for the training of the feed forward ANN (Thirumalaiah & Deo, 1998; Jain & Srinivasulu, 2004; Fernando & Shamseldin, 2009).

Bayesian Regularization (BR), an objective function that considers both the ANN's structure and error, minimizes a linear combination of the resulting ANN's squared errors, weights, and biases in order to develop a less complex model so that at the end of training the resulting network has good generalization qualities. One can refer to MacKay (1992) and Foresee and Hagan (1997) for more detailed discussions of BR. The Levenberg–Marquardt (LM) training algorithm is a trust region based method with a hyper-spherical trust region (Burney, Jilani, & Ardil, 2005). This algorithm was implemented in this study using the Neural Network Toolbox of MATLAB.

2.3. Least Squares – Support Vector Regression (LS-SVR)

SVR based models are applied in a wide range of contexts since they are just as effective as ANNs at function approximation, and hence prediction. In the hydrological context, LS-SVR has been used recently in a number of studies (Goyal & Ojha, 2011; Guo & Ma, 2010; Bhagwat & Maity, 2013; Kisi, 2013; Mellit, Benghanem, & Pavan, 2013). A wide range of literature is available on all aspects of SVR (theory, parameter selection, etc.). The reader is therefore directed to Vapnik (1995), Cristianini and Shawe-Taylor (2000), and Smola and Schölkopf (2004) for a more detailed and formal coverage of the topic.

Similar to ANNs, SVR based algorithms use an implicit feature space mapping from the dimension of the data to a possibly infinite feature space, providing a non-linear representation of the modeled data; this is done through the 'kernel trick' (Smola & Schölkopf, 2004). One of the most common kernels with wide applicability within SVR methods is the Radial Basis Function (RBF) kernel (Crone, Lessmann, & Pietsch, 2006; Rippa, 1999). As a result, it was also applied in this study. When using the RBF kernel one has to choose the kernel width parameter, σ. If the σ is too large, it will tend to cause input patterns to appear too similar and lead to under-fitting of the function. If the σ is too small, patterns will be considered very disimiliar and over-fitting may occur (Chang, Chen, & Wang, 2005). The SVR methodology reduces model error by incorporating the structural risk minimization (SRM) approach, and is also seen as a form of regulairzation by a factor, C. The factor, C, controls the trade-off between training error and model complexity (i.e., the size of model weights (Basak, Pal, & Patranabis, 2007)) and must be chosen by the user. If C is too small, this would mean that the model does not fit the learning data, while a C that is too large will overfit the data as well as the noise (Lendasse et al., 2005).

The LS-SVR differs somewhat from the standard SVR approach in that an ε-insensitive zone does not exist (meaning slackness is not preserved and thus every constraint is active). This means that the support values (LS-SVR weights) are proportional to the error at each datapoint; this can be interpreted as a support value spectrum (Suykens & Vanderwalle, 1999). The advantage in solving a LS-SVR over a standard SVR formulation is that one less parameter is required to optimize the model (as mentioned above). Given data, the user interested in developing an LS-SVR model will have to specify the parameter pair (C, σ), and then follow a principled routine to optimize the parameters thereafter. In this study, we adopt a logarithmic grid search over the aforementioned parameter pairs using a validation set as suggested in Camps-Valls and et al. (2012); likewise, we adopted the Cholesky decomposition on the kernel matrix to improve computational speed while inverting the regularized kernel. All LS-SVR models in this study were designed in MATLAB using custom scripts.

2.4. Fuzzy Logic

Fuzzy set theory has been used to represent uncertain information in mathematical form (Zadeh, 1965), and has also been applied for different purposes in engineering, business, and many other areas. It is a superset of Boolean logic that has been extended to handle the concept of partial truth–truth values between "completely true" and "completely false", and provides a convenient framework to map an input domain to output domain. The central

concept of fuzzy set theory is the membership function, which numerically represents the degree to which an element belongs to a set. For example, if an element is a member of a fuzzy set to some degree, the value of its membership function can be between 0 and 1, as determined by eliminating the sharp boundary dividing members of the set from nonmembers (Klir & Foger, 1988; Ojha, Goyal, & Kumar, 2007). Fuzzy Logic is a useful and practical technique for modeling complex phenomena that may not yet be fully understood owing to its ability to deal with imprecise, uncertain data, or ambiguous relationships among data sets (Metternicht, 2001). Fuzzy Logic theory and fuzzy set theory provide an excellent means for representing imprecision and uncertainty in the decision-making process and for defining the reasoning in such processes (Zadeh, 1983). This approach provides a simple method to draw definite conclusions from vague, ambiguous, or imprecise information (Klir & Foger, 1988).

