

Raingauge Network Augmentation Based on Geostatistical Analysis and Simulated Annealing

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Abstract — The benefits of an integrated Geographical Information System (GIS) and a geostatistics approach to accurately model the spatial distribution pattern of precipitation are known. A number of interpolation methods were proposed for the spatial mapping of rainfall data. Even by using the best available interpolation, there would certainly be an estimation error and hence it is required to improve this error in the form of minimization of variance of the estimation error. On the basis of this criterion a methodology is developed for assessing the optimal localization of new monitoring stations within an existing rain gauge monitoring network. The methodology presented uses geostatistics and probabilistic techniques (Simulated Annealing) combined with GIS. This could be extremely useful in any area where an extension of whatever existing environmental monitoring network is planned. This methodology was applied to the design of an extension to a rainfall monitoring network along the Karuvannur river basin.

Keywords— *Geographical Information System (GIS); Geostatistics; Simulated Annealing*

I. INTRODUCTION

Assessing the spatial distribution of rainfall is frequently required for water resource management, hydrologic and ecologic modeling, recharge assessment and irrigation scheduling. Rainfall data is traditionally presented as point data. However, hydrological modelling requires spatial representation of rainfall and thus the gauge measurements need to be transformed into areal coverages. Direct measurement of rainfall can only be achieved by rain-gauges, and rain-gauge networks are often installed to provide measurements that characterize the temporal and spatial variations of rainfall. Measured rainfall data are important to many problems in hydrologic analysis and designs. For example the ability of obtaining high resolution estimates of spatial variability in rainfall fields becomes important for identification of locally intense storms which could lead to floods and especially to flash floods. The accurate estimation of the spatial distribution of rainfall requires a very dense network of instruments, which entails large installation and

operational costs. It is thus necessary to estimate point rainfall at unrecorded locations from values at surrounding sites.

Data collection from a finite number of monitoring points randomly or systematically distributed is necessary to infer the spatial variability of any parameter under study. The number and distribution of such stations are constrained by numerous factors of which cost and feasibility are quite common to consider. Therefore, it is imperative that an optimal monitoring network can be evolved using a minimum number of observation stations that can provide maximum information. At the same time configuration of a network also depends on the objectives and the end use of the project. Obviously even by using the best available interpolation/estimation techniques, there would certainly be an estimation error and the further objective should be to improve on this error in the form of minimization of variance of the estimation error. On the basis of this criterion a procedure of optimizing a raingauge network using a geostatistical technique can be developed. Performance evaluation of a network focuses on reducing the estimation variance of the areal rainfall. Geostatistical estimation variance reduction is one of the unbiased ways of optimizing a network with a desired degree of accuracy.

Raingauge network designs consist of two key terms, i.e., an objective function and a typical algorithm for its optimization. Rain gauge network design assumes a variety of approaches as pertains to the selection of these two key terms. These approaches concerning the objective function are generally known as variance-based methods, entropy based techniques, fractal-based methods, and distance-based approaches. After casting the required objective function, an optimization algorithm has to be employed to either minimize or maximize the corresponding objective function. Early studies were mostly based on random searches and enumeration. However, for the past three decades or so, researchers have considered some other more systematic

approaches, including the simplex method, the gradient method, simulated annealing, Tabu search genetic algorithm and Ant Colony as common optimization techniques in multiple fields of network design.

II. METHODOLOGY

ArcGIS Geostatistical Analyst was chosen as the tool to implement the interpolations. Geostatistical Analyst is an extension of ArcMap used to generate surface from point data. The software is a powerful, user-friendly package and is flexible for implementation. ArcGIS Geostatistical Analyst provides capability for surface modeling using deterministic and geostatistical methods. The tools it provides are fully integrated with the GIS modeling environments and allow GIS professionals to generate interpolation models and assess their quality before using them in any further analysis.

In Matlab, Global Optimization Toolbox provides methods that search for global solutions to problems that contain multiple maxima or minima. It includes global search, multistart, pattern search, genetic algorithm, and simulated annealing solvers. These solvers are used to solve optimization problems. Simulated annealing is an effective and commonly optimization algorithm used to solve non linear optimization problems. The method models the physical process of heating a material and then slowly lowering the temperature to decrease defects, thus minimizing the system energy.

A. Kriging

An interpolation technique in which the surrounding measured values are weighted to derive a predicted value for an unmeasured location. Weights are based on the distance between the measured points, the prediction locations, and the overall spatial arrangement among the measured points. Kriging is unique among the interpolation methods in that it provides an easy method for characterizing the variance, or the precision, of predictions. Kriging is based on regionalized variable theory, which assumes that the spatial variation in the data being modeled is homogeneous across the surface. That is, the same pattern of variation can be observed at all locations on the surface. Kriging was named for the South African mining engineer Danie G. Krige (1919).

