# Forecasting Seasonal and Annual Rainfall Based on Nonlinear Modeling with Gamma Test in North of Iran

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***Abstract***

Rainfall plays a key role in hydrological application and agriculture in wet climatic regions. Lack of short-run rainfall forecasting is considered as a significant impediment for scheduling the root zone moisture preparation. Although many mathematical techniques are available for use, basic concerns remain unsolved such as simplicity, high accuracy, real time use in many stations of a region, and the low availability of inputs. In this study, a nonlinear modeling with Gamma Test (GT) has been presented to solve some of the mentioned problems. Forecasting seasonal and annual rainfall with the variables of four years lagged rainfall data and geographical longitude, latitude and elevation has been performed in the North of Iran during 1956-2005. The results show that Gamma Test is an effective tool for rainfall forecasting. The applied nonlinear modeling techniques are Local Linear Regression (LRR), Dynamic Local Linear Regression (DLLR), and three separate Artificial Neural Networks (ANN) using Back Propagation Two Layer, Broyden-Fletcher-Goldfan-Shanno (BFGS), and the Conjugate Gradient training Algorithms. The training and testing data are partitioned by random selection from the original data set. Not only does the Gamma Test yield the best input combination, but also the model's good performance leads to the best achievable result. The study results demonstrate that developed models based on Local Linear Regression (LRR) technique have better performance comparing with ANN models. Also, developed ANN model based on Back Propagation Two Layer training Algorithm is preferred because of its better performance compared with the other ANN models.

***Keywords***

*Gamma Test; Artificial Neural Network; Local Linear Regressio; Rainfall*

## Introduction

Predicting the hydrological variables like rainfall, flood stream, and runoff flow as stochastic or probabilistic events, is one of the principal subjects in water resource planning. The hydrological variables are usually measuring across the time. Therefore, time series analysis of their occurrences in discrete periods is urgent for monitoring and simulating the hydrological behavior of a region. Rainfall Forecasting, as the most affecting factor on hydrological cycle, is vital in water resources management, irrigation scheduling, and agricultural management especially in humid climates (Mimikou, 1983; Hamlin et al., 1987). In wet and semi-wet climates, irrigation isn't common and farmers use rainfall water for supplying crop water requirements. When rainfall isn't enough the supplemental irrigation will be applied. Therefore forecasting, modeling and monitoring of rainfall are of a high importance in agricultural actions (Geng et al., 1986; Hoogenboom, 2000; Sentelhas et al., 2001).

Notably, while weather forecasting deals with daily development of the weather up to several days ahead, seasonal forecasting is concerned with the average weather condition on timescale of a month to about a year ahead. Seasonal forecasts are also known as long-run weather forecasts or short-run climate forecasts (Chang et al., 2003). Because seasonal forecasts give information of several months ahead, they can be used by government, business, agriculture, and industry to increase productivity, maximize economic benefits and minimize losses. Specific examples of the applications of seasonal forecasts are presented in ECMWF (1999). The seasonal forecasts based on slow variation in the earth's boundary conditions (i.e. sea surface temperature, soil wetness, and snow cover) can influence global atmospheric circulation and rainfall, too (Fu et al., 2007; Rajeevan, 2007; Gonzalez et al., 2009; Ousmane et al., 2011). A detailed discussion of the differences between weather and seasonal forecasting can be found in WMO (WMO, 2002).

In last decades, researchers developed many empirical methods in the form of statistical or analogue models with a long history in seasonal forecasting (Bell, 1976; Hui et al., 2000). Statistical methods based on historical observed data, try to build relationships between predictors (e.g. sea surface temperature (SST), atmospheric parameters) and predictands (e.g. rainfall and temperature). Gilbert Walker used them at the first part of 20th century to forecast Indian monsoon rainfall (Allan et al., 1996). Analogue methods try to find matches between past cases and the current case, if the initial conditions are alike; the climate pattern would evolve in much a similar way (Chang et al., 2003). Empirical models are easy to run and need relatively little computational resources. The major disadvantage is that they try to predict complex nonlinear atmosphere-ocean processes by linear relationships. They use Markov model (singular value Decomposition), optimum climate normals, regression, and canonical correlation analysis (Reason, 2001; Gissila et al., 2004; Singhrattna et al., 2005; Frederiksen, 2006; Ousmane et al., 2011; Shamsnia et al., 2011). Among suggested techniques, Markov chain has been used the most (Caskey, 1963; Gates etal., 1976; Delleur et al.,1978; Garbutt et al., 1981; Richardson et al., 1984; Geng et al., 1986; Katz, 1977; Richardson, 2000), though Markov chain is mostly applied for considering rainfall occurrence. Moreover, some researchers present this technique combined with other techniques like Gamma, exponential distributions for finding rainfall value in rainy days (Woolhiser et al., 1982; Sanchez-Cohen et al., 1997; Aksoy, 2000; Fooladmand, 2006). Also, the Markov chain is usually used for short timescale such as daily data (Haan et al., 1976; Chin, 1977; Buishand, 1977; Bruhn et al., 1980; Coe et al. 1982; Mimikou, 1983; Woolhiser et al., 1986; Geng et al., 1986; Hanson et al., 1990).