A Takagi–Sugeno fuzzy inference system was developed in this study using the subtractive clustering (Chiu, 1994) algorithm integrated with a linear least squares estimate algorithm for the modeling of pan evaporation. The Fuzzy Inference System (FIS) model was developed based on the assumption that the cluster estimation method, when applied to a collection of input and output data, produces cluster centers where each cluster center is in essence a prototypical data point that represents a characteristic behavior of the system. Hence, each cluster center can be used as the basis of a rule that illustrates the system behavior (Chiu, 1994). The Fuzzy Logic Toolbox (MATLAB) is a library of functions implementing a framework for creating, editing, and executing fuzzy inference systems. This toolbox was used to develop the Fuzzy Logic model for modeling the daily evaporation in this study.

2.5. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS), first introduced by Jang (1993), is a universal approximator and as such is capable of approximating any real continuous function on a compact set to any degree of accuracy (Jang, Sun, & Mizutani, 1997). This technique has human-like expertise within a specific domain – it can adapt itself and learns to do better in changing environments (Kurian, George, Bhat, & Aithal, 2006). An ANFIS aims at systematically generating unknown fuzzy rules from a given input–output data set (Abraham, Koppen, & Franke, 2003). ANFIS is functionally equivalent to fuzzy inference systems (Jang et al., 1997). The main objective of the ANFIS is to determine the optimum values of the equivalent fuzzy inference system parameters by applying a learning algorithm using input–output data sets. The parameter optimization is done in such a way during the training session that the error between the target and the actual output is minimized. In this study, in each application, different numbers of membership functions were tested and the best one that gave the minimum mean square errors (MSEs) was selected. Two or three membership functions for the ANFIS models were considered sufficient for modeling evaporation (Kisi, 2006). More information for ANFIS can be found in Jang (1993).

2.6. Empirical models

Hargreaves and Samani (1982, 1985) recommended a simple equation to estimate crop evapotranspiration (ET_0)

$$ET_0 = 0.0135(KT)(R_a)(TD)^{0.5}(TC + 17.8) \quad (1)$$

where $TD = Tmax - Tmin$ (°C), TC is the average daily temperature (°C), R_a = extraterrestrial radiation (mm/day) and KT is an empirical coefficient. Eq. (1) explicitly accounts for solar radiation and temperature. Although relative humidity is not explicitly contained in the equation, it is implicitly present in the difference in maximum and minimum temperature. The temperature difference (TD) is linearly related to relative humidity (Hargreaves & Samani, 1982). Eq. (1) has been successfully used in some locations for estimating ET_0 where sufficient data were not available to use other methods (Orang, Grismer, & Ashktorab, 1995). Even though Eq. (1) does not account for advection, it has been successfully used even in advective conditions when calibrated against wind data (Salazar, 1987). Hargreaves (1994) recommended using $KT = 0.162$ for "interior" regions and $KT = 0.19$ for coastal regions.

The study carried out by Hargreaves and Samani (1982), who correlated solar radiation (R_s) with temperature and extraterrestrial radiation, has been used by many researchers (Morid, Gosain, & Keshari, 2002). As such, it was used as a comparison method in this study since it is a method that has widely been used to date. Hargreaves and Samani (1982) calculated R_s as

$$R_s = KT\,R_a(TD)^{0.5} \quad (2)$$

Al-Shalan and Salih (1987) evaluated 23 well-known climatic methods for evaporation estimation and concluded that the Stephens–Stewart (SS) model was found to perform better than all other methods. As such, the SS method was also used as a comparison method in this study. The model is given by Al-Shalan and Salih (1987)

$$E = R_s(a + bT) \quad (3)$$

where E is the daily class A pan evaporation, T is the mean daily air temperature, and a and b are the fitting parameters. The least squares method was used to obtain the values of the parameters, a and b. The values for a and b in this study were calculated as 0.23 and 0.012, respectively.

