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Comparative efficiency of different artificial intelligence based models for predicting density dependent saltwater intrusion processes in coastal aquifers and saltwater intrusion management utilizing the best performing model

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ABSTRACT

Artificial intelligence based data driven models are useful tools in approximating density dependent coupled flow and salt transport processes in coastal aquifer systems. These emulators often serve as computationally efficient substitutes of rigorous numerical simulation models within a linked simulation-optimization (S/O) methodology. In this study, fuzzy c-means clustering based fuzzy inference systems (FIS) and adaptive network based fuzzy inference systems (ANFIS) are proposed to approximate the physical processes of an illustrative coastal aquifer system. FIS and ANFIS based models are also utilized to identify the most influential input variables in predicting salinity concentrations at three monitoring locations (C1, C2, and C3). Solution results obtained are compared with those obtained using a genetic programming (GP) based modelling approach. Performance evaluation results show that the developed FIS and ANFIS models perform equally well on training and testing datasets. It is also demonstrated that performances of both the FIS and ANFIS models are better than that of GP based models. Root mean square error (RMSE) and mean absolute percentage relative error (MAPRE) values obtained by using GP are larger than those obtained by both ANFIS and FIS models. The maximum prediction errors of GP represented by RMSE and MAPRE at the three monitoring locations are 22.43 mg/l and 2.84% respectively. On the other hand, GP results in lowest values of correlation coefficient (0.96) and Nash–Sutcliffe efficiency coefficient (0.91). FIS model outperforms both ANFIS and GP models in terms of a more detailed comparison criteria, including computation time and model complexity. FIS requires only 0.65 min for training in order to predict salinity concentrations at all three locations C1, C2, and C3. For the similar purpose, ANFIS and GP require 17.35 min and 276.5 min, respectively. Therefore, FIS model can be successfully applied as a computationally efficient substitute of complex numerical simulation models for predicting coupled flow and salt transport processes. Such applications can be very useful in developing a computationally feasible linked S/O methodology for regional scale management of saltwater intrusion in coastal aquifers. Results of the management model using the best performing global FIS model indicates that FIS model provides acceptable, accurate, and reliable groundwater extraction patterns to limit the saltwater concentrations within the pre-specified maximum allowable limits.

Keywords: Coastal aquifer; Saltwater intrusion; C-means clustering; Genetic programming; Fuzzy inference system; Adaptive neuro-fuzzy inference system; Management model

1. Introduction

Coastal regions experience excessive withdrawal of fresh groundwater supplies due to increased human settlements and economic developments. This overexploitation of groundwater resources to satisfy domestic and industrial demands causes saltwater intrusion and degradation of groundwater quality in coastal aquifers [1]. Therefore, optimal use of groundwater resources in these areas is of great importance to ensure adequate supply of freshwater to different sectors. An important prerequisite for optimal

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management of coastal aquifers is to identify reliable and appropriate models to simulate physical processes of a coastal aquifer system. Mathematical models have been used to understand complex and highly non-linear physical processes of coastal aquifers [2]. These physically based models involve simulation of complex physical systems using simulation models requiring large number of calibration data pairs, as well as expertise and experience of the modelers. On the other hand, data driven models are able to provide approximate prediction of saltwater intrusion processes with acceptable prediction accuracies. Although data driven models do not provide useful information about the physical processes involved in modelling [3,4], such models can replace numerical simulation models for predicting saltwater concentrations in coastal aquifers [2,5].

Typically, simulation of coupled flow and salt transport processes in coastal aquifers using simulation models is time consuming and computationally intensive [2,6]. This is especially true for a linked simulation-optimization (S/O) problem where simulation models are called by the optimization algorithm several thousand times to obtain an optimal or near optimal management strategy as solution. Therefore, this methodology demands computationally efficient approximate models to accurately predict saltwater concentration at different monitoring locations (MLs) [5]. Sufficiently accurate and computationally efficient data driven models are suitable for this purpose [6]. Previous literature reveals the use of approximate models to achieve computational efficiency in linked S/O models [6–11].

Fuzzy Inference System (FIS) based on fuzzy set theory has received considerable attention in the recent years. FIS is recognized as a successful computing framework due to its applicability in multi-dimensional fields [12]. FIS is capable of capturing non-linear relationships between input and response variables, and is an effective tool to model non-linear processes [13,14]. The most widely used FISs in different applications are Mamdani FIS, Sugeno FIS, and Tsukamoto FIS. They differ in the way they use consequent parts of their fuzzy rules, and the way they accomplish the aggregation and defuzzification steps. The Sugeno fuzzy model [15], also known as Takagi-Sugeno-Kang model, is especially suited for modelling non-linear systems by interpolating between multiple linear models. Despite the potential capability of emulating complex and non-linear systems, the application of FIS to approximate physical processes of coastal aquifer systems is quite limited. Recently, Roy and Datta [9] proposed a FIS model to approximate density dependent coupled flow and salt transport processes in a multi-layered coastal aquifer system. The authors recommend FIS to be an accurate and reliable prediction tool to approximate coupled flow and salt transport processes. The present study intends to utilize FIS model as a computationally efficient substitute of the complex numerical simulation model within a linked S/O methodology to develop saltwater intrusion management model.

Adaptive network based fuzzy inference systems (ANFIS), proposed by Jang [16] is a multi-layer adaptive network based FIS that integrates the merits of both neural networks and fuzzy logic approaches. It incorporates the basic advantages of Artificial Neural Network (ANN) such as massive parallelism, robustness, and learning in data-rich environments [17]. A large number of studies utilized ANFIS in groundwater modelling applications, for example, in predicting groundwater level [18], characterizing groundwater quality parameters [19], forecasting river flow [20], assessing groundwater quality [19], spatial distribution of groundwater quality [21], predicting water quality index [22], estimating groundwater level [23], predicting daily discharge responses of a large karstic aquifer [24] and predicting electrical conductivity of groundwater [25] etc. The present study considers saltwater concentration in mg/l as a measure of saltwater intrusion in coastal aquifers. An ensemble of ANFIS models was proposed by Roy and Datta [26] to approximate coupled flow and salt transport processes in a multi-layered coastal aquifer system. However, prediction capability of a single ANFIS model has not been utilized so far to predict saltwater concentrations at specified MLs within coastal aquifers with transient pumping stress applied to the aquifer. Our study compares the performances of genetic programming (GP), FIS, and ANFIS in predicting coupled flow and salt transport processes in a coastal aquifer system. In addition, a saltwater intrusion management model is also developed by utilizing the best performing model among GP, FIS, and ANFIS models.

However, one of the major challenges of using fuzzy logic based prediction-modelling approach is to manage large-dimensional input datasets, in particular to handle large number of spatially and temporally varying groundwater extraction patterns for saltwater intrusion management in coastal aquifers. In such situations, reducing the dimensionality of the input space by using fuzzy c-mean clustering algorithm (FCM) [27] provides a reasonable practical solution. FCM is used to compress the entire input space into a number of identical clusters. This clustering technique significantly reduces the number of fuzzy if-then rules and the number of modifiable parameters (linear and non-linear) of the generated FIS. Roy and Datta [9] utilized the FCM algorithm to divide the 80-input variables decision space into few identical clusters for using as inputs to the FIS based prediction model. The present study utilizes FCM technique to reduce the dimensionality of the input space for developing the single global FIS model and the ANFIS models.

GPmodels are based on Darwinian principle of natural selection. GPs are genetic algorithm based computer programs evolved to solve a particular task [28]. GPs perform this specific task in the form of simple regression models. GP was utilized as a data driven model in few recent studies [2,29–32]. Some other uses of GP include predicting run off and river stage [33–35]. GP was also employed to predict salinity concentrations at specified MLs in coastal aquifers [2,32] as a computationally efficient substitute of numerical simulation models. Sreekanth and Datta [2] compared two linked S/O models based on ANN and GP surrogate models in determining the optimal groundwater extraction rates for an illustrative coastal aquifer. They observed the relative superiority of GP over ANN based surrogate models. In another study, Sreekanth and Datta [32] compared the performance of GP and Modular Neural Network (MNN) based surrogate models for an illustrative study area. The authors observed lesser uncertainty in prediction of GP models compared to MNN models as the number of parameters used in GP is much smaller than that in MNN models.

In this study, two fuzzy logic based data driven models, FIS and ANFIS are developed using the data from an illustrative coastal aquifer system utilized in Sreekanth and Datta [2]. Prediction capability of these two models is compared with the GP models developed in Sreekanth and Datta [2]. ANN is not used for comparison in this study because Sreekanth and Datta [2] have already discussed the relative superiority of GP over ANN. The comparison is performed by evaluating the errors in prediction, and time required to train the models. Finally, a saltwater intrusion management model is developed by utilizing a linked S/O approach in which the best performing saltwater intrusion prediction model is used to replace the computationally intensive numerical simulation model within the optimization framework. Properly learned and verified prediction model is then linked externally to a Controlled Elitist Multi-objective Genetic Algorithm (CEMGA) [36] to develop saltwater intrusion management model that prescribes optimal extraction patterns of coastal groundwater resources. The proposed methodology with two conflicting management objectives integrates prediction model and CEMGA within a general framework of linked S/O based optimal management strategy development. Evaluation of the proposed approach is demonstrated by means of an illustrative coastal aquifer system.

2. Methodology

Methodology involves solution of a numerical simulation model, use of three trained data driven models to approximate the coupled flow and salt transport processes, and a saltwater intrusion management model to prescribe optimal groundwater extraction patterns. To maintain consistency in comparison, the input-output patterns generated using numerical simulation model, FEMWATER in Sreekanth and Datta [2] are used in this study for training of the models.

2.1. Numerical simulation model

FEMWATER [37], a three dimensional (3D) finite element based coupled flow and salt transport numerical simulation model is used to generate the required input-output patterns to obtain training and testing datasets for developing the data driven models. Thirty three input variables, representing combined groundwater extraction from a set of 8 production and 3 barrier extraction wells, and for 3 time steps are generated using Latin Hypercube Sampling [38]. Variables 1–8, 12–19, and 23–30 represents pumping from 8 production wells during the first, second, and third time steps, respectively. In addition, variables 9–11, 20–22, and 31–33 denotes pumping from the 3 barrier extraction wells during the first, second, and third time steps, respectively. These input pumping values are fed to the simulation model to simulate the physical processes in the aquifer. Initial condition refers to the initial groundwater heads and the salinity concentrations of the aquifer water before starting of the simulation. These initial conditions are based on an approximate steady state condition of the aquifer obtained by running the simulation model in transition mode for a long time horizon. Boundary conditions (e.g. seaside boundary with assigned salinity concentrations, aquifer recharge etc.) remained constant during this transient simulation. After obtaining a nearly steady state condition, saltwater concentrations at different MLs are obtained through simulating the aquifer processes by using spatially and temporally varying groundwater extraction values differed in different simulations. Steady state groundwater head and salinity concentrations serve as initial conditions to this transient simulation. Boundary conditions as well as the aquifer properties including hydraulic conductivity values remained constant while transient groundwater extraction values varied in subsequent simulations. One set of pumping from different locations and for different time steps, and the corresponding output concentration constitute one set of input-output pairs. A number of such patterns are used to train and test the proposed models. The governing 3D density reliant combined flow and salt transport equations can be expressed by the following sets of equations [37]:

$$\frac{\rho}{\rho_0} F \frac{\partial h}{\partial t} = \nabla \cdot \left[\mathrm{K} \cdot \left(\nabla h + \frac{\rho}{\rho_0} \nabla z \right) \right] + \frac{\rho}{\rho^*} q \tag{1}$$

$$F = \alpha' \frac{\theta}{n} + \beta' \theta + n \frac{dS}{dh} \tag{2}$$

where F stands for storage coefficient, h represents pressure head, t indicates time, K symbolizes hydraulic conductivity tensor, z is the potential head, q represents either a source or a sink, r indicates the water density at chemical concentration C, ρ_o symbolizes referenced water density at zero chemical concentration, ρ^* represents density of injection fluid or that of the withdrawn water, θ is moisture content, α' and β' indicates respectively modified compressibility of water and the medium, n represents porosity of the medium, and S stands for saturation.