The other approach to seasonal forecasting which is more recent is dynamic modeling. Dynamic models use prognostic physical equations: atmospheric general circulation models, two-tiered coupled ocean-atmosphere climate models (first predict SST and then climate), fully coupled ocean-atmosphere-land-ice general circulation models (CGCMs) that predict ocean and atmosphere together (Ousmane et al., 2011). Dynamic models try to predict the complex atmosphere-ocean processes using the nonlinear equations of mass conservation, motion, and energy. They need enormous computer resources to run, but can better simulate the physical processes and therefore have the potential to produce more accurate forecasts (chang et al., 2003). The rapidly increasing power and falling costs of computers have resulted in a growing popularity in the use of dynamic models. The reader is referred for reviewing the global atmospheric models and their performance to Gates et al. (1999), for the dynamic models to Dalcher et al.(1988), Latif et al. (1994), Trenberth (1997), Gadgil et al. (1998), Anderson et al. (1999), Krishnamurti et al. (1999), Derome (2001), Gadgil et al. (2005), Krishna Kumar et al. (2005), Saha et al. (2006), Wang et al. (2005) and Wang et al. (2009) and for studying the comparison of forecasting skills of empirical models versus dynamic models to Shukla et al.(2000), Wang et al.(2001), Glantz (1998), and Anderson et al. (1999).

In last decades, for simulating and modeling of the systems behavior that are usually nonlinear multivariate, unknown, and noisy with high uncertainty, researchers used the potentiality of other tools; Such tools, that are applicable for forecasting rainfall, include mostly Artificial Neural Networks; ANN, Fuzzy Inference System; FIS, Adaptive NeuroFuzzy Inference System; ANFIS, and Artificial Intelligent; AI (French et al., 1992; Halff et al., 1993; Ozelkan et al., 1996; Wong et al., 2003; Galambosi et al., 1999; ASCE, 2000a, b; Sahai et al., 2000; Hadli et al., 2002; Karamouz et al., 2004; Maria et al., 2005; Suwardi et al., 2006; Kumarasiri et al., 2006; El-Shafie et al., 2007; El-Shafie et al., 2008; El-Shafie et al., 2009; Fallah-Ghalhary et al., 2009; El-Shafie et al., 2010a, b, c; El-Shafie et al., 2011).

Despite a plenty of studies on prediction and modeling of seasonal and annual rainfall as empirical statistic and dynamic models with ANNs and FISs, the application of nonlinear and nonparametric models and lagged time series data have not been much considered. Also, there is still certain question to be answered like which lagged data are relevant to make a reasonable model. These concerns can be effectively tackled by using novel technique called the Gamma Test (GT). The GT was first reported by Koncar (1997) and Agalbjorn et al. (1997) and later improved and discussed in details by many other researchers (Durrant, 2001; Tsui et al., 2002). The domain of a possible model is now restricted to the class of smooth functions bounded first partial derivatives. The basic idea is distinct from the earlier tries with nonlinear analysis. Before model construction, the Gamma Test evaluates and estimates the best mean-squared error for a given selection of inputs that can be achieved by any smooth model on unseen data. This technique can be used to find the best embedding dimension and data length for modeling to achieve a particular target output. A formal mathematical justification of the method can be found in Evans and Jones (2002).

Accordingly, the objective of the study reported here is to apply the Gamma Test capability for specification of the affecting parameters on seasonal and annual rainfall. Also, it makes use of GT-derived input data for nonlinear modeling of rainfall with Local Linear Regression (LLR) and Artificial Neural Networks (ANNs). However, evaluating nonlinear models is carried out in training and validation phases after model construction.

## Method and Materials

### *The Study Area and Used Data*

Mazandaran province is in north of Iran with wet and very wet climate (based on Domarten method), and it is selected as the study area. This region is near 23842 square Kms. For carrying out the study, we used monthly rainfall data that have been collected from four synoptic stations including Gorgan, Rasht, Ramsar and Babolsar; some of meteorological and geographical characteristics of these stations are presented in TABLE 1. The average rainfall of winter, spring, summer, autumn seasons and annual is equal to 434, 255, 126, 198, and 1013 mm, respectively. The rainfall time series are from 1956 to 2005 with a total of 204 monthly records after removing the missing data. Meteorological data were gained from weather database of meteorology Organization of Iran. In this research, after selecting the 204 records and according to the principal objective, the initial inputs which influence outputs were determined. Outputs of forecasting models were summer, spring and annual rainfall. The forecasting seasonal rainfall especially in summer and spring in north of Iran is so important, because it is in accordance with the growth season of summer crops. During this period temperature and crops evapotranspiration is high and farmers need scheduling for supplying crop water requirements. As, the farming year in Iran starts from October, rainfall data are arranged based on it, initially. Therefore, a time series based on four-year monthly lagged data has been provided. Moreover, the average seasonal and annual rainfall, height of sea level and geographical longitude and latitude are selected as inputs. Because, there were many input variables, total analyses were carried out for two distinctive input sets: 1) the average seasonal and annual lagged rainfall data were just used as inputs and 2) the average seasonal and annual lagged rainfall with monthly lagged rainfall data were used as inputs. According to the inputs and outputs, we proposed six models as in TABLE 2.