3. Dataset preparation

As stated earlier, the primary objective of this study was to evaluate the potential of ANN, LS-SVR, Fuzzy Logic, and ANFIS for estimating evaporation. To accomplish this objective, a continuous record of all climatic variables is required, which is rarely available. The required data on a daily basis was available for more than 10 years (01 January 2000–31 May 2010) for the study area; this data was used in this study. It is common practice to divide the available data into three sub-sets: a training, validation, and testing set (Maier & Dandy, 2000). Approximately 40% of data was used for training, ~30% for validation, and the remaining ~30% of the data was used for testing purposes. Training, validation, and testing indices were randomly chosen from the available climatic records.

3.1. Input variable determination

Different structures of ANN, LS-SVR, Fuzzy Logic, and ANFIS were explored with various combinations of input data to estimate evaporation. Four different combinations of input variables were considered in the study. First, all the variables, viz. rainfall [mm], air temperature (maximum and minimum) [°C], relative humidity (maximum and minimum) [%], and sunshine hours [hours] were considered, resulting in six input variables. The other combinations considered were: (i) five input variables, representing rainfall, temperature (maximum and minimum), relative humidity (maximum and minimum); (ii) three input variables, representing rainfall, maximum temperature, minimum temperature; and finally (iii) only two input variables, representing maximum and minimum temperatures. The following are the input variable short form identifications: rainfall (Rainfall), maximum temperature (Tmax), minimum temperature (Tmin), maximum relative humidity (Hmax),

minimum relative humidity (Hmin), and sunshine hours (Shours). Table 1 provides descriptive statistics for each input variable considered in the machine learning models in this study.

The input variable combinations were determined in a logical manner assuming the availability of such climatic data. This is the reason why the input variable set with six variables contained rainfall, air temperature (maximum and minimum), relative humidity (maximum and minimum), and sunshine hours, and the input variable sets thereafter followed a common trend where a particular variable type (for example Shours in the second input variable combination) was removed to signify different datasets that may be used in cases where certain variables may be unavailable in other similar watersheds. Of course, if a model is able to provide more accurate predictions using fewer inputs (i.e., principle of parsimony) one would prefer such a model because it would be easier to collect and process such data in addition to providing a better predictive model. This is the reason for assessing each of the four input variable combinations in this study. Each input variable combination was evaluated using the GT as mentioned earlier. In this study the combination displaying the smallest GT score was assumed to be the input variable combination that was likely to provide the best outputs (i.e. smaller error) from each machine learning model. The GT statistic was calculated for training, validation, and testing data sets as well as for the entire set of records. The inputs were standardized to fall in the range of [0, 1]. By standardizing the variables and recasting them into dimensionless units, the arbitrary effect of similarity between objects was also removed (Sudheer et al., 2002).

3.2. Model parameter optimization

For each machine learning method used in this study, optimal model parameters were chosen such that they minimized the mean squared error (MSE) function between observed records and model outputs on the validation dataset. The ANN, LS-SVR, Fuzzy Logic, and ANFIS models were trained using the functions in MATLAB.

3.3. ANN model development

The ANN models were trained using Bayesian Regularization (BR) and Levenberg–Marquardt (LM) algorithms. For the ANN models the number of neurons in the hidden layer was found by a trial and error procedure. The optimum structure of the best ANN models was found to be 2 neurons in the hidden layer. The activation functions used for the hidden and output layers were the 'logsig' and 'purelin' functions, respectively.

3.4. LS-SVR model development

The parameter pairs (C, σ) of the LS-SVR model were determined via logarithmic grid-search. If performance was poor after the first grid search, we tuned the bounds of the grid search more closely to the best performing parameter pair from the first trial; it was determined that this was a reasonable approach to follow in this study as the LS-SVR models required under 105 s for training, validation, and testing of the model for all input variable combinations (and required less training, validation, and testing time for those input variable sets of smaller dimension). For all LS-SVR models in this study the (C, σ) parameter pairs had optimal values in the ranges ([0.01, 0.13], [0.20, 1.00]).