Hydraulic conductivity tensor, K can be expressed as

$$K = \frac{\rho g}{\mu} k = \frac{(\rho/\rho_o)}{\mu/\mu_o} \frac{\rho_o g}{\mu_o} k_s k_r = \frac{\rho/\rho_o}{\mu/\mu_o} K_{so} k_r \tag{3}$$

in which μ stands for waters' dynamic viscosity at chemical concentration C, μ_o represents the reference dynamic viscosity at zero chemical concentration, k_s is saturated permeability tensor, k_r is relative permeability or relative hydraulic conductivity, K_{so} stands for referenced saturated conductivity tensor.

$$\begin{aligned} &\theta \frac{\partial C}{\partial t} + \rho_b \frac{\partial S}{\partial t} + V \cdot \nabla C - \nabla \cdot (\theta D \cdot \nabla C) \\ &= -\left(\alpha' \frac{\partial h}{\partial t} + \lambda \right) (\theta C + \rho_b S) - (\theta K_w C + \rho_b K_s S) \\ &+ m - \frac{\rho^*}{\rho} q C + \left(F \frac{\partial h}{\partial t} + \frac{\rho_o}{\rho} V \cdot \nabla \left(\frac{\rho}{\rho_o} \right) - \frac{\partial C}{\partial t} \right) C \end{aligned} \tag{4}$$

where ρ_b symbolizes bulk density of medium, C stands for material concentration in aqueous phase, S is material concentration in adsorbed phase, t is the time, V represents groundwater velocity, ∇ stands for del operator, D indicates Dispersion coefficient tensor, l denotes the decay constant, $M = qC_m$ is the artificial mass rate, q is the source rate of water, C_m is the material concentration in the source, K_w is the first order biodegradation rate constant through dissolved phase, K_s is the first order biodegradation rate through adsorbed phase, K_d is the distribution coefficient.

The dispersion coefficient tensor D in Eq. (4) is written as

$$\theta D = a_T|V|\delta + (a_L - a_T)\frac{VV}{|V|} + a_m\theta\tau\delta \quad (5)$$

where $|V|$ is the magnitude of V, d the Kronecker delta tensor, a_T is lateral dispersivity, a_L is longitudinal dispersivity, a_m is the molecular diffusion coefficient, and τ is tortuosity.

2.2. Data driven models

Data driven models based on FIS and ANFIS are trained and tested using the same input-output patterns used to train GP models in Sreekanth and Datta [2]. This facilitates the comparison with the performance of GP based models as reported in Sreekanth and Datta [2]. According to Sreekanth and Datta [2], a total of 230 data pairs are sufficient to train the developed GP models without model overfitting. Therefore, for comparison purpose, FIS and ANFIS models are also trained using the same 230 data pairs, and with the same compartmentalization of the datasets into training (75%) and testing (25%). Similar to GP approach used in Sreekanth and Datta [2], three ANFIS models are developed to predict salinity concentrations at three MLs. Moreover, number of variables used by Sreekanth and Datta [2] is 33, which is too many for ANFIS structure development. To overcome this problem, FCM algorithm is used to compress the datasets into identical clusters. This clustering technique reduces the number of linear and non-linear parameters of the developed FIS structures, and suppresses the number of rules in developing initial FIS structures. These initial FIS structures are then used to develop ANFIS models. On the other hand, a single global FIS structure is developed,which is able to predict salinity concentrations at three MLs at a time. In addition, the same set of training and testing data pairs are used for training and validation of all ANFISs and the global FIS model.

Partitioning of the input space for FIS and ANFIS model development

Partitioning can be accomplished by using grid partition, tree partition, scatter partition, or by implementing clustering algorithms such as sub-clustering or FCM algorithm [12]. Clustering approach is applied for both effective partition of the input space and for reducing the number of rules. Subtractive clustering technique is used as a fast, one-pass algorithm for estimating the number of clusters and the cluster centres for a set of data [39]. FCM, on the other hand, is one of the most popular and widely used clustering algorithm [27]. In the present study, input space is partitioned using FCM algorithm to build the antecedent parts of fuzzy rules and to develop Sugeno-type FIS structures. FCM performs clustering by minimizing the following objective function:

$$O_m = \sum_{i=1}^{K}\sum_{j=1}^{N}\mu_{ij}^{m}\left\|\alpha_i - c_j\right\|^2 \quad (6)$$

where, O_m = function to be minimized, m = fuzzy partition matrix exponent, K = sample index, N = number of clusters, α_i = i^{th} data point, c_j = center of the j^{th} cluster, μ_{ij}= membership degree of α_i in the j^{th} cluster.

2.2.1. C-means clustering based FIS

FIS is a well-known computing framework successfully applied to a wide variety of fields, and is named differently by different researchers due to its multi-dimensional application fields [12]. Fig.1 illustrates block diagram of a three inputs, one output, and four rules FIS.

A rule base, a database, and a reasoning mechanism constitute the basic structure of FISs. Rule base consists of fuzzy if-then rules, database determines the membership functions (MF) used in fuzzy rules, and reasoning mechanism accomplishes the inference process [12]. The inputs to a basic FIS can either be crisp or fuzzy whereas the outputs from the FIS are fuzzy sets. Therefore, an additional

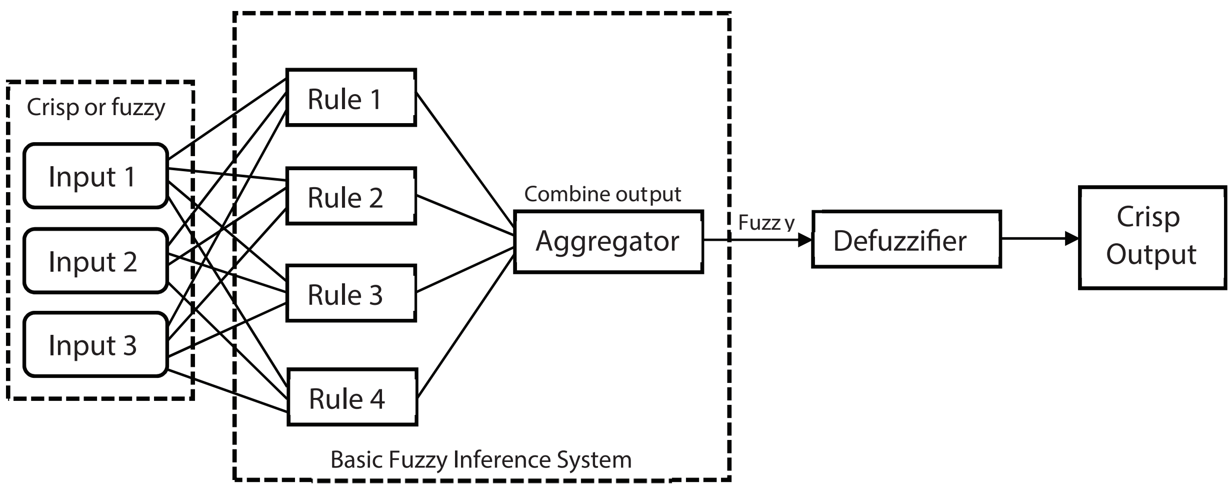


Fig. 1. Basic structure of a fuzzy inference system.

defuzzification step is required for defuzzifying the output. The role of the defuzzification block is to transform an output fuzzy set to a crisp single value (Fig. 1).

FIS is applied to implement non-linear mapping of input and output spaces by utilizing a number of fuzzy if-then rules. The antecedent part of any rule specifies a fuzzy region within the input space whereas the output space of the fuzzy region is specified by consequent part of the fuzzy rules. A typical FIS for the illustrative saltwater intrusion problem [2] can be represented by the flow chart shown in Fig. 2.

A Sugeno-type FIS, also known as Takagi-Sugeno-Kang model introduced in 1985 [15] is developed and utilized in the present study. The input and output MFs of the proposed FIS are Gaussian and linear, respectively. A Gaussian MF is determined by two parameters {c, σ}. It can be expressed mathematically as [12]

$$Gaussian(x;c,\sigma) = \exp\left[-\frac{1}{2}\times\left\{\frac{x-c}{\sigma}\right\}^2\right] \tag{7}$$

where c represents the center of MF, and σ is the width of MF. As an example, a Gaussian MF with $c = 25$ and $\sigma = 10$ is shown in Fig. 3.

2.2.2. ANFIS

ANFIS [16] is a multi-layer adaptive network based FIS that integrates the merits of both the neural networks and fuzzy logic approaches. ANFIS structures can be constructed using the principle of Sugeno, Mamdani, or Tsukamoto FIS. Despite having a simple architecture, Sugeno ANFIS provides better learning capabilities compared to other types of ANFIS structures [12]. Therefore, in the present study, a first order Sugeno-type FIS is adopted for developing the ANFIS model structures.

For a first-order Sugeno FIS with two inputs, α and β, and one output γ, the simplest form of the fuzzy if-then rule set can be expressed as

$$\text{Rule 1: If } \alpha \text{ is } A_1 \text{ and } \beta \text{ is } B_1\text{, then } \gamma_1 = a_1\alpha + b_1\beta + c_1 \tag{8}$$

$$\text{Rule 2: If } \alpha \text{ is } A_2 \text{ and } \beta \text{ is } B_2\text{, then } \gamma_2 = a_1\alpha + b_2\beta + c_2 \tag{9}$$

The resulting ANFIS structure consists of five layers, namely a fuzzy layer, a product layer, a normalized layer, a defuzzification layer, and a total output layer as shown in Fig. 4. The detailed description of each of these layers is stated (page-670) in Jang [16], and is not repeated here.

2.2.3. GP

GP is a search methodology that applies genetic algorithm to computer programming [28]. GP can be utilized to obtain the best-fit computer programs that provide the desired output from a set of input variables. GP is analogous to genetic algorithm in the sense that it starts with an initial population that compounds the randomly generated chromosomes [31]. A detailed description of GP along with a parse-tree structure can be found in Sreekanth and Datta [2].

2.3. Management model

A saltwater intrusion management model that prescribes optimal groundwater extraction patterns at a coastal aquifer is developed through a linked S/O approach. CEMGA [36] is used to search for the optimal groundwater extraction strategies, while maintaining the maximum allowable saltwater concentration limits at the specified MLs. Two conflicting objectives of groundwater extraction strategy are considered in this study. The first objective ensures the maximum withdrawal of groundwater for beneficial purposes. The second objective minimizes the water extraction from barrier pumping wells to control saltwater intrusion by establishing a hydraulic head barrier near the coastal boundary. The multi-objective management model provides a tradeoff between these conflicting objectives in terms of a Pareto optimal front, which consists of several non-dominated feasible alternative groundwater extraction

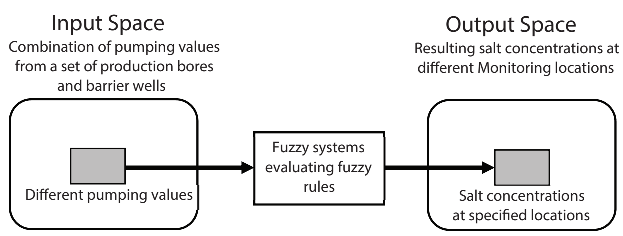


Fig. 2. Input-output mapping of fuzzy logic systems for a typical saltwater intrusion problem.