TABLE 1 GEOGRAPHICAL AND METEOROLOGICAL CHARACTERISTICS OF FOUR SYNOPTIC STATIONS

| Parameters | Synoptic Stations | | | |
|---|---|---|---|---|
| | Gorgan | Baolsar | Ramsar | Rasht |
| height (m) | 13.3 | -20 | -21 | -6.9 |
| longitude | 54 16 e | 52 39 e | 52 39 e | 49 36 e |
| latitude | 36 51 n | 36 43 n | 36 43 n | 37 15 n |
| mean monthly rainfall (mm) | 51.6 | 72.5 | 101.8 | 113.4 |
| mean seasonal rainfall (mm) | 154.8 | 217.4 | 305.5 | 340.2 |
| mean annual rainfall (mm) | 619 | 870 | 1222 | 1361 |

TABLE 2. FORECASTING MODELS AND INITIAL INPUTS

| Sets | Model No. | output | Geographical data | Combination Inputs rainfall |
|---|---|---|---|---|
| First | Model I | Annual Rainfall | Height, latitude and longitude (inputs 1 to 3) | Seasonal and annual rainfall Lagged for 4 year (inputs 4 to 25) |
| | Model II | Spring Rainfall | Height, latitude and longitude (inputs 1 to 3) | Seasonal and annual rainfall Lagged for 4 year (inputs 4 to 25) |
| | Model III | Summer Rainfall | Height, latitude and longitude (inputs 1 to 3) | Seasonal and annual rainfall Lagged for 4 year (inputs 4 to 25) |
| Second | Model IV | Annual Rainfall | Height, latitude and longitude (inputs 1 to 3) | Monthly, Seasonal and annual rainfall Lagged for 4 year (inputs 4 to 41) |
| | Model V | Spring Rainfall | Height, latitude and longitude (inputs 1 to 3) | Monthly, Seasonal and annual rainfall Lagged for 4 year (inputs 4 to 41) |
| | Model VI | Summer Rainfall | Height, latitude and longitude (inputs 1 to 3) | Monthly, Seasonal and annual rainfall Lagged for 4 year (inputs 4 to 41) |

Time series analysis is complicated because of the fact that we probably do not know how far back in time we should look to build our prediction model. This initial decision is not irrevocable and should be guided by some degree of commonsense analysis on what is likely to be the case for the given data set and how many data are available. But, the first considerations showed that four-year lagged data yielded proper models and we accepted this assumption and we did not use a longer lagged period. For this assumption and according to two selected data sets and six models, we used inputs presented in TABLE 2. These inputs and outputs normalized before analysis. Also, records were divided into two phases, randomly; training and validation phases with 146 and 58 records, respectively.

*Gamma test*

The trends of almost climatological variables such as rainfall are complex and involve nonlinear dynamic systems that usually are unknown. Therefore, data-driven modeling is useful for modeling especially when the inner workings of the systems aren't understandable. Gamma test, as one of such analytical tools, assists to select input data before modeling (i.e., its result is independent of the models to be developed). The Gamma test can model the unseen data with any continuous nonlinear models using minimum mean square error (MSE) estimation (Remesan et al., 2008). Also, one reason the Gamma test is so useful is that it can immediately tell us directly from the data whether we have sufficient data to form a smooth non-linear model and how well that model is liable to be (Dunn et al., 2001). As before explained, the Gamma test was firstly reported by Koncar (1997) and Agalbjorn et al. (1977) and later discussed in details by many researchers (Durrant, 2001; Jones et al., 2002; Evans, 2002). In this research, WinGamma software was used, which has been developed for accomplishing GT process. Some definitions used in software and Gamma test processes are given as follows (Jones, 2001):

**Model**: The basic idea is quiet distinct from the earlier attempts with nonlinear analysis. A smooth data model is a differentiable function from inputs x = ($x_1$... $x_m$) containing predicatively useful factors that can influence the output. It is assumed that the data can be represented by an unknown model, so:

$$y = f(x_1,...,x_m) + r \qquad (1)$$

Where the input vectors $x_i \in R^m$ are vectors confined to some closed bounded set $C \in R^m$ and, without loss of generality, the corresponding outputs $y_i \in R^m$ are scalars, and is a random variable that represents noise. Without loss of generality it can be assumed that the mean of the distribution is zero and that the variance of the noise var(r) is bounded. The domain of a possible model is now restricted to the class of smooth functions which have bounded first partial derivatives.

**Gamma Test:** An algorithm to estimate the variance of the noise module Var(r) on each of the outputs is bounded and independent of the input values. For each choice of inputs found out, as the number of data points increases, we try to set up the asymptotic Gamma statistic for each output. Both the inputs and outputs should be continuous real variables from some bounded range. The underlying function presumes smooth and this means bounded first and second derivatives. If the independence condition is false, this is not necessarily fatal, and the Gamma test will return an average noise variance over the whole input space. This test is used to show how the Gamma statistics estimation varies as more data is used. Eventually, if enough data are used, the Gamma statistic should converge to the true noise variance on the output for which it has been computed. The Gamma test calculates the mean-squared $p^{th}$ nearest neighbour distances δ(p) ( $1 \le p \le p_{max}$ ) and the matching γ(p). Although, the Gamma test is an unknown function of, it can directly estimate Var(r) from data:

$$\delta_M(p) = \frac{1}{M}\sum_{i=1}^{M}\left|x_{N[i,p]} - x_i\right| \qquad (2)$$

and γ(p), is:

$$\gamma_M(p) = \frac{1}{2M}\sum_{i=1}^{M}\left(y_{N[i,p]} - y_i\right)^2 \qquad (1 \le p \le p_{max}) \qquad (3)$$

Finally, the fitted regression line passes through $\delta_M(p), \gamma_M(p))(1 \le p \le p_{max})$ points, like:

$$\gamma = A\delta + \Gamma \qquad (4)$$

The vertical intercept of the (δ(p), γ(p)) regression line referred to "Gamma Statistic, $\overline{\Gamma}$". Effectively, $\overline{\Gamma}$ is the limit γ as δ→0, which in theory is Var(r). Also, gradient (A) is an index of model complexity, as the lager value of gradient represents the more model complexity (Jones, 2001).