3.5. Fuzzy Logic model development

The parameter radius used in Fuzzy Logic model development was determined in the range of 0.2–0.9 and the result of the parameter radius for the best Fuzzy Logic model was optimized with the radius as 0.6.

3.6. ANFIS model development

In the ANFIS model development, Sugeno's fuzzy approach was used to obtain the values for the output variable from the input variables provided to the fuzzy inference system structure. The input membership function was 'gaussmf' and the output membership function was 'linear'.

3.7. Performance evaluation of various models

The whole data length was divided into three parts: one for training, one for validation, and another for testing for the ANN, LS-SVR, Fuzzy Logic, and ANFIS models. The performance during training, validation, and testing was evaluated using performance indices including Root Mean Square Error (RMSE) and Coefficient of Correlation (CORR). These performance measures are defined as follows:

$$\text{Root Mean Squared Error(RMSE)} = \sqrt{\frac{\sum_{k=1}^{K}(t-y)^2}{K}} \tag{4}$$

$$\text{Coefficient of Correlation(CORR)} = \frac{\sum TY}{\sqrt{\sum T^2 \sum Y^2}} \tag{5}$$

where K is the number of observations; t is the observed data; y is the computed data; $T = t - \bar{t}$ in which $\bar{t}$ is the mean of the observed data; and $Y = y - \bar{y}$ in which $\bar{y}$ is the mean of the computed data.

4. Results and discussion

The normalized statistics from the GT for each input variable combination can be seen in Table 2. When examining the results of the GT it is evident that the input variable combinations with the most amount of input variables (i.e. input variable combination with 6 input variables) explains the most variance in the target function (evaporation). This trend continues as the amount of input variables present in the input dataset is reduced. It is clear that the input variable combination only considering temperature (maximum and minimum) explains the least amount of variance in the evaporation process. This result is also complimentary to the result of the magnitude of coefficients in the SS equation in the Empirical Models section, where the coefficient ('b') representing the evaporation's response to fluctuations in temperature signifies that temperature at this particular site is not a dominant factor in the evaporation process when compared to the other studied explanatory variables at the daily scale. Generally, evaporation depends on various meteorological parameters such as temperature, wind speed, solar radiation, pressure, sunshine hours, and the shape of evaporation surface. These factors also depend on geographical location, season, time of day, etc. Thus, the process of evaporation is rather complicated. This may perhaps demonstrate that temperature is better correlated with pan evaporation at short time-scales such as hourly as suggested by Xu and Singh (1998).

The values of the performance criteria from various models for both calibration (training and validation sets) and testing (test set) are presented in Tables 3–7. The training, validation, and testing results are compared with the performance indices of the best models for each modeling paradigm.

From Tables 3–7, it is evident that all the indices illustrate a reasonably good performance for all the models during training. However, it is worth noting that all the models have poor efficiency

Table 2
Results of the Gamma Test for each input variable combination.

Input variable combinations	Normalized Gamma Test statistic			
	Training set	Validation set	Testing set	Entire set
Rainfall, Tmax, Tmin,Hmax, Hmin, Shours	0.0103	0.0058	0.0052	0.0097
Rainfall, Tmax, Tmin, Hmax, Hmin	0.0102	0.0062	0.0056	0.0103
Rainfall, Tmax, Tmin	0.0143	0.0081	0.0102	0.0128
Tmax, Tmin	0.0152	0.0093	0.0118	0.0139

Table 3
Results of ANN model with Bayesian Regularization (BR) algorithm during training, validation, and testing.