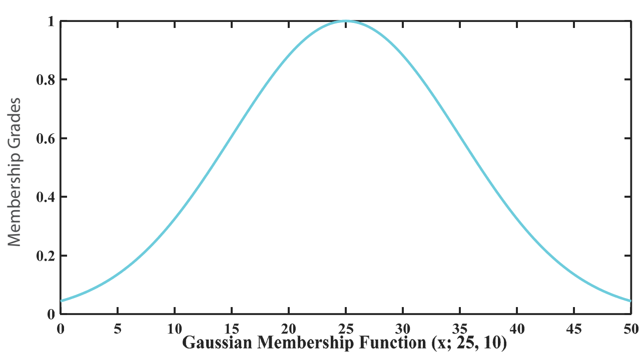


Fig. 3. Gaussian MF with c = 25 and σ = 10 as an example.

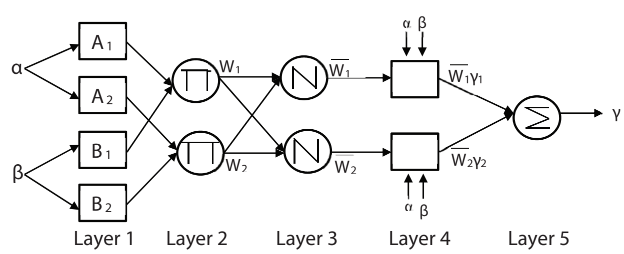


Fig. 4. ANFIS architecture based on a two-input first-order Sugeno FIS.

strategies that meet the pre-specified allowable saltwater concentration limits at specified MLs.

Mathematical formulation for the proposed saltwater intrusion management methodology is expressed by the following equations

$$Maximize: f_1(Q_{PW}) = \sum_{r=1}^{R}\sum_{t=1}^{T} Q_{PW_r}^{\ t} \tag{10}$$

$$Minimize: f_2(Q_{BW}) = \sum_{k=1}^{K}\sum_{t=1}^{T} Q_{BW_k}^{\ t} \tag{11}$$

Subject to

$$C_i = \xi(Q_{PW}, Q_{BW}) \tag{12}$$

$$C_i \le C_{\max} \forall_i \tag{13}$$

$$Q_{PW\min} \le Q_{PW_r}^{\ t} \le Q_{PW\max} \tag{14}$$

$$Q_{BW\min} \le Q_{BW_k}^{\ t} \le Q_{BW\max} \tag{15}$$

where $Q_{PW_r}^{\ t}$ represents water extraction from the r^{th} pumping well throughout t^{th} time phase; $Q_{BW_k}^{\ t}$ stands for water extraction from k^{th} barrier extraction well throughout t^{th} time phase; C_i symbolizes saltwater concentrations at i^{th} monitoring locations at the closure of the management period; ξ() denotes the density reliant coupled flow and salt transport simulation model, and constraint (Eq. (12)) indicates linking of the simulation model within the optimization framework; constraint (Eq. (13)) specifies the maximum allowable salt concentration at specified monitoring locations; Eqs. (14) and (15) provide the lower and upper limits on the water extraction rate from the pumping wells and barrier extraction wells, respectively; subscripts PW and BW stands for production bores and barrier extraction wells, respectively; *R*, *K*, and *T* stands for the entire pumping wells, barrier extraction wells, and time periods, respectively. The first objective of maximization of groundwater extraction from the pumping wells for beneficial use is represented by Eq. (10), and the second objective of minimizing the water extraction from barrier pumping wells is given by Eq. (11).

2.4. Optimization algorithm

A population based search algorithm, CEMGA [36] is utilized for optimization. This algorithm demonstrated better convergence for a number of complex optimization problems [36]. The key feature of CEMGA lies in its ability to prefer individuals, who despite having low fitness values, help increasing the diversity of the population. The diversity of the population is preserved by regulating the populations' elite members during the progress of the algorithm, making the new population more diverse. More specifically, this regulated elitist tactic allows a particular fraction of the population (dominated populations) to be part of the current preeminent non-dominated solutions. This inclusion of a particular portion of the dominated solutions in the non-dominated solutions greatly reduces the effect of elitism. 'Pareto Fraction' and 'Distance Function' are the two parameters that control the extent of elitism. The first parameter restricts the number of individuals (elite members) on Pareto front, whereas the second one is intended to preserve the diversity on the Pareto front by giving preference to individuals who are reasonably far-off on the front [36].

2.5. Performance evaluation criteria

Following statistical indices were used to compare performances of the proposed data driven models.

Root mean square error (RMSE)

$$RMSE = \sqrt{(1/N)\sum_{n=1}^{N}(C_n^O - C_n^P)^2} \tag{16}$$

Mean absolute percentage relative error (MAPRE)

$$MAPRE = (1/N)\sum_{n=1}^{N}\left|(C_n^O - C_n^P)/C_n^O\right| \times 100 \tag{17}$$

Nash–Sutcliffe efficiency coefficient (NS)

$$NS = 1 - \frac{\sum_{n=1}^{N}\left(C_n^O - C_n^P\right)^2}{\sum_{n=1}^{N}\left(C_i^O - \overline{C^O}\right)^2} \tag{18}$$

Coefficient of correlation (R)

$$R = \frac{\sum_{n=1}^{N}\left(C_n^O - \overline{C^O}\right)\left(C_n^P - \overline{C^P}\right)}{\sqrt{\sum_{n=1}^{N}\left(C_n^O - \overline{C^O}\right)^2}\sqrt{\sum_{n=1}^{N}\left(C_n^P - \overline{C^P}\right)^2}} \tag{19}$$

where, C_n^C = observed concentration of saltwater, C_n^P = predicted saltwater concentration, $\overline{C^O}$ = mean of observed saltwater concentration, $\overline{C^P}$ = mean of predicted saltwater concentration, and N = number of data points.

2.6. Relative importance of input variables

Relative importance of individual input variables in determining the input-output mapping is computed for both FIS and ANFIS models. Results obtained are compared with those obtained by using GP models [2]. For GP models, Sreekanth and Datta [2] used impact factors to evaluate the relative importance of individual input variables. In Discipulus software [40], impact factor refers to the percent of times a variable is used in the best 30 models developed by GP. It is expressed in a 0–1 scale, where 0 indicates no contribution of an input variable whereas 1 indicates full contribution.

For FIS and ANFIS models, stepwise approach [41] is utilized to evaluate the relative importance of input variables. Steps followed byPerendeci et al. [41] are used in this study. In this approach, separate FIS structures are generated using FCM algorithm by sequentially dropping one of the variables from the variable matrix of total variables. Model performance for each individual case is compared with the case where all variables are used to generate the FIS structure. Similar technique is used for ANFIS models. RMSE criterion is utilized to evaluate the relative importance of input variables in the present study. Mohammadi et al. [42] mentioned that training RMSE is an appropriate indicator for determining the relative importance of input variables. On the other hand, Perendeci et al. [41] used testing RMSE in determining the influence of input variables in ANFIS model development. We realize that RMSE obtained in the testing phase is a relevant statistical index to determine variable importance. Therefore, testing RMSE values are used to determine the relative contribution of input variables in developing the FIS and ANFIS model structures.

Impact factor between 0 and 1 scale for FIS and ANFIS models is calculated using the following two equations

$$A_i = \{\text{RMSE (Xidropped)} - \text{RMSE (all variables)}\} / \text{RMSE (all variables)} \tag{20}$$

$$\text{Impact factor for } X_i = A_i/\max(A_i). \tag{21}$$

where X_i represents input variables.

2.7. Selection of optimum number of clusters for FIS and ANFIS

Selecting optimum number of clusters is a crucial aspect of the FIS model development using FCM algorithm or, any other clustering algorithm. The number of clusters determines the number of rules and level of complexity of the developed FIS structure. Although a model with simple architecture is always preferable in terms of input variables [42], the model should also represent the complexity of the problem itself. Optimal number of clusters for ANFIS and FIS are selected by conducting several trials and observing RMSE values between actual and predicted saltwater concentrations in the testing dataset. Number of clusters that minimizes the RMSE value is used to develop the FIS and ANFIS based data driven models.

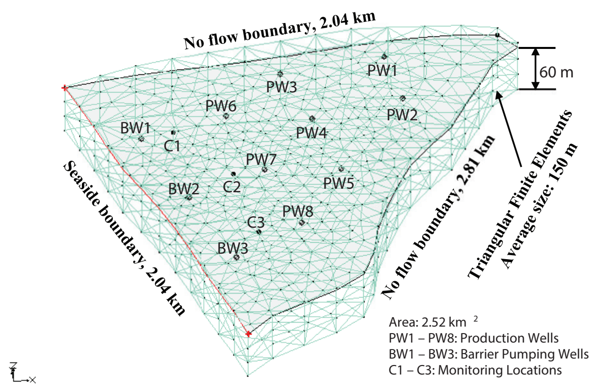


Fig. 5. Three-dimensional view of the study area with finite elements and location of different production and barrier wells.

3. Application of the proposed methodology using an illustrative study area

3.1. Study area and aquifer properties

This study uses a small illustrative coastal aquifer system of 2.52 km² aerial extent, and an aquifer thickness of 60 m [2]. The aquifer system with finite element meshes, and location of different production and barrier pumping wells with MLs is illustrated in Fig. 5. The seaside boundary (2.04 km long) is assumed to have a constant head of 0.0 m and a constant concentration of 35 kg/m³. The other two sides of the model domain (total length = 4.85 km) and the bottom of the aquifer are considered as no flow boundaries. The average thickness of the aquifer is 60 m, which is vertically discretized into 3 layers of 20 m each. However, the aquifer properties are the same at all of these 3 layers. These sizes of the triangular finite elements are decided based on the mesh dependency test. Element sizes smaller than 150 m induce an additional computational burden but did not achieve any further improvement in terms of computational efficiency and accuracy. Therefore, the entire model domain is divided into triangular finite elements of 150 m size. A finer element size of 60 m is used near the production and barrier extraction wells. Abstraction of water is carried out from 8 production wells placed inside the model domain for beneficial purposes, and 3 barrier extraction wells placed near the coastline to hydraulically control saltwater intrusion. Barrier extraction wells are placed near the coastline to create a hydraulic barrier along the coastline. When water is pumped out of the barrier extraction wells, a gradient is created that is filled in by the adjacent freshwater due to the natural gradation of freshwater towards the ocean, thereby preventing saltwater to enter into the aquifer. Aquifer recharge of 0.2 m/year is assumed to be uniformly distributed over the entire model domain. Therefore, it is unlikely that the aquifer gets filled with saltwater within a simulation period more than 3 years. Moreover, the illustrative aquifer including the initial and boundary conditions are chosen carefully to avoid trivial scenarios. Aquifer parameters used in the simulation is provided in Table 1 [2].