**Near Neighbor:** This records the index of the $k^{th}$ nearest neighbor that has setTABLE boundary in the Gamma test. When estimating the Gamma statistic, $p_{max}$ should be selected proportional to the size of the data set. In general, in a Gamma test experiment, we should keep the number of near neighbors less than 30. Usually 10-20 is a good choice (Jones, 2001). We wish to find the nearest set of points to a query point with near Neighbor search.

**M-Test:** The M-test is a way to assess whether the

Gamma statistic estimates Var(r) reliably. It is performed by computing the Gamma statistic for a given subset of the available data. Whereby at each successive calculation of the Gamma statistic we increase by a insignificant extension, until we have either used all the data or the statistic has converged enough towards a fixed value.

**Model Identification:** This is used to select those inputs which can be best applied to predict a selected output (some inputs may be noisy or irrelevant). The most applicable model identification techniques are Full Embedding, Genetic Algorithm, Hill Climbing, Sequential Embedding and Increasing Embedding.

**Mean Squared Error (MSError):** If y (i) (1, 2… M) is a set of values of an output and y*(i) is a set of predictions for y(i) then the MSError of the predictions is:

$$\text{MSError} = \frac{1}{\text{M}}\sum_{i=1}^{M}\left(y^*(i) - y(i)\right)^2 \quad (5)$$

**Standard Error (SE):** The standard error of regression line is calculated as follows:

$$\text{SE}(\Gamma) = \sqrt{\frac{1}{\text{n - 2}}\sum_{i=1}^{p_{\max}}\left(\Gamma(i) - \overline{\Gamma}\right)^2} \quad (6)$$

Where, identifier i is the ith Gamma regression point value and $\overline{\Gamma}$ is its mean.

*The Modeling Procedures*

In this study, the Gamma test explored different combinations of inputs to assess their influence on the rainfall forecasting. There were meaningful combinations of inputs; from which, the best one can be determined by evaluating the Gamma value. This shows a measure of the best attainable estimation using any modeling methods for unseen smooth functions of continuous variables. We divided data into two parts; training data (70% of data) and testing data (30% of data), before modeling. When, we choose the set of inputs for a particular output that has the minimum asymptotic Gamma statistic - this is known as model identification. According to the selected inputs and output in training period, using the WinGamma software, rainfall forecasting models were built by: 1) Static local linear regression, 2) Dynamic local linear regression, and 3) three different types of neural network training algorithms. The ANNs contain two layer back propagation, Conjugate gradient descent and BFGS neural network. Predictions on new input data for which the outputs are unknown can also be made using the best identified model.

Local linear regression models are fast to make. These models can also be easily updated as new training data becomes available, which is not the case with neural networks. Indeed WinGamma also offers a dynamic local linear regression option which is exactly local linear regression with dynamic updating. This choice is useful for time series prediction and then it is not used in this research. Neural network models cost time to compose but in parts of the input space where data are sparse, their generalization is better than local linear regression. Neural networks can predict at blinding speeds compared with local linear regression based algorithms, so for some applications it is well worth the time and effort to set up a neural model.

**Local linear regression:** Local Linear Regression (LLR) can produce accurate predictions in regions of high data density in input space, but it is liable to produce unreliable results for non-linear functions in regions of low data density.

**Dynamic local linear regression:** It is basically identical with LLR with the extra feature that as new data are seen for the first time they are incorporated into the model. You can see its effect by starting the model with little training data and running a test on many data. As new test data is encountered, dynamic LLR will make steadily better predictions. This Method is mainly applicable for the time series analysis (Jones, 2004).

**Two layer back propagation:** This technique uses the standard back propagation algorithm to produce a two-layer feed forward neural network. With all the neural network training algorithms, one should note the choice to recalculate the target MSError. This is useful if a part of the data for training and testing has been altered. Two layer back propagation also needs: a) the initial learning rate with positive value that controls the first step size in weight adjustment, b) Momentum constant which is positive, and controls the extent to which the size and direction of the current step in weight space is influenced by the size and direction of the previous step, and c) Regularization constant that is positive, and limits the size of weights.

**Conjugate gradient descent:** This shows variation and improvement on two-layer vanilla back propagation, and it is more effective but wants more memory. The procedures for set up are similar.

**BFGS neural network:** BFGS neural network training algorithm is a quasi-Newton method performed iteratively using successively improved estimations to the inverse Hessian. It provides progressive adjustment of the neural network weights by gradient descent (Fletcher, 1987). Probably the fastest and the most efficient neural network training algorithm offered by winGamma is a varied version of the Broyden-Fletcher-Goldfarb-Shanno learning algorithm. This algorithm uses second differences and is sometimes degraded by very noisy data, but generally it is proper to use this alternative first when trying to produce a neural model. We know that feed forward networks with as few as one hidden layer can act as universal approximation for continuous functions over a compact set (Cybenko, 1989; Hornik et al., 1989). Details of such modeling for chaotic systems can be found in (Jones et al., 2002; Tsui et al., 2002), and (Evans et al., 2002).