Model No.	Input combinations	ANN structure	Training		Validation		Testing	
			CORR	RMSE	CORR	RMSE	CORR	RMSE
ANNBP11	Rainfall, Tmax, Tmin,Hmax, Hmin,Shours	6-2-1	0.76	1.79	0.67	2.14	0.72	2.34
ANNBP12	Rainfall, Tmax, Tmin,Hmax, Hmin,Shours	6-4-1	0.76	1.71	0.66	2.19	0.73	2.39
ANNBP21	Rainfall, Tmax, Tmin,Hmax, Hmin	5-2-1	0.74	1.69	0.68	2.27	0.74	2.41
ANNBP22	Rainfall, Tmax, Tmin,Hmax, Hmin	5-4-1	0.74	1.71	0.67	2.29	0.75	2.45
ANNBP31	Rainfall, Tmax, Tmin	3-2-1	0.71	1.86	0.65	2.37	0.74	2.48
ANNBP32	Rainfall, Tmax, Tmin	3-4-1	0.72	1.83	0.64	2.46	0.73	2.49
ANNBP41	Tmax, Tmin	2-2-1	0.69	1.84	0.66	2.49	0.74	2.54
ANNBP42	Tmax, Tmin	2-4-1	0.68	1.87	0.65	2.47	0.73	2.52

Table 4
Results of ANN model with Levenberg–Marquardt (LM) algorithm during training, validation, and testing.

Model No.	Input combinations	ANN structure	Training		Validation		Testing	
			CORR	RMSE	CORR	RMSE	CORR	RMSE
ANNLM11	Rainfall, Tmax, Tmin,Hmax, Hmin,Shours	6-2-1	0.77	1.71	0.69	2.12	0.71	2.45
ANNLM12	Rainfall, Tmax, Tmin,Hmax, Hmin,Shours	6-4-1	0.79	1.79	0.70	2.27	0.70	2.49
ANNLM21	Rainfall, Tmax, Tmin,Hmax, Hmin	5-2-1	0.76	1.81	0.71	2.36	0.71	2.51
ANNLM22	Rainfall, Tmax, Tmin,Hmax, Hmin	5-4-1	0.77	1.83	0.67	2.38	0.72	2.49
ANNLM31	Rainfall, Tmax, Tmin	3-2-1	0.74	1.81	0.69	2.47	0.69	2.51
ANNLM32	Rainfall, Tmax, Tmin	3-4-1	0.74	1.82	0.68	2.36	0.68	2.50
ANNLM41	Tmax, Tmin	2-2-1	0.71	1.84	0.67	2.39	0.67	2.61
ANNLM42	Tmax, Tmin	2-4-1	0.72	1.86	0.65	2.51	0.69	2.67

Table 5
Results of LS-SVR model during training, validation, and testing.

Model No.	Input combinations	(C,σ)	Training		Validation		Testing	
			CORR	RMSE	CORR	RMSE	CORR	RMSE
LSSVR11	Rainfall, Tmax, Tmin,Hmax, Hmin,Shours	(0.09, 0.44)	0.79	1.72	0.79	1.35	0.80	1.92
LSSVR 21	Rainfall, Tmax, Tmin,Hmax, Hmin	(0.13, 0.22)	0.80	1.67	0.80	1.33	0.78	2.02
LSSVR 31	Rainfall, Tmax, Tmin	(0.01, 0.21)	0.75	1.86	0.75	1.49	0.73	2.13
LSSVR 41	Tmax, Tmin	(0.01, 0.23)	0.74	1.91	0.71	1.57	0.74	2.12

Table 6
Results of Fuzzy Logic model during training, validation, and testing.

Model No.	Input combinations	Radius	Training		Validation		Testing	
			CORR	RMSE	CORR	RMSE	CORR	RMSE
FL11	Rainfall, Tmax, Tmin,Hmax, Hmin,Shours	0.40	0.79	1.56	0.68	1.93	0.79	1.95
FL13	Rainfall, Tmax, Tmin,Hmax, Hmin,Shours	0.60	0.76	1.63	0.73	1.77	0.82	1.88
FL21	Rainfall, Tmax, Tmin,Hmax, Hmin	0.40	0.76	1.65	0.72	1.78	0.80	1.98
FL22	Rainfall, Tmax, Tmin,Hmax, Hmin	0.60	0.75	1.66	0.73	1.77	0.82	1.91
FL31	Rainfall, Tmax, Tmin	0.40	0.74	1.69	0.70	1.83	0.77	2.02
FL32	Rainfall, Tmax, Tmin	0.60	0.74	1.69	0.70	1.83	0.77	2.01
FL41	Tmax, Tmin	0.40	0.73	1.73	0.70	1.83	0.75	2.05
FL42	Tmax, Tmin	0.60	0.73	1.73	0.70	1.84	0.75	2.06

during validation and testing suggesting large amounts of unexplained variance for all the models. This is illustrated by the RMSE and CORR performance measures on these sets. The RMSE statistic measures the residual variance; the optimal value is 0.0. The CORR statistic measures arbitrary linear dependence and can range between −1 (indicating perfect decorrelation) to 1 (indicating a perfectly increasing linear relationship). The performance indices reveal that the models using six input variables performed better

Table 7
Results of ANFIS model during training, validation, and testing.