Table 1
Aquifer properties

Parameters	Assigned values
Hydraulic conductivity in x-direction, m/d	25
Hydraulic conductivity in y-direction, m/d	25
Hydraulic conductivity in z-direction, m/d	0.25
Molecular diffusion coefficient, m²/d	0.69
Lateral dispersivity, m	35
Longitudinal dispersivity, m	80
Density reference ratio	0.025
Soil porosity	0.2
Aquifer recharge, m/y	0.2

Total numbers of pumping wells considered in this study are 11 (8 production wells + 3 barrier extraction wells), and the simulation is performed over a period of 3 years. The simulation is performed in the transient mode in which total simulation period of 3 years is divided into 219 uniform time steps of 5 days each. Trials are conducted using four time steps of 1 day, 3 days, 5 days, and 15 days. Simulation time step of 5 days is selected by considering a trade-off between computational time requirement and accuracy of the simulation. The management period of 3 years is divided into 3 uniform time steps of one year each. Abstraction of water in this 1-year time step is assumed constant. Therefore, the study considers 33 pumping variables (11 pumping locations × 3 time steps) that are fed to the models as inputs. The lower and upper bounds of pumping values for these variables are set as 0 and 1300 m^3/d, respectively. Salinity concentrations are monitored at the end of the simulation period at three potential MLs.

3.2. Results and discussion

3.2.1. Architecture of FIS, ANFIS, and GP based models

A single global FIS structure (Fig. 6a) is developed to predict saltwater concentration at three MLs. However, due to the incapability of ANFIS to handle more than one output variable, three individual model structures for ANFIS (Figs. 6b, c, d) are developed to predict saltwater concentrations at individual MLs. For GP models, Sreekanth and Datta [2] also developed three individual model to predict salinity levels at three individual locations. Further details of the GP model architecture can be found in Sreekanth and Datta [2]. In the present study, training of ANFIS is carried out using the hybrid algorithm that combines least-squares estimation and back-propagation algorithm.

The input MFs used to develop the single global FIS, and initial FISs for ANFIS training are presented in Fig. 7.

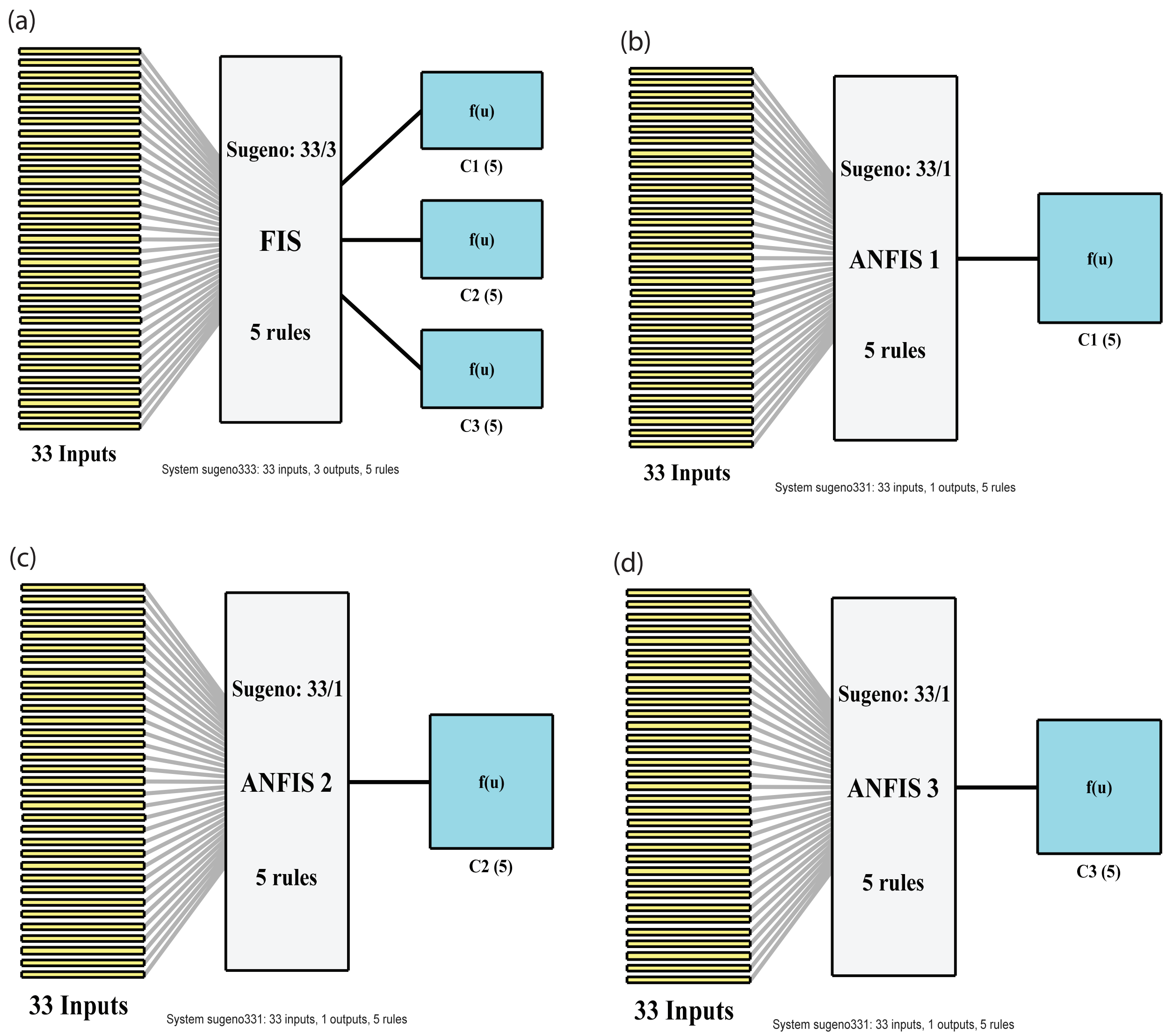


Fig. 6. Architecture of developed models (a) single global FIS, (b) ANFIS for predicting salinity at location C1, (c) ANFIS for predicting salinity at location C2, (d) ANFIS for predicting salinity at location C3.

Number of clusters for the developed Sugeno-type FIS are selected based on several trials while keeping the other parameters of the FIS constant. For this dataset and the number of variables, five clusters are found appropriate without model overfitting. Therefore, a total number of 165 (33 input variables × 5 clusters) Gaussian input MFs and 15 (3 outputs × 5 clusters) linear output MFs are considered in the study.

To develop ANFIS models, three initial FIS structures is fed to the network structure, and trained using the hybrid algorithm. Parameters used for developing the initial FIS are same as parameters used to develop the global FIS except that the initial FIS for ANFIS training necessarily have single output variable. The initial FIS used five (1 output × 5 clusters) output MFs whereas the number of input MFs remained same as the global FIS. Unlike the FIS models, each developed ANFIS is able to predict salinity concentrations only at a single ML. Therefore, three ANFIS models are developed to predict saltwater concentrations at different MLs. FIS and ANFIS models are developed using commands and functions of MATLAB and fuzzy logic toolbox of MATLAB [43].

Three individual GP models are also developed to predict salinity concentrations at 3 MLs, i.e., unlike the single global FIS model an individual GP model must be developed at every single ML. The parameters used to develop

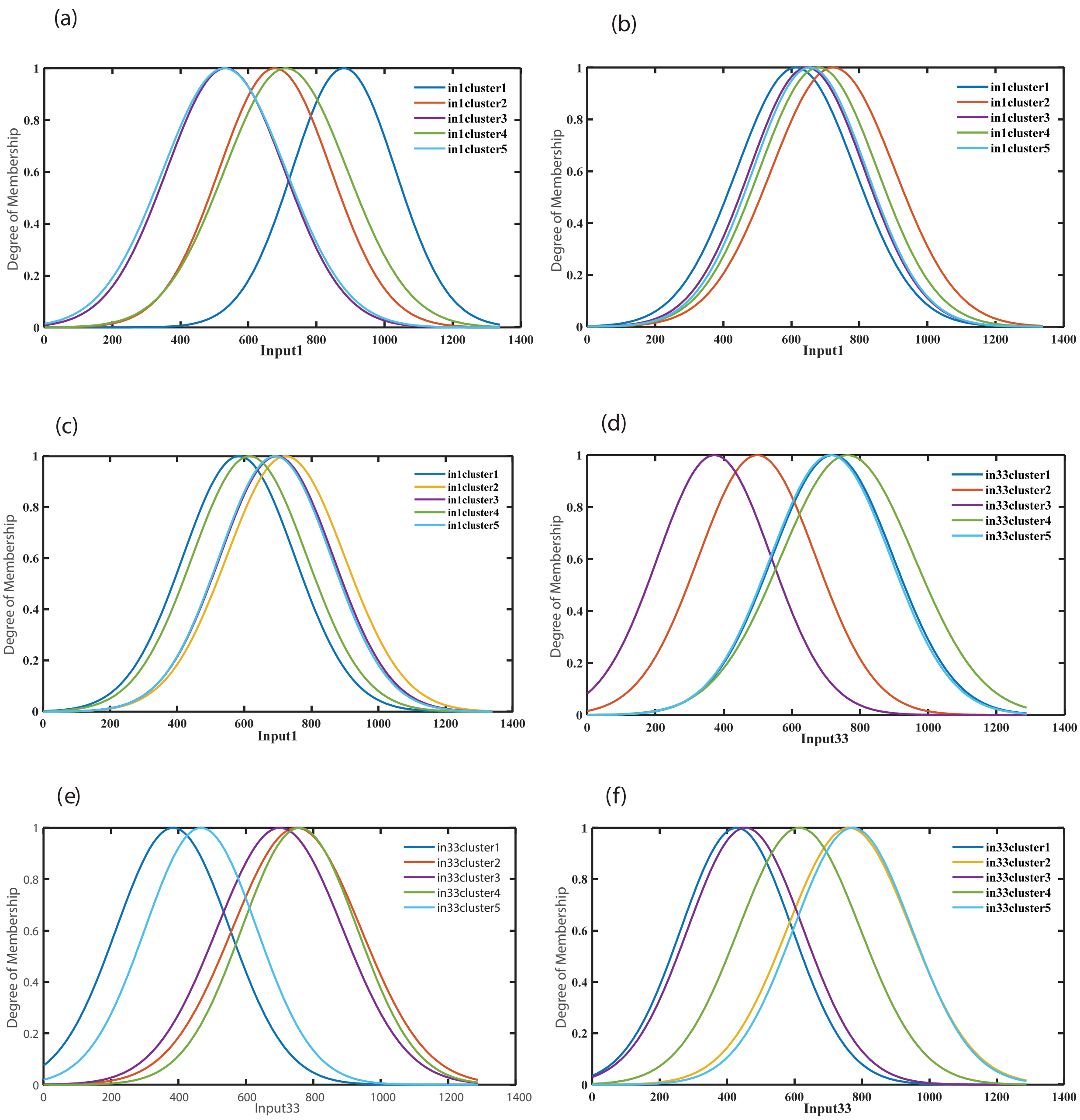


Fig. 7. Input membership functions used to develop initial FIS (a) input 1 location C1, (b) input 1 location C2, (c) input 1 location C3, (d) input 33 location C1, (e) input 33 location C2, and (f) input 33 location C3.