### *Model Selection Criteria*

For evaluation constructed model, we used three reference statistics containing logical values. These three reference statistics are Correlation Coefficient (R), Root Mean Standard Error (RMSE) and Mean Biased Error (MBE).

If known_y's and known_y*'s are observations and predictions respectively and have a different number of data points, RMSE equation for the standard error is:

$$RMSE = \sqrt{\frac{1}{n-2}\left[\sum\left(y^* - \overline{y^*}\right)^2 - \frac{\left[\sum (y-\overline{y})(y^* - \overline{y^*})\right]^2}{\sum (y-\overline{y})^2}\right]} \qquad (7)$$

the equation for the Pearson product moment correlation coefficient, R, is:

$$RMSE = \sqrt{\frac{1}{n-2}\left[\sum\left(y^* - \overline{y^*}\right)^2 - \frac{\left[\sum (y-\overline{y})(y^* - \overline{y^*})\right]^2}{\sum (y-\overline{y})^2}\right]} \qquad (8)$$

and the mean biased error, MBE, is:

$$MBE = \frac{1}{n}\sum\left(y - y^*\right) \qquad (9)$$

## Results and Discussion

### *Data Analysis and Model Input Selection Using the Gamma Test*

The GT estimates the minimum mean square error (MSE) that can be achieved when modeling the unseen data using any continuous nonlinear models. As mentioned, discovering effective parameters on annual and seasonal rainfall is difficult and time-consuming. Therefore, much vital information is derived from rainfall data with different lags using the Gamma test. The GT provides input data guidance before a model is developed and greatly reduces construction time of the model. At first, we loaded all data to WinGamma and considered rainfall time series and tried to find the best embedding (i.e. the embedding with Γ closest to zero). But, before selecting the best embedding we should determine near neighborhood and the number of inputs. The measurement data noise and sampling rate are the basis for finding out the near neighbor in the Gamma test. If the data are noisy, this adjusTABLE factor will be larger to get a reliable Gamma value. Also, high rate of measurement sampling needs many near neighbors. However, if the measurement sampling rate is low, too many near neighbors will make the Gamma value fuzzy. A compromise needs to select a suiTABLE number of near neighbors, so the Gamma value is relatively reliable and close to its true value. We tested different near neighbors and selected a suiTABLE amount of $p_{max}$ for different data sets. Neighbor values earned 16 for Annual rainfall models I and IV, 13 for spring seasonal rainfall model II, 10 for spring seasonal rainfall model V and summer seasonal rainfall model VI and 20 for summer seasonal rainfall model III (TABLE 3).

One of the key questions we need to answer practically is how much data we need to get an accurate estimation of Gamma, and subsequently to build a model which can be predicted with suiTABLE accuracy. Answering this question, we run the Gamma test using increasing M and then plot a graph of Gama values against M values. Typically, what will happen is that for small M the graph will have much variability, but as M increases the graph will stabilize to an asymptote which reflects the true value of the noise variance. When the graph has stabilized, there is nothing more to gain by using a larger M sets and it is maximum number of points shared in nearest neighbors' selection. Therefore, the quantity of data was analyzed using M-test and selecting sufficient data to provide an asymptotic Gamma estimate and subsequently a reliable model. The results showed that there was sufficient data around M=198 data points, so all the data were used for selecting inputs. Moreover, available data are relatively suiTABLE in forecasting annual and seasonal rainfall. These are values what the graph stabilizes such that we can have some confidence that our estimate is reasonably accurate (Fig. 1 and TABLE 3).

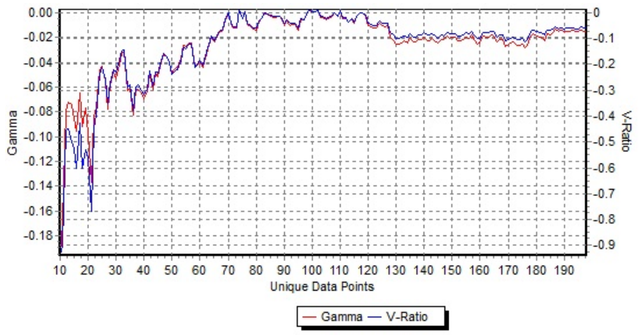



FIG. 1 M-TEST FOUND FOR DATA SETS OF MODEL IV

We have seen that combining Gamma regression line, scatter plot, and M-test can provide an estimate of Var(r) as a qualitative degree of confidence. Also, this combination marks the measure of the best index MSError attainable for modeling the unseen smooth functions of continuous variables. Here we can see interesting variations of the best MSError level with different input combinations in all models. Since a single Gamma test is a relatively fast procedure it is possible to find that selection of inputs which minimizes the asymptotic value of the Gamma statistic and it makes the 'best selection' of inputs. Thus, expected inputs were assessed by the Gamma test and classified into two categories; effectiveness and non-effectiveness. As far as the inputs are many (41 inputs for annual rainfall model I), the possible combinations are too much, ($2^{41}$-1=2199023255551 combinations); therefore, running Gamma test is impractical for all the combinations. For resolving it, we used three shortcut approaches of model identification: Genetic algorithm, Hill climbing and Sequential Embedding for selecting the best inputs. The mentioned methods presented the different combinations of inputs with the lowest Gamma statistic and MSError level. In this study, Genetic algorithm was used for the best selection, more often. We examined possible embeddings. However, the minimum value of was observed when we used the lagged different input data sets, and the best embeddings were presented in TABLE 3. The gradient (A) is considered as the indicator of model complexity (a larger value gradient indicates a model of greater complexity). A low MSE and low gradient data model can be considered as the best scenario for modeling. V-Ratio measures the degree of predictability for given outputs using available inputs. The smaller value of V-Ratio was observed when we considered all the inputs. We can see that the various combinations of lagged rainfall data influence outputs and can make a good model and don't need to apply all inputs. Notably, the lagged data through 4 years ago have high effect on output in all models.