Model No.	Input combinations	Training		Validation		Testing	
		CORR	RMSE	CORR	RMSE	CORR	RMSE
ANFIS11	Rainfall, Tmax, Tmin,Hmax, Hmin,Shours	0.89	1.33	0.59	2.46	0.56	2.94
ANFIS21	Rainfall, Tmax, Tmin,Hmax, Hmin	0.81	1.47	0.62	2.18	0.69	2.37
ANFIS31	Rainfall, Tmax, Tmin	0.75	1.66	0.71	1.8	0.73	2.15
ANFIS41	Tmax, Tmin	0.37	2.35	0.38	2.38	0.58	2.47

than all other models except for the ANFIS model type (which provides the best validation and testing performance when using 3 input variables, refer to Table 7). This emphasizes the factors influencing evaporation, since the majority of models considered all available input variables and provided the best performance measures using these particular input variables; this finding is directly supported by the GT results, which can be seen as an impartial measure to rank the various input variable combinations tested in this study by assessing (non-parametrically) the amount of unexplained variance that remains in an input–output dataset compared against the target function (evaporation).

Beginning with the ANN models one can see the differently structured ANN models developed in this study provided consistent RMSE values during training, validation, and testing when compared to other ANN models with different network topology; this supports the extent of the generalization capabilities of the ANN models developed in this study. During training, all of the models performed well, as expected, but during validation and testing, the model performance was found to deteriorate (as mentioned above). For six input variables, the model ANNBR11 (refer to Table 3) and ANNLM11 (refer to Table 4) for BR and LM algorithms respectively performed better than all other ANN models for each respective training algorithm. The best LS-SVR model, LSSVR11 (refer to Table 5), used all six input variables and provided CORR = 0.79 and RMSE = 1.72 for the training phase, CORR = 0.79 and RMSE = 1.35 for the validation set, and CORR = 0.80 and RMSE = 1.92 for the testing phase. The best Fuzzy Logic model, FL13 (see Table 6), had CORR = 0.76 and RMSE = 1.63 during training, CORR = 0.73 and RMSE = 1.77 during validation, and CORR and RMSE of 0.82 and 1.88, respectively for the testing phase. The ANFIS11 model (see Table 7) performed exceptionally well with CORR = 0.89 and RMSE = 1.33 during the training phase but provided very poor validation and testing performance, indicating a model that overfits the training data and which is unable to generalize effectively to unseen input patterns (refer to Table 7).

Considering the empirical models the correlation coefficient was 0.51, 0.50, and 0.40, while the RMSE was 2.19, 2.23 and 2.29 during training, validation, and testing, respectively as computed by the Stephens–Stewart (SS) method. The correlation coefficient was 0.52, 0.50, and 0.15, respectively while the RMSE was 2.19, 2.26 and 2.42 during training, validation and testing, respectively as computed by the HGS method. The poor estimation results calculated from the aforementioned empirical methods shows that these linearized pan evaporation estimation techniques were not very useful for the considered data, and further support the use of non-linear machine learning techniques such as those explored in this study for the Karso watershed.