GP models are selected by conducting several trials using different combinations of the parameters. Based on the trials, all GP models are developed by using a population size of 500, mutation frequency of 95, and cross over frequency of 50. The functional set consists of a set of arithmetic operations (addition, multiplication, and subtraction) as well as the comparison and data transfer operators. In addition, all developed GP models uses a terminal set size of 30 to prevent model overfitting.

3.2.2. Optimum number of clusters for FIS and ANFIS

The optimal number of clusters is determined by observing the RMSE values of the training and testing data set between the actual and predicted concentrations at three MLs separately. Fig. 8 shows the variation in RMSE values between the training and testing data sets against the number of clusters. A point in the graph is selected where the difference between training and testing RMSE values are minimum, and where testing RMSE values are close to training RMSE values. Considering the complexity and accuracy of the model, five clusters are chosen as adequate for all MLs. In order to ensure a fair comparison, the specified number of clusters and the architecture of all ANFISs, and the single global FIS model are kept same.

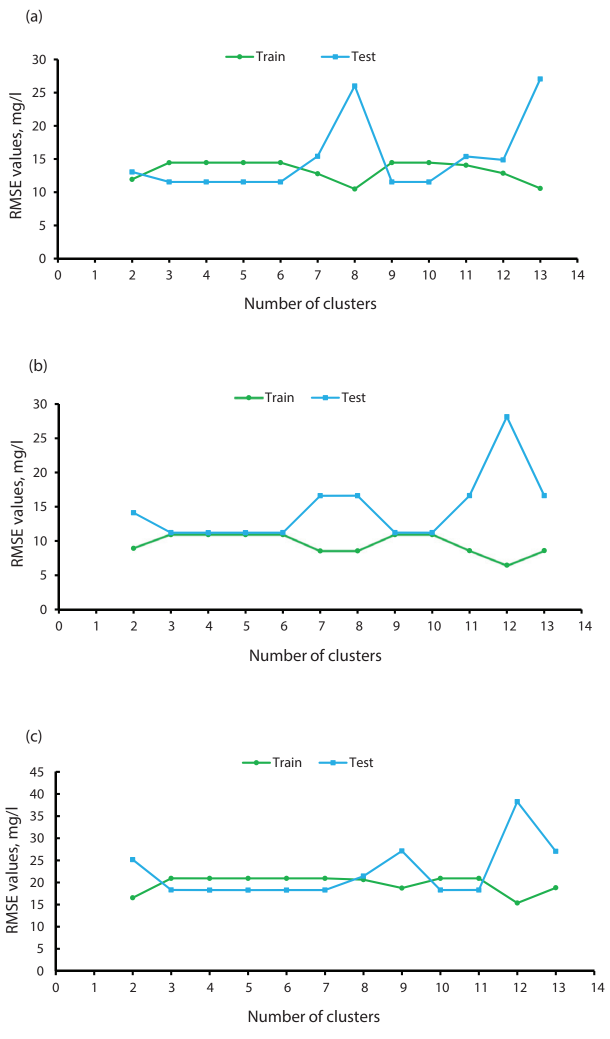


Fig. 8. Number of clusters vs RMSE values for prediction of salinity at (a) location C1, (b) location C2, (c) location C3.

3.2.3. Numerically simulated versus predicted saltwater concentrations

Performance of the developed FIS and ANFIS models are evaluated by comparing the numerically simulated and predicted saltwater concentration values in the testing period for all MLs. Figs. 9–11 illustrate numerically simulated vs. predicted concentrations and scatter plots of the testing datasets for both models at all three MLs.

As seen from Fig. 9, at ML C1, the performance of both ANFIS models and global FIS model is similar. This is also evident from the scatter plot diagrams, where R value obtained for both models are the same (0.99081). This indicates that additional training step required by ANFIS models is unable to improve the prediction capability at least for this illustrative study area.

At ML C2 (Fig. 10), performance of the global FIS predicting salinity concentrations at three MLs together is slightly better than that of the ANFIS models. It is also seen from the fit line equation of the actual vs predicted concentrations that the global FIS model produces higher R value (0.98013) than the more complex ANFIS model (R value = 0.98011). Fig. 11 also demonstrates the superiority of the global FIS model based on R criteria. The R value is higher in FIS (0.98222) than in ANFIS (0.97616).

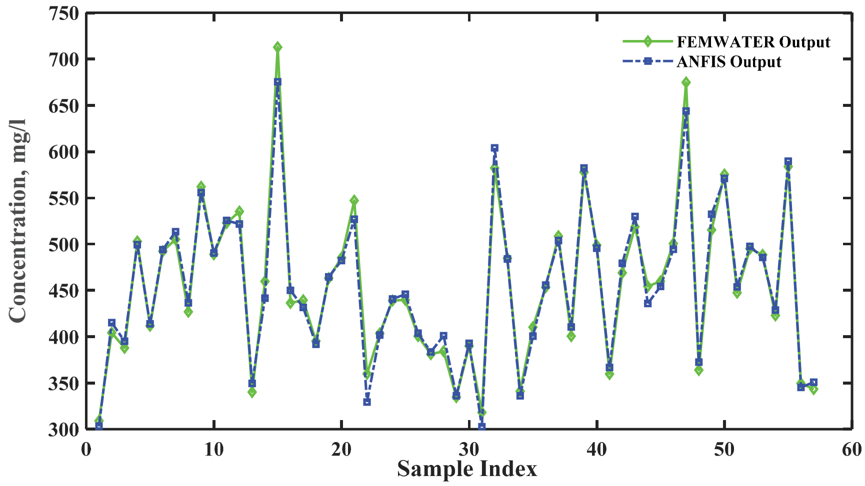
3.2.4. Performance evaluation based on statistical indices and computational time

Comparison of FIS, ANFIS, and GP based data driven models is performed by using some statistical indices that calculates error between the numerically simulated and predicted saltwater concentration values. The computational times required to train the models using a standard PC (Intel (R) Core (TM) i7-4790 CPU@3.60GHz 3.60GHz, 16.0 GB RAM) are noted. These prediction models are developed, trained, and validated by using the same data used to train GP based surrogate models in Sreekanth and Datta [2]. The time required is based on a desktop computer with processor configuration mentioned above (Table 2).

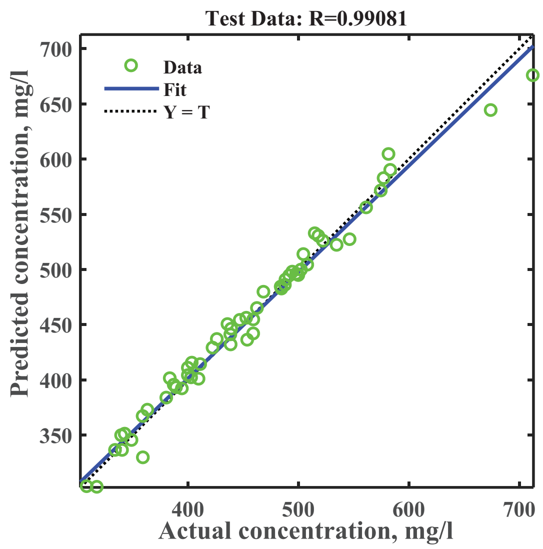
Table 3 gives an overview of computational time required for different processes in the developmental phase of both global FIS and ANFIS models. The computational time required for training and testing of the global FIS is only 0.65 min (Table 3). In addition to time saving, the global FIS has additional advantage of handling multiple outputs, thereby avoiding the need to develop multiple models for multiple output problems. Therefore, the developed global FIS can be a good candidate for use in a linked S/O methodology for deriving optimal groundwater pumping strategy in coastal aquifer systems.

ANFIS models are suitable for single output problems, and multiple ANFISs are required for multiple output problems. The computational time for training and testing of ANFIS structures at MLs C1, C2, and C3 are 6.56, 5.38, and

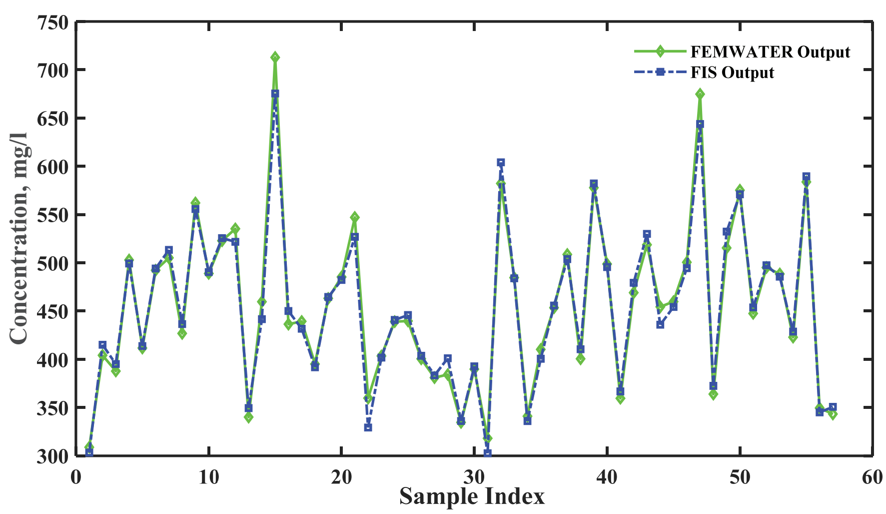
(a)


FEMWATER Output
ANFIS Output
Concentration, mg/l
Sample Index

(b)


Test Data: R=0.99081
Data
Fit
Y = T
Predicted concentration, mg/l
Actual concentration, mg/l

(c)