### *Nonlinear Model Construction and Testing*

After selecting the "optimal" inputs with Gamma test, we built predictive models for six sets of outputs and performed the usual analysis. As the model identification process is massive, we summarized their implications. Two types of models were constructed 1) LLR models and 2) ANN models. Nonparametric producer based on LRR models does not need training in the same way as neural network models. But, we randomly divided data set into two parts: training and validation. For constructing LLR models, the optimal number of near neighbors was determined by trial and error, that principally depend on the noise level.

TABLE 3 THE GAMMA TEST AND THE BEST SELECTIVE MASKS AND THEIR PERFORMANCE CRITERIA FOR FORECASTING FUNCTION IN DIFFERENT MODELS (INCLUSION AND EXCLUSION INDICATED BY A 1 OR 0 IN THE MASK RESPECTIVELY)

| **Parameters** | **Modell I** | **Modell II** | **Modell III** | **Modell IV** | **Modell V** | **Modell VI** |
|---|---|---|---|---|---|---|
| | **Annual** | **Spring** | **Summer** | **Annual** | **Spring** | **Summer** |
| Selected mask | 1111001<br>1101100<br>1110101<br>1111 | 1011011<br>1011101<br>1110111<br>0010 | 01010111<br>01110011<br>11101111<br>0 | 1101000<br>0111100<br>0110101<br>1101101<br>0011011<br>111111 | 0110111<br>0100001<br>0101111<br>1100110<br>1101111<br>110101 | 11101100<br>11011010<br>01110000<br>01111101<br>11010011<br>0 |
| Gamma (Γ) | 5.88e-6 | 0.0627 | 0.0738 | 4.14e-7 | 5.21e-5 | 4.09e-6 |
| Gradient (A) | 0.0234 | 0.0451 | 0.0262 | 0.0117 | 0.0385 | 0.0337 |
| MSError | 0.0041 | 0.0142 | 0.0118 | 0.0048 | 0.0155 | 0.0120 |
| Coef. of Deter. ($R^2$) | 1 | 0.7488 | 0.7046 | 1 | 0.9998 | 1 |
| V-Ratio | 2.35e-5 | 0.2512 | 0.2954 | 1.65e-6 | 0.0002 | 1.64e-5 |
| Neighborhood values | 16 | 13 | 20 | 16 | 10 | 10 |
| M values | 198 | 198 | 198 | 198 | 198 | 198 |

A proper number of near neighbors was 13 to 15 for LLR models. The performance of LLR models were compared to developed models based on neural network technique. The various general statistics were applied to select the best models and to compare the results of the LLR and the neural networks models. The used statistics were namely correlation, root mean squared error (RMSE) and MBE. The details of modeling statistics are given in TABLE 4 for the validation phase. In this study, other than the three different ANN models, we constructed ANN models trained with various hidden layer neuron number combinations and selected the best value for the number of hidden layer neurons, and their performance was compared to other models (TABLE 4).

Forecasting rainfall using the LLR model resulted in the best statistics value. For all presented models, it was seen that the LLR model had a better performance compared to BFGS, conjugate gradient and two layer back propagation ANN models in the training and validation. From TABLE 4, one can find that models presented based on ANN is struggling to produce high quality performance. In general, for ANN models, the results of the study also indicate that the predictive capability of constructed model based on two layer back propagation neural network is better compared to BFGS algorithm and conjugate gradient networks for all the mentioned statistics. The comparative analysis of these models using mentioned basic statistic has been carried out for the training and validation and the results of validation period are shown in TABLE 4.

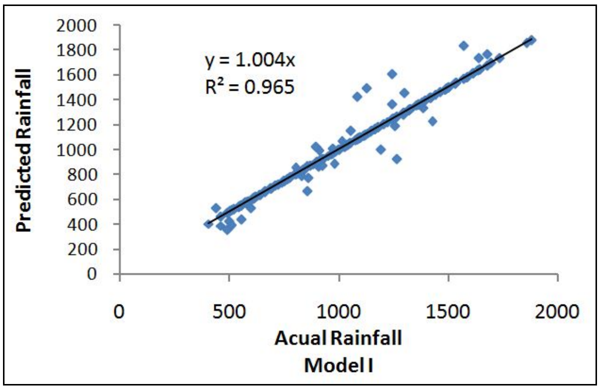
Moreover, it was seen that the extracted results for forecasting annual and spring rainfall have superior performance when input variables are the combinations of monthly and seasonal data to only seasonal rainfall data used. But this is not validated for modeling summer rainfall. Also, the best modeling results by Gamm test obtained for forecasting annual rainfall, especially when input variables are combinations of monthly and seasonal rainfall, namely Model IV.