It can be observed from Tables 3–7 that the models developed using the Fuzzy Logic and LS-SVR techniques outperformed all other models investigated in this study for training, validation, and testing. During model development trials it was observed that the ANN model with LM algorithm learned faster than the other models, while the ANFIS models have very poor generalization properties except for the ANFIS31 model considering only 3 input variables (rainfall, minimum and maximum temperature). All the models developed using machine learning approaches performed better than the Hargreaves and Samani method (HGS) and Stephens–Stewart (SS) method. Thus, it can be concluded from the overall performance of the models that the Fuzzy Logic, FL13 (CORR = 0.76 and RMSE = 1.63 during training, CORR = 0.73 and RMSE = 1.77 during validation, and CORR and RMSE of 0.82 and 1.88), and LS-SVR, LS-SVR11 (CORR = 0.79 and RMSE = 1.72 for the training phase, CORR = 0.79 and RMSE = 1.35 for the validation set, and CORR = 0.80 and RMSE = 1.92 for the testing phase), models performed the best, the ANN models trained using BR and LM algorithms performed moderately well, and the performances of the ANFIS models were for the most part inadequate. The use of the GT was also well supported as the results of this test coincided with the performance results for each respective input variable combination tested on the majority of the models (with the exception of the ANFIS model type). Furthermore, the results of the GT (supported by the machine learning models used in this study) in addition to the determination of model coefficients for the SS model support the notion that temperature in the Karso watershed is not a major driver of the evaporation process at the daily scale.

5. Conclusion

The potential of the ANN, LS-SVR, Fuzzy Logic, and ANFIS modeling techniques for estimation of evaporation using climatic variables was explored in this paper. The study demonstrated that modeling of daily evaporation is best estimated through the use of Fuzzy Logic and LS-SVR approaches, specifically the FL13 and LSSVR11 models (for the case study explored in this study), respectively, rather than the traditional Hargreaves and Samani method (HGS) and Stephens–Stewart (SS) method. The models with the input variables of rainfall, minimum and maximum temperature, minimum and maximum humidity, and sunshine hours performed the best among the various input combinations explored in the study. This indicates that all the aforementioned variables are needed for better evaporation modeling. The GT provided an effective method for assessing input variable combinations for the machine learning methods used in this study and also provided insight to the salient nature of temperature as an evaporation influence in the Karso watershed at the daily scale. Because of this characteristic of the Karso watershed, it was found that using only the minimum and maximum temperatures as inputs gives poor estimates for all machine learning models, and thus indicates that the evaporation process in the studied watershed is a complex process requiring information related to not only temperature but also rainfall, humidity, and sunshine hours in order to develop more accurate machine learning models.

The LS-SVR and Fuzzy Logic (namely, LSSVR11 and FL13) models whose inputs are rainfall, minimum and maximum temperature, minimum and maximum humidity, and sunshine hours show the best performance in this study. This implies that all explanatory variables used in this study are needed for better evaporation modeling. In developing countries such as India, such data is usually easily available compared to other parameters such as wind speed, pressure, solar radiation, etc. Therefore, the

developed models can be used effectively within the Karso watershed and have the potential to be of use in similar sub-tropical watersheds. These techniques could be useful in water budgeting of river basins, as well as in the design and management of reservoirs where other models (such as the HGS and SS methods) may be inappropriate due to their linear nature and ineffectiveness at reducing the variance between predictions and the true evaporation response. In addition, these accurate machine learning methods could be used for effective irrigation policy planning and implementation. Furthermore, the LS-SVR model is simple to develop, and can be implemented within a spreadsheet based program due to its simple formulation and ease of solving for optimal model parameters (which is reduced to solving a linear system of equations). This is important in developing countries where water resources operators may lack the computing required for most machine learning techniques but still require accurate modeling of the evaporation process.

This study only used data from one study area and further work using additional data from two or more sub-tropical watersheds is recommended to strengthen these conclusions and extend the studied machine learning methods to other watersheds. It is also worthwhile to extend the machine learning methods used in this study to include watersheds with varying climates. Future research will explore multiple watersheds, include additional new state-of-the-art machine learning methods, employ wavelets as a pre-processing method, create ensembles of models, and will also look to develop various forms of uncertainty assessment for model predictions. This study considered ANN, LS-SVR, Fuzzy Logic, and ANFIS modeling (in addition to two traditional empirical models HGS and SS) for pan evaporation in sub-tropical climates and concluded that LS-SVR and Fuzzy Logic machine learning methods provide the best estimations, and can be used to successfully estimate evaporation in the studied watershed. These two new methods provide a promising new approach for evaporation estimation in sub-tropical climates.

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