FEMWATER Output
FIS Output
Concentration, mg/l
Sample Index

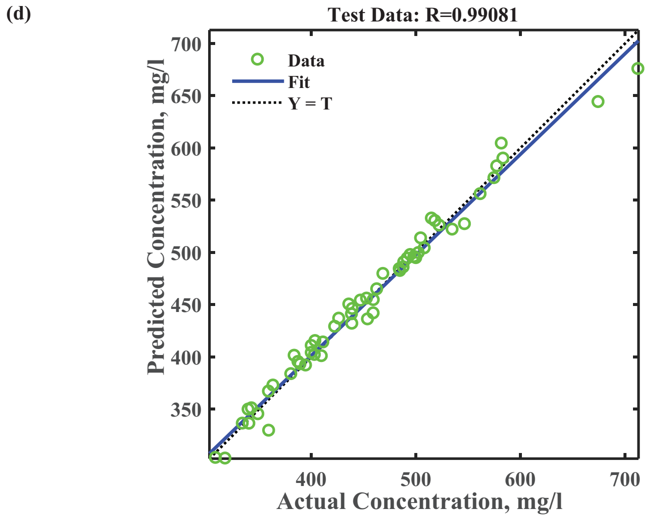
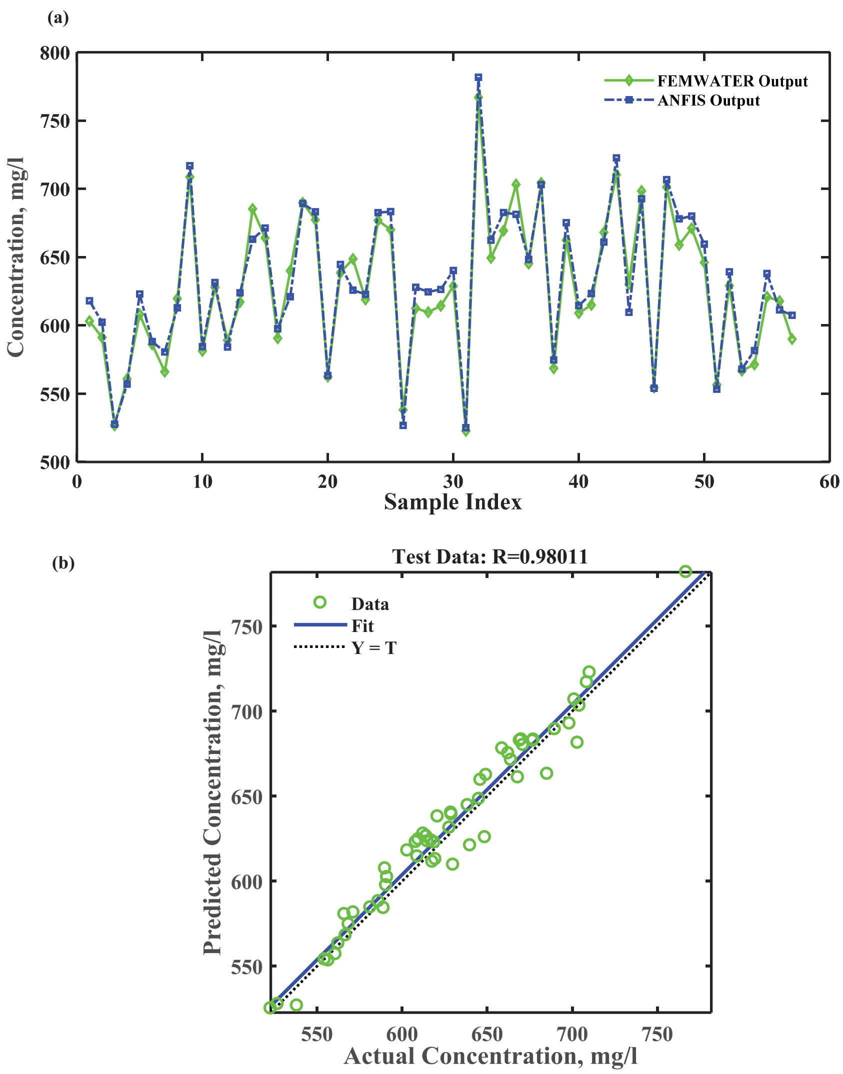


Fig. 9. Numerically simulated and predicted salinity at location C1 in the testing data set (a) FEMWATER simulated vs ANFIS predictions, (b) regression plot of (a), (c) FEMWATER simulated vs FIS predictions, (d) regression plot of (c). The dotted line indicates perfect fit in which the predicted response, Y equals the numerically simulated target, T. Actual concentration refers to numerically simulated saltwater concentration values.



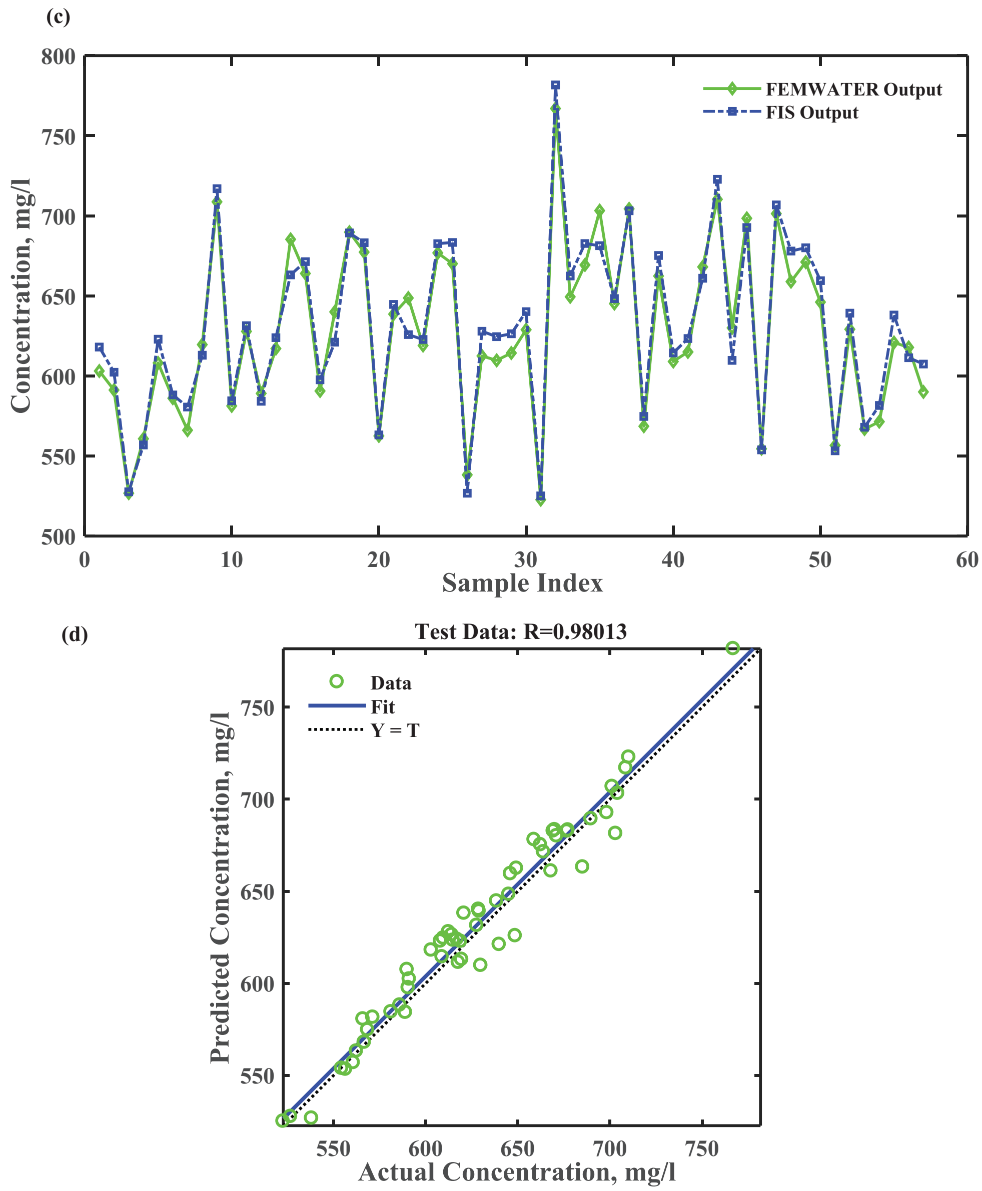
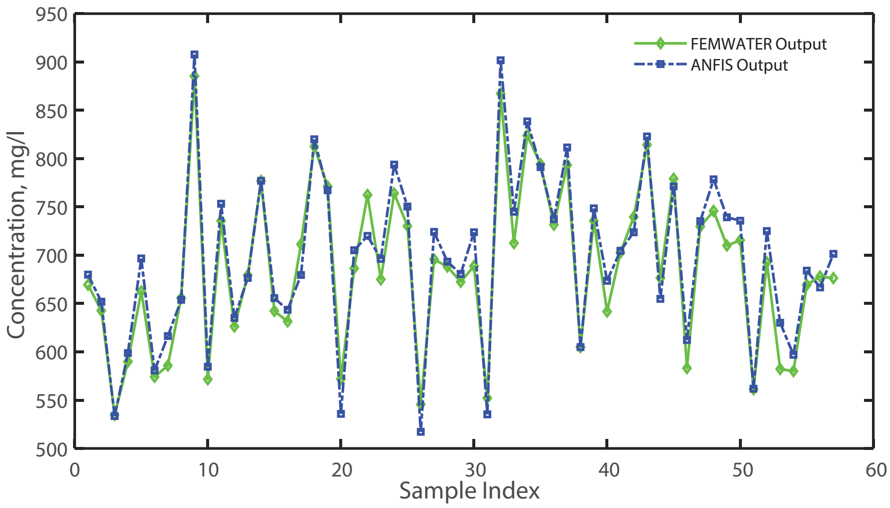


Fig. 10. Numerically simulated and predicted salinity at location C2 in the testing data set (a) FEMWATER simulated vs ANFIS predictions, (b) regression plot of (a), (c) FEMWATER simulated vs FIS predictions, (d) regression plot of (c). The dotted line indicates perfect fit in which the predicted response, Y equals the numerically simulated target, T. Actual concentration refers to numerically simulated saltwater concentration values.

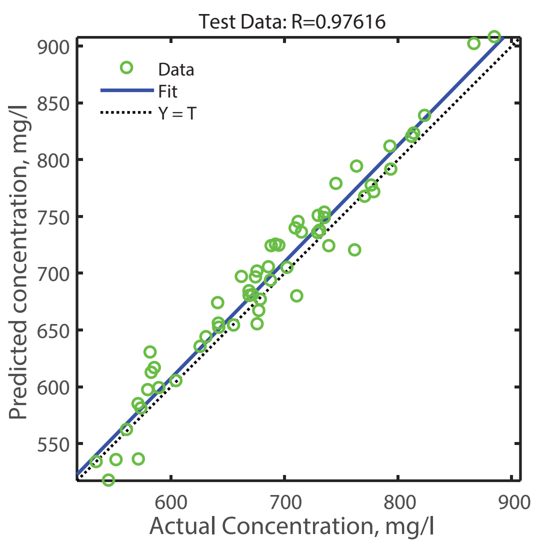
5.41 min, respectively. Time required for the entire problem is 17.35 min which is very large compared to time required by the global FIS model (0.65 min) (Table 2). GP models proposed by Sreekanth and Datta [2] are also unable to handle multiple outputs, and as such multiple GP models need to be developed for multiple output problems. Same PC configuration as in case of FIS and ANFIS models development is used to develop three GP models at three MLs. The corresponding time required (Table 2) is much higher than that required by FIS and ANFIS at all MLs.

R values between numerically simulated and predicted saltwater concentrations by GP, FIS, and ANFIS models are presented in Table 4. At all MLs, R values of testing datasets are slightly higher than those of training datasets. This indicates that both FIS and ANFIS models are trained without model overfitting. Moreover, R values for both FIS and ANFIS models are almost similar which indicates that additional training step to obtain ANFIS models from initial FIS models makes the generated models more complicated but does not improve the prediction capability significantly. On the other hand, GP produces lower values of R compared to both ANFIS and global FIS models at MLs C1 and C2. At C3, GP produced slightly higher testing R value. This means that the learning and prediction capability of both FIS and ANFIS models are better compared to that for GP models at least for this example problem.