We graphically presented the more complete results of Local Linear Regression models in FIGURES 2 and 3. FIGURE 2 shows scatter plots of computed and observed annual (Model I and Model IV), spring (Model II and V) and summer (Model III and VI) rainfall during training and validation phases. Moreover, FIGURE 3 is a close up view of the actual annual rainfall and forecasting results of Local Linear Regression model comparison on a subset 100 on the test data constructed. The applied inputs include height, latitude and longitude and monthly, seasonal and annual rainfall for 4 years ago. We clearly found out the LRR models, which use different combinations of inputs, works well in forecasting.

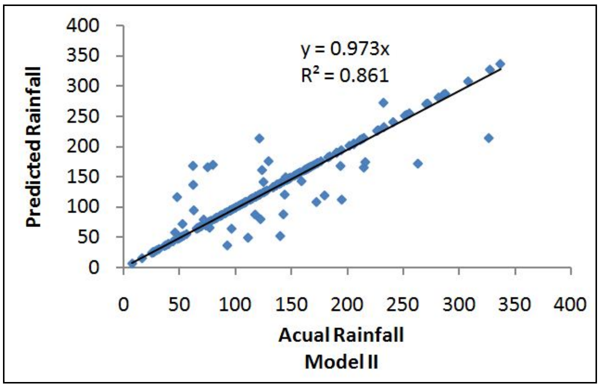
TABLE 4. COMPARISON OF THE GENERAL STATISTICS VALUES OF VALIDATION FOR THE SELECTED MASKS BASED ON TABLE 3

| **Sets** | **Model No.** | **Output (Rainfall)** | **Statistics** | **Local-linear regression** | **Neural network** | | |
|---|---|---|---|---|---|---|---|
| | | | | | **BFGS neural network** | **Conjugate gradient neural networks** | **Two layer back propagation on neural network** |
| First | Model I | Annual | R | 0.844 | 0.783 | 0.655 | 0.819 |
| | | | RMSE | 104.18 | 120.05 | 179.35 | 111.56 |
| | | | MBE | 11.39 | -17.94 | 25.33 | 9.74 |
| | Model II | Spring | R | 0.656 | 0.308 | 0.190 | 0.399 |
| | | | RMSE | 38.72 | 61.93 | 61.45 | 42.64 |
| | | | MBE | -2.84 | -11.64 | -7.47 | -5.67 |
| | Model III | Summer | R | 0.653 | 0.626 | 0.594 | 0.549 |
| | | | RMSE | 65.86 | 70.18 | 64.70 | 69.65 |
| | | | MBE | 13.65 | 1.76 | 9.77 | 12.73 |
| Second | Model IV | Annual | R | 0.9350 | 0.821 | 0.848 | 0.853 |
| | | | RMSE | 91.05 | 160.49 | 152.41 | 146.59 |
| | | | MBE | 25.43 | 36.25 | 10.93 | 21.42 |
| | Model V | Spring | R | 0.675 | 0.169 | 0.133 | 0.317 |
| | | | RMSE | 35.78 | 76.02 | 96.35 | 72.03 |
| | | | MBE | 2.18 | 2.22 | 10.18 | -2.98 |
| | Model VI | Summer | R | 0.554 | 0.279 | 0.381 | 0.454 |
| | | | RMSE | 75.30 | 141.79 | 120.31 | 114.38 |
| | | | MBE | -11.92 | 25.30 | 18.46 | 10.11 |

(a)




(b)