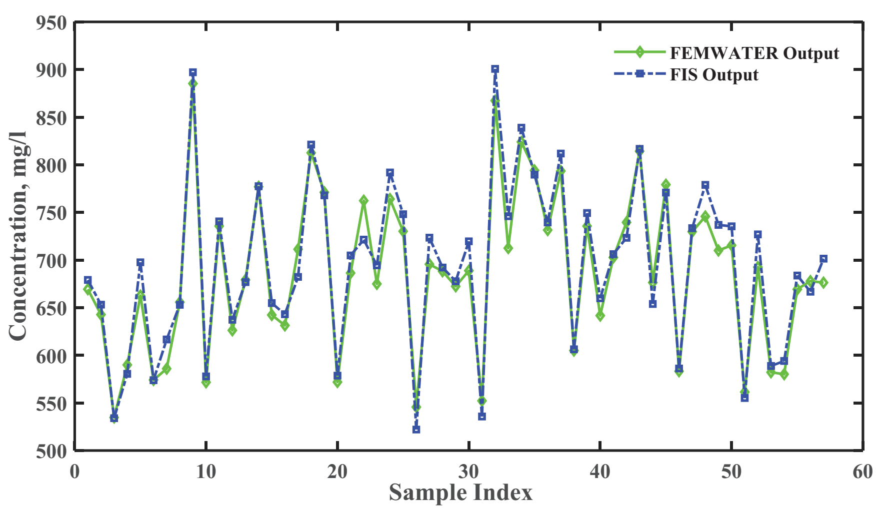
(a)


FEMWATER Output
ANFIS Output
Concentration, mg/l
Sample Index

(b)


Test Data: R=0.97616
Data
Fit
Y = T
Predicted concentration, mg/l
Actual Concentration, mg/l

(c)


FEMWATER Output
FIS Output
Concentration, mg/l
Sample Index

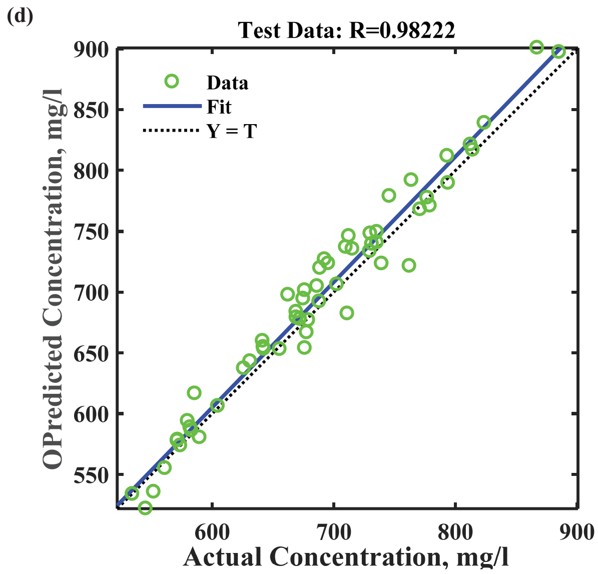


Fig. 11. Numerically simulated and predicted salinity at location C3 in the testing data set (a) FEMWATER simulated vs ANFIS predictions, (b) regression plot of (a), (c) FEMWATER simulated vs FIS predictions, (d) regression plot of (c). The dotted line indicates perfect fit in which the predicted response, Y equals the numerically simulated target, T. Actual concentration refers to numerically simulated saltwater concentration values.

Table 2
Training time requirement (min)

Model	C1	C2	C3
GP	58.8	90.65	127.05
ANFIS	6.56	5.38	5.41
FIS	0.65 (for C1, C2, and C3)		

*Values obtained by using data taken from Sreekanth and Datta [2], M. L. = monitoring locations

Table 3
Individual time breakdown for ANFIS and FIS training

Processes	ANFIS			FIS
	C1	C2	C3	C1, C2, and C3
Main	132.96	108.14	108.90	13.46
ANFIS	92.27	91.32	91.11	–
ANFISMex	92.23	91.32	91.09	–
Uiwait	34.48	13.97	15.03	11.19
Inputdlg	27.13	12.53	13.87	11.38
Questdlg	8.88	2.05	1.73	–
Plotting of results	5.79	3.18	3.15	3.08
Total, s	**393.73**	**322.51**	**324.89**	**39.11**
Total, min	**6.56**	**5.38**	**5.41**	**0.65**

Model performance is also judged using RMSE criteria. RMSE provides a good measure of prediction capability because it incorporates both the variance and bias of the prediction error. Therefore, RMSE criteria provide an indication of how well the model fits the test data. The minimum difference in values between training and testing RMSE gives an indirect indication that the model learned from the training dataset without overfitting [42]. RMSE values obtained for training and testing datasets by using GP, ANFIS, and FIS based prediction models at three MLs are presented in Table 5. It can be seen from Table 5 that FIS model outperforms ANFIS model at location C3 based on training and testing RMSE values. At C3, ANFIS gives a testing RMSE value slightly higher than the training RMSE value. However, this small deviation does not indicate model overfitting. Overall, performance of both FIS and ANFIS models are satisfactory based on RMSE values. GP results in higher RMSE values for the training and testing periods at all MLs except that in the testing phase at C3, at which the RMSE value is lower than RMSE values produced by both ANFIS and FIS models. However, the downside of using RMSE is that it gives more weights to the outlying observations. Therefore, MAPRE and NS criteria are also used to evaluate prediction performance of the developed models.

MAPRE provides information on the distribution of errors, and is a measure of testing robustness of the developed model [20]. The MAPRE index also provides an indication on whether a model tends to overestimate or underestimate [20]. In general, MAPRE values of training and testing datasets at all MLs are very small (less than 3%) as seen in Table 6. Therefore, the developed FIS and ANFIS models seem to perform well in terms of relative error. At locations C1 and C2, both FIS and ANFIS models result in almost the same MAPRE values. For training dataset at C3, ANFIS results in smaller MAPRE (1.55%) value than FIS (MAPRE value = 1.71%). On the other hand, FIS results in smaller MAPRE value (2.13%) compared to ANFIS (MAPRE value = 2.59%) for testing dataset at C3. GP produced larger errors in terms of MAPRE criteria at C1 on both training and testing periods, and training phase at C2. The testing

Table 4
R values between numerically simulated and predicted saltwater concentrations using GP, ANFIS, and FIS during training and testing periods

M. L.	C1		C2		C3	
Dataset	Training	Testing	Training	Testing	Training	Testing
GP	0.97	0.98	0.96	0.98	0.97	0.99
ANFIS	0.98	0.99	0.98	0.99	0.97	0.97
FIS	0.98	0.99	0.98	0.98	0.97	0.98

*Values obtained by using data taken from Sreekanth and Datta [2], M. L. = monitoring locations

Table 5
RMSE values in mg/l between numerically simulated and predicted saltwater concentrations using GP, ANFIS, and FIS during training and testing periods

M. L.	C1		C2		C3	
Dataset	Training	Testing	Training	Testing	Training	Testing
GP	18.65	17.16	15.51	12.00	22.43	12.80
ANFIS	14.46	11.55	10.92	11.21	20.63	21.33
FIS	14.46	11.55	10.91	11.21	20.93	18.29

* Values obtained from data taken from Sreekanth and Datta [2], M. L. = monitoring locations

Table 6
MAPRE values between numerically simulated and predicted saltwater concentrations using GP, ANFIS, and FIS during training and testing periods

M. L.	C1		C2		C3	
Dataset	Training	Testing	Training	Testing	Training	Testing
GP	2.84	2.68	1.76	1.44	1.49	1.46
ANFIS	1.95	1.86	1.29	1.48	1.55	2.59
FIS	1.95	1.87	1.29	1.48	1.71	2.13

* Values obtained by using data taken from Sreekanth and Datta [2], M. L. = monitoring locations

Table 7
NS values between numerically simulated and predicted saltwater concentrations using GP, ANFIS, and FIS during the training and testing periods

M. L.	C1		C2		C3	
Dataset	Training	Testing	Training	Testing	Training	Testing
GP	0.94	0.96	0.91	0.95	0.94	0.98
ANFIS	0.96	0.98	0.95	0.95	0.95	0.93
FIS	0.96	0.98	0.95	0.95	0.95	0.95

* Values obtained by using data taken from Sreekanth and Datta [2], M. L. = monitoring locations

period at C2, and both training and testing periods at C3, GP produced slightly smaller MARPE values.

Models are also evaluated based on NS criteria. A NS value of 1 indicates that the performance of the model is 100% perfect, however, in practical situations, NS values of around 0.8 is generally sufficient to evaluate the accuracy of a model [44]. NS values for both training and testing datasets obtained for all the developed models are greater than 0.8 (Table 7), which suggests that the developed FIS and ANFIS models can produce acceptable results. Although NS values for both FIS and ANFIS are similar, the global FIS results in higher NS value (0.95) for testing dataset at C3, compared to NS value (0.93) produced by the ANFIS model. In most of the cases, GP resulted in lower values of NS compared to both the global FIS and ANFIS models.

From the preceding discussion, it is clear that performance of the developed FIS and ANFIS models are similar based on the R, RMSE, MAPRE, and NS criteria; and both of these models perform better than GP models based on these performance measures. The most important criterion for any data driven model is the computational time required for training and testing. This criterion makes global FIS the best model among the data driven models used in this study for comparison.

3.2.5. Relative importance of input variables

The relative influence of input variables in determining the output are calculated for both FIS and ANFIS models, and compared with the impact factor of the GP model proposed in Sreekanth and Datta [2]. Comparison of the relative contribution of input variables for both GP, FIS, and ANFIS models are presented in Fig. 12. According to Sreekanth and Datta [2], GP is parsimonious in selecting the input variables at specific locations. On the other hand, FIS and ANFIS models can be directly used to select the most influential input variables and combination of important variables in determining the output [41,42,45]. Present study utilizes sequential dropping of input variables to calculate the relative importance of input variables by utilizing the stepwise approach described in section 2.6.

The global FIS has additional benefit of predicting the salinity concentrations at multiple locations while parsimoniously selecting the most relevant input variables. On the other hand, ANFIS models are also capable of selecting the most relevant input variables, which are particularly important for predicting concentrations at individual MLs.

It is seen from Fig. 12a that for predicting salinity concentration at C1, fifteen out of 33 variables are identified to have a 0 impact factor by both GP and FIS whereas ANFIS found 13 variables having no significant influence on prediction. However, at this ML, the most influential variable identified by both GP, FIS, and ANFIS is variable 9 (pumping from BW1 at time step 1). Variables 6 (pumping from PW6 at time step 1), 17 (pumping from PW6 at time step 2), and 20 (pumping from BW1 at time step 2) also have strong influence as identified by both models.

Fig. 12b shows that GP uses 14 variables in determining salinity concentrations at C2; 19 variables have 0 impact factor. Both FIS and ANFIS models are a bit less parsimonious in selecting input variables at this location: a total number of 16 and 18 variables at this location have very little or no influence identified by ANFIS and FIS, respectively. Variable 10 (pumping from BW2 at time step 1) is found most influential at this location because this variable has an impact factor of 1 as specified by all the models.

The relative contribution of input variables in determining the salinity concentrations at C3 is illustrated in Fig. 12c. At this location, GP did not use 11 variables in reaching the conclusion whereas the numbers of variables that have no influence are 11 and 13 identified by ANFIS and FIS, respectively. Both GP and FIS identified variable number 21 (pumping from BW2 at time step 2) as most influential while ANFIS found variable 7 (pumping from PW7 at time step 1) as most relevant.

3.3. Management model performance

Prediction accuracy and feasibility of incorporation of any surrogate model within a linked S/O methodology determines the robustness of the approach. Proposed FCM based FIS and ANFIS models as well as the GP based prediction models are good candidates for replacing and approximating numerical simulation models within a linked S/O approach to determine Pareto optimal groundwater extraction policies. Present study proposes a saltwater intrusion management model by utilizing the best performing FIS based prediction model. The single global FIS based surrogate model predicting saltwater concentration values at pre-defined MLs is linked to the CEMGA based optimization algorithm. The global FIS model is externally linked as binding constraint within the optimization framework in order to ensure that the assigned maximum allowable salt concentration limits for the specified MLs are not exceeded. The optimal parameter values for the optimization algorithm are chosen by conducting several trials using different combinations of these parameters. Based on this trial, a population size of 2000, crossover fraction of 0.9, mutation probability of 0.1, and migration fraction of 0.2 with an interval of 20 in the forward direction are selected. The function and constraint tolerances are set to 1e-05 and 1e-03, respectively. A Pareto front population fraction of 0.7 is chosen to allow 1400 (2000 × 0.7) non-dominated feasible optimal solutions in the Pareto front. The optimization algorithm needs to evaluate 7,896,000 (3948 generations × 2000 populations) groundwater extraction patterns to arrive optimal solution.

The saltwater intrusion management model in the present study considers two conflicting objectives of the groundwater extraction strategy. These are maximizing water extraction from 8 potential production wells for beneficial purposes and minimizing water abstraction from 3 barrier extraction wells. The role of barrier extraction wells is to produce suitable hydraulic gradient along the seaward boundary to control salinity intrusion. The optimization model considers 33 input variables relating to pumping of water from 11 locations for 3 time steps, and 3 output variables that correspond to saltwater concentration at specified MLs at the completion of the management time horizon of 3 years. The optimization model provides optimal solution in the form of a Pareto optimal front that represents the non-dominated tradeoff between these two conflicting objectives. The Pareto optimal front presented in Fig. 13 provides several sets of optimal groundwater extraction values obtained while ensuring that the maximum permissible saltwater concentrations at specified MLs are not exceeded.

It is observed from Fig. 13 that increasing the rate of extraction from production wells requires an additional amount of water withdrawal from the barrier extraction wells. Water extracted from barrier extraction wells generally cannot be used for beneficial purposes due to high salinity contents. Therefore, managers can choose the rate of barrier well pumping based on the demand for beneficial water use, while keeping the pre-set maximum allowable saltwater concentrations at certain MLs in mind. These Pareto optimal solutions show the conflicting nature of the two objectives, a necessary condition for a multiple objective optimal management.

The validity of the proposed coastal aquifer management model is evaluated by observing the actual violation of any one of the constraints within the optimization model.

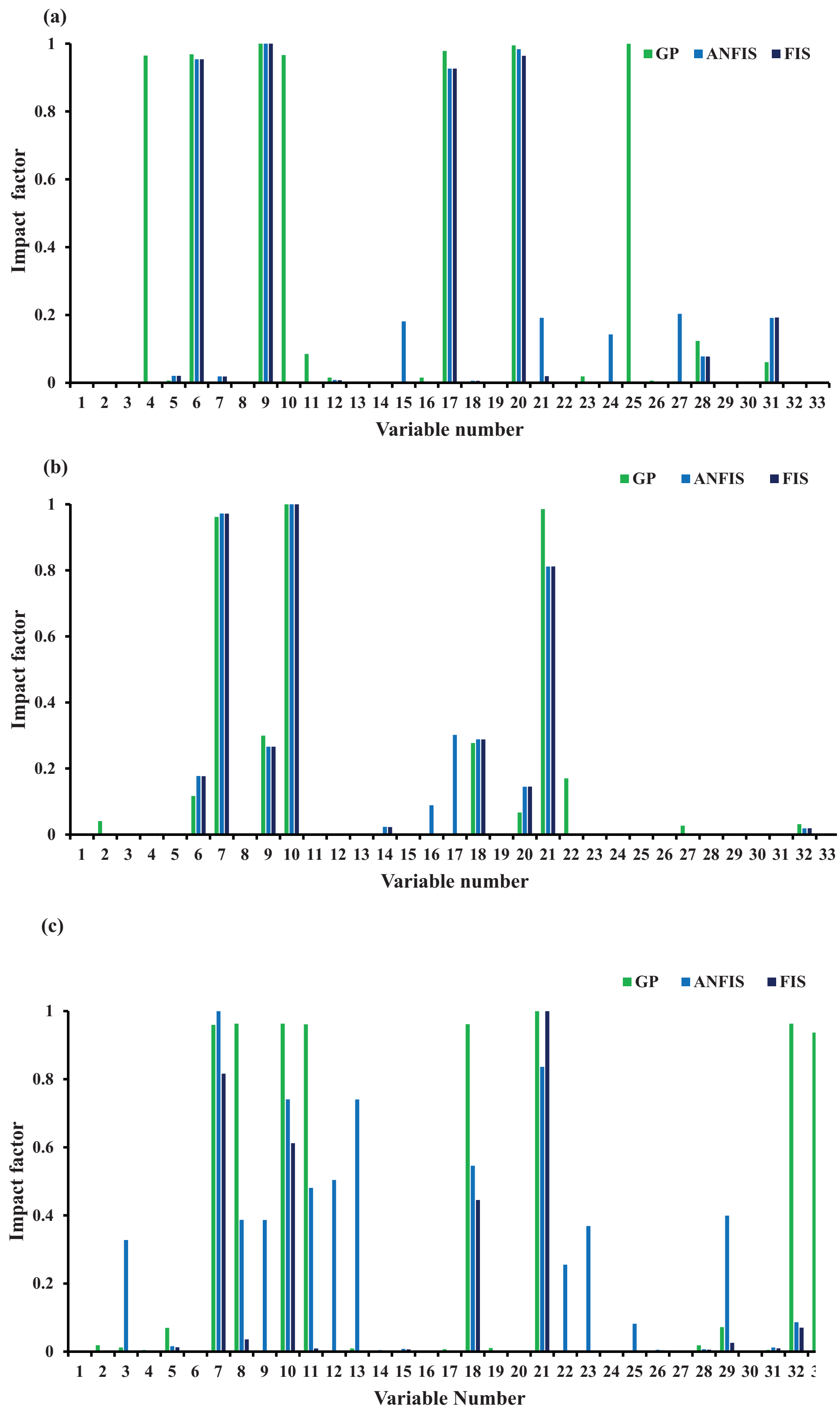


Fig. 12. Impact of individual input variables on salinity prediction using GP, ANFIS, and FIS models at (a) location C1, (b) location C2, (c) location C3.

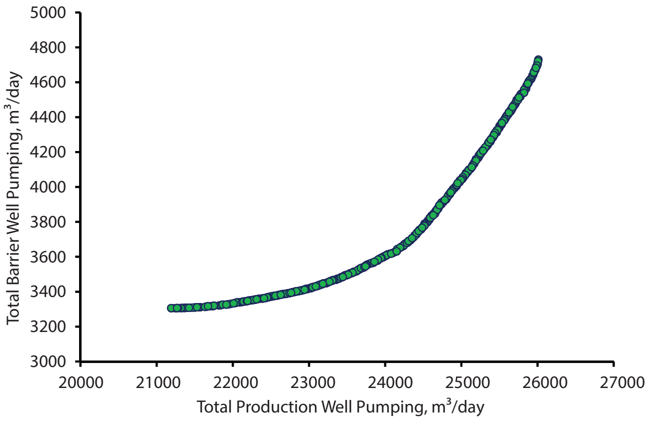


Fig. 13. Pareto optimal front of the developed saltwater intrusion management model.

It is noted that the saltwater concentrations obtained from the optimization model solution (determined by the global FIS model within the optimization framework) are smaller than the pre-specified maximum allowable saltwater concentrations at all MLs. This implies that all the imposed constraints are satisfied, and no constraint violation occurs during the search process. Moreover, obtained saltwater concentrations are very close to the prescribed values, which indicate that the optimization model converges to the upper limit of the saltwater concentration constraints. Ten solutions are selected randomly from different regions of the Pareto front to check the constraint satisfaction and constraint violations. This is shown in Table 8. It is observed from Table 8 that FIS predicted saltwater concentration values within the optimization model is very close to the pre-assigned saltwater concentration limits at different MLs. Therefore, the limited performance evaluation of the proposed FIS-CEMGA based saltwater intrusion management methodology demonstrate its potential applicability to prescribe accurate Pareto optimal solutions for optimal groundwater extraction from a set of beneficial pumping wells and barrier extraction wells in a coastal aquifer.

4. Conclusions

Two fuzzy logic based data driven modelling approaches, FIS and ANFIS to approximately predict salinity concentration at specified MLs of an illustrative coastal aquifer system is developed, and compared with the results obtained using GP based modelling approach. Comparison of FIS and ANFIS model performances demonstrates that the prediction capability of these models do not vary significantly. However, in terms of computation time and degree of model complexity, FIS performs comparatively better than ANFIS does. When compared to GP, performances of both FIS and ANFIS are better in terms of R values at all specified MLs. A comparison between training and testing time required by the models indicate that global FIS model is computationally more efficient compared to both ANFIS and GP models. GP models are a simple explicit mathematical formulation [46] that are intended to develop simpler models, which are simple regression models [2]. On the other hand, fuzzy logic based FIS and ANFIS models incorporate elements of the human reasoning process in mapping input-output patterns of a complex system. Therefore, FIS and ANFIS based models may be more suited to represent complex systems.

Time required for training and validation is much smaller for FIS compared to both ANFIS and GP models. In addition, FIS has additional advantage of predicting salinity concentrations at multiple MLs. Overall, the results presented in this study indicate that FIS model seems to be superior to both ANFIS and GP models in predicting salinity intrusion in coastal aquifers. In addition, as the computational time is relatively very small, FIS model can be an ideal candidate for integration in a linked S/O technique to develop sustainable regional scale optimal groundwater extraction strategies in coastal aquifers. A coastal aquifer management model is developed and solved to demonstrate the feasibility of incorporating the proposed FIS based surrogate model to a CEMGA based optimization algorithm within a linked S/O methodology in order to determine Pareto optimal strategies for groundwater abstraction. Evaluation results indicate that extraction of water according to the prescribed management strategy successfully limits

Table 8
Constraint satisfaction within the management model in reaching the global Pareto optimal solution

Solution number	C1 ≤ 500 mg/l			C2 ≤ 600 mg/l			C3 ≤ 600 mg/l		
	FIS, mg/l	Diff.	% Diff.	FIS, mg/l	Diff.	% Diff.	FIS, mg/l	Diff.	% Diff.
1	499.81	0.19	0.04	587.09	12.91	2.15	599.96	0.04	0.01
2	499.81	0.19	0.04	587.19	12.81	2.14	599.84	0.16	0.03
3	499.89	0.11	0.02	585.50	14.50	2.42	599.86	0.14	0.02
4	499.91	0.09	0.02	585.06	14.94	2.49	599.85	0.15	0.03
5	499.85	0.15	0.03	587.38	12.62	2.10	599.96	0.04	0.01
6	499.94	0.06	0.01	587.46	12.54	2.09	599.98	0.02	0.00
7	499.86	0.14	0.03	586.21	13.79	2.30	599.95	0.05	0.01
8	499.92	0.08	0.02	587.59	12.41	2.07	599.92	0.08	0.01
9	499.84	0.16	0.03	587.36	12.64	2.11	599.97	0.03	0.01
10	499.89	0.11	0.02	586.80	13.20	2.20	599.97	0.03	0.00

*FIS = FIS output within the optimization model, Diff. = Difference between imposed constraint and the FIS output the salt concentrations at MLs to pre-specified limits. The results demonstrate the potential applicability of the global FIS model as computationally efficient substitute of numerical simulation model within a coupled S/O approach for obtaining saltwater intrusion management strategy for a coastal aquifer system.

Although the results presented here are limited in scope, the evaluation results point towards the suitability and choice of different data driven models. This study may help in identifying the most suitable model for modelling saltwater intrusion problems in coastal aquifers. These evaluation results may also provide more generalized guidance for selection of appropriate models. However, more rigorous application of these artificial intelligence techniques needs to be evaluated in a real-world problem setting.

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