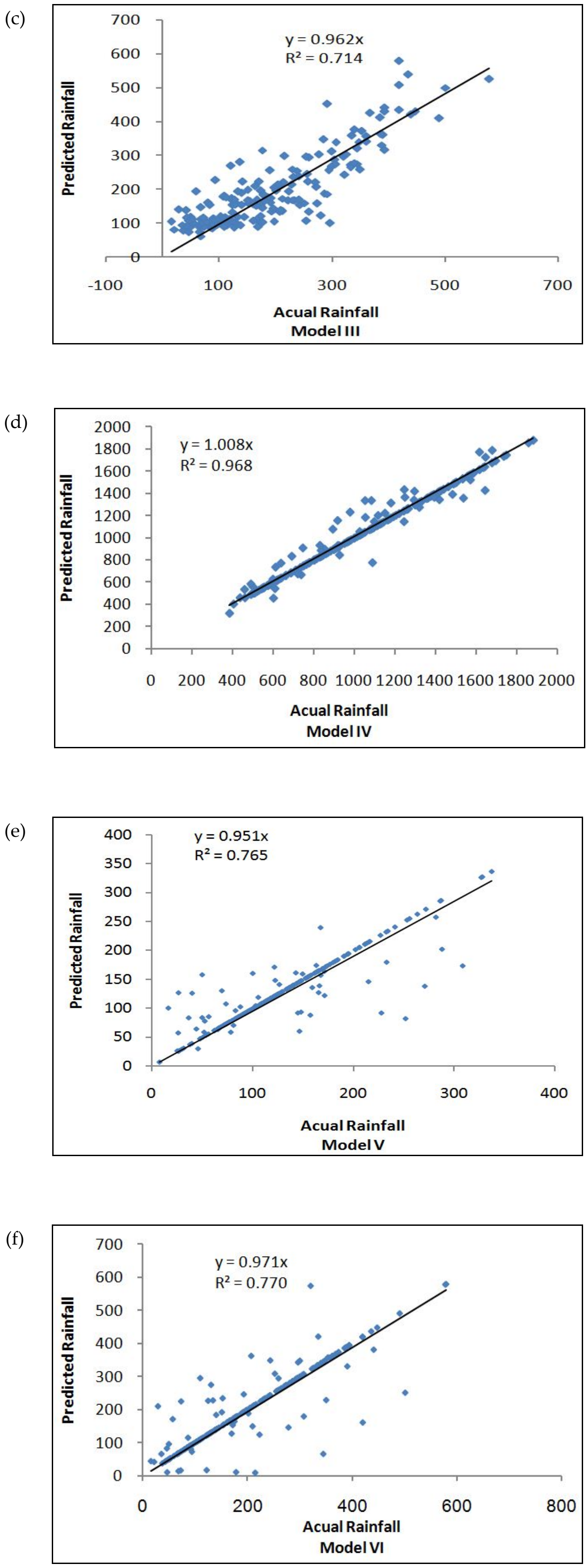



FIG. 2 A COMPARISON OF THE ACTUAL RAINFALL DATA AND PREDICTION OUTPUT BASED ON LRR MODEL (A TO F)

## Conclusion

Rainfall forecasting plays an important role in water resource, agriculture and environment management. We've investigated the prediction models that are simple, applicable, and accurate and also need reachable data. Therefore, constructing models based on only lagged monthly rainfall and its timely combination is mentioned and different models are created and tested.

In application areas, such as meteorological modeling, where the underlying processes have high uncertainty and caveats and are conjectural, applying Gamma test to the selection of relevant variables in the construction of nonlinear models is a useful technique. In this study, we have illustrated how Gamma test is in combination with nonlinear techniques engaged in the construction of non-parametric smooth models for forecasting rainfall. This study deals with an approach to predict rainfall in north of Iran just using lagged monthly rainfall data sets for four years ago and geographical longitude, latitude and elevation in every station. The nature of selecting input variables were analyzed by considering the effects of different input combinations on general statistics related to Gamma test. The quantity of data needed to construct proper models for forecasting annual, spring and summer rainfall was determined using M-test in WinGamma, which has identified to 198.

Also, we have demonstrated the use of nonlinear modeling methods such as Local-linear regression (LLR) and ANNs with BFGS neural network, Conjugate gradient neural networks and Two layer back propagation neural network training algorithms in modeling annual, spring and summer rainfall.

LLR models reasonably performed well in comparison with ANNs training algorithms in validation. Moreover, two layer back propagation neural network training algorithms is to be preferred because of its better performance compared to the other ANN Model. In the meantime, the LRR technique was able to provide more reliable estimations compared to ANN models. It would be interesting to explore this to confirm whether similar results could be repeated in other regions in future.

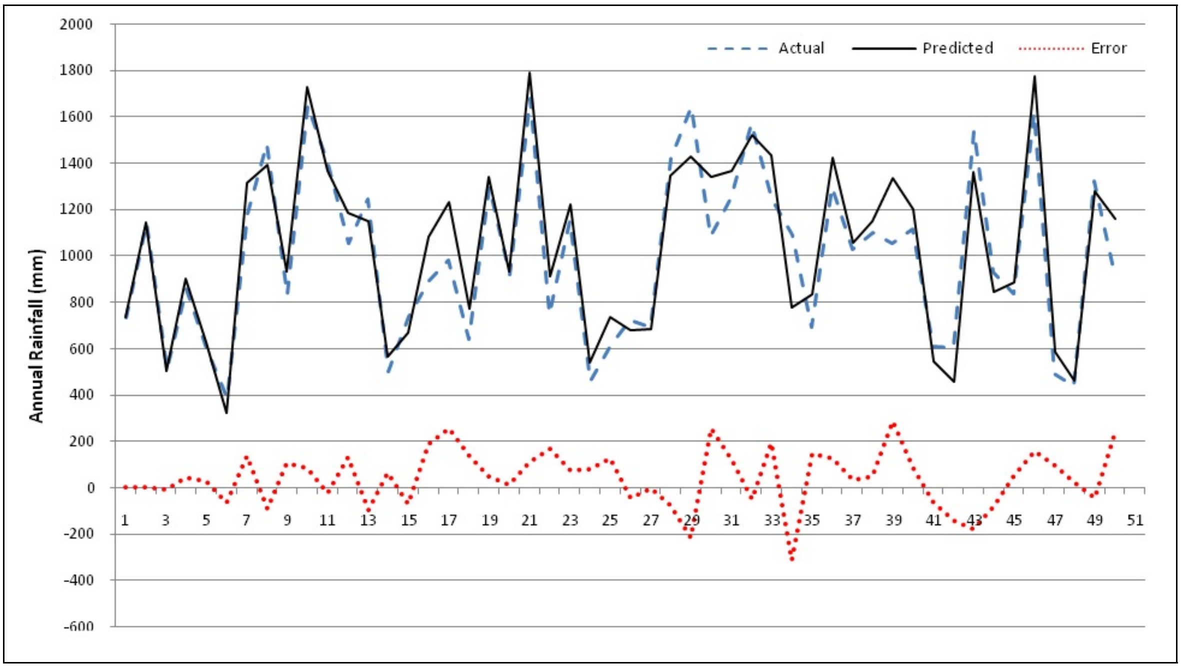



FIG. 3 A CLOSER INSPECTION OF THE LRR MODEL PERFORMANCE ON THE (RANDOMIZED) UNSEEN DATA SHOWS AN ACCEPTABLE ERROR LEVEL. BLACK - MODEL PREDICTION, BLUE - ACTUAL DATA, RED – ERROR

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