Kriging assumes that the distance or direction between sample points reflects a spatial correlation that can be used to explain variation in the surface. The Kriging tool fits a mathematical function to a specified number of points, or all points within a specified radius, to determine the output value for each location. Kriging is a multistep process; it includes exploratory statistical analysis of the data, variogram modeling, creating the surface, and (optionally) exploring a variance surface.

$$z(x_0) = \sum_{i=1}^n w_i z(x_i) \quad (1)$$

$$\sum_{i=1}^n w_i = 1 \quad (2)$$

B. Semivariogram

Kriging uses the semivariance to measure the spatially correlated component. The semivariance is computed by:

$$\gamma(h) = \frac{1}{2} [z(x_i) - z(x_j)]^2 \quad (3)$$

where $\gamma(h)$ is the semivariance between known points, x_i and x_j , separated by the distance h and z is the attribute value

semivariogram cloud plots $\gamma(h)$ against h for all pairs of known points in a data set. A semivariogram cloud is an important tool for investigating the spatial variability of the phenomenon under study. But because it has all pairs of known points, a semivariogram cloud is difficult to manage and use. A process called binning is typically used in kriging to average semivariance data by distance and direction. The first part of the binning process is to group pairs of sample points into lag classes. The second part of the binning process is to group pairs of sample points by direction. The Geostatistical Analyst extension to ArcGIS uses grid cell for binning.

The result of the binning process is a set of bins that sort pairs of sample points by distance and direction. The next step is to compute the average semivariance by:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{\alpha=1}^{N(h)} [z(u_\alpha) - z(u_\alpha + h)]^2 \quad (4)$$

where $\gamma(h)$ is the average semivariance between sample points separated by lag h , $N(h)$ is the number of pairs of sample points sorted by direction in the bin, and z is the attribute value.

A semivariogram plots the average semivariance against the average distance. Because of the directional component, one or more average semivariances may be plotted at same distance. If spatial dependence exists among the sample points, then pairs of points that are closer in distance will have more similar values than pairs that are farther apart.

C. Models

A semivariogram may be used alone as a measure of spatial autocorrelation in the data set. But to be used as an interpolator in kriging, the semivariogram must be fitted with a mathematical function or model. The fitted semivariogram can then be used for estimating the semivariance at any given distance. Fitting a model to a semivariogram is a difficult and often controversial task in geostatistics. One reason for the difficulty is the number of models to choose from. GeoStatistical Analyst offers 11 models. The other reason is

the lack of a standardized procedure for comparing the models.

A fitted semivariogram can be dissected into three possible elements: nugget, range, and sill. The nugget is the semivariance at the distance of zero, representing measurement error. The range is the distance at which the semivariance starts level off. In other words, the range corresponds to the spatially correlated portion of the semivariogram. Beyond the range, the semivariance at which the levelling takes place is called the sill. The sill comprises two components: the nugget and the partial sill.

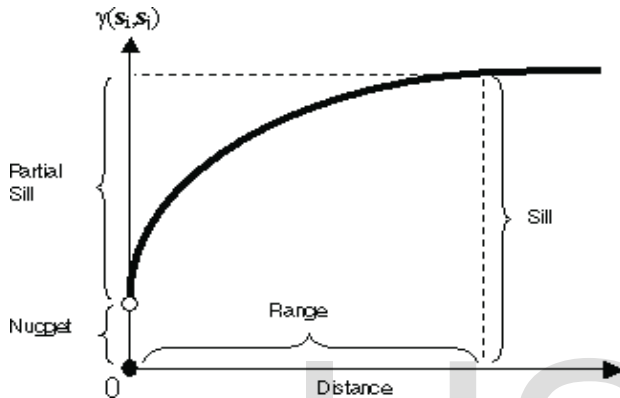


Fig.1 Semivariogram Elements

Two common models for fitting semivariograms are spherical (the default model in Geostatistical Analyst) and exponential. A spherical model shows a progressive decrease of spatial dependence levels off. An exponential model exhibits a less gradual pattern than a spherical model.

Below are the general shapes and the equations of the spherical models used to describe the semivariance.

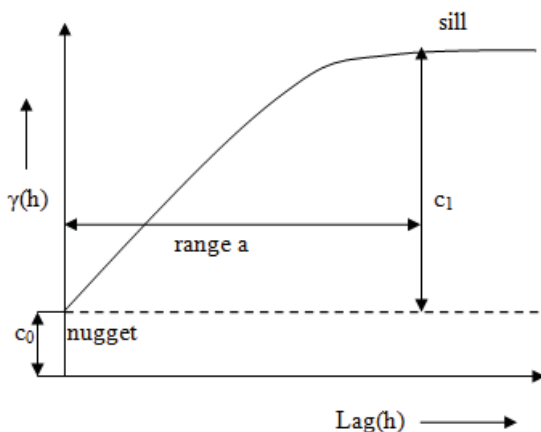


Fig. 2 Spherical semivariogram model

$$\gamma(h) = c_0 + c_1 \left\{ \frac{3h}{2a} - \frac{1}{2} \left(\frac{h}{a} \right)^3 \right\} \text{ for } 0 < h < a \quad (5)$$

$$c_0 + c_1 \text{ for } h \geq a \quad (6)$$

D. Ordinary Kriging

Ordinary kriging focuses on the spatially correlated component and uses the fitted semivariogram directly for interpolation. The general equation for estimating the z value at a point is:

$$z(x_0) = \sum_{i=1}^n w_i z(x_i) \quad (7)$$

where $z(x_0)$ is the estimated value, $z(x_i)$ is the known value at point x_i , w_i is the weight associated with point x_i and n is the number sample points used in estimation. The weight can be derived from solving a set of simultaneous equations.

$$\sum_{i=1}^n w_i \gamma(h_{ij}) + \lambda = \gamma(h_{i0}) \quad (8)$$

$$\sum_{i=1}^n w_i = 1 \quad (9)$$

where $\gamma(h_{ij})$ is the semivariance between known points i and j , $\gamma(h_{i0})$ is the semivariance between the i^{th} known point and the point to be estimated and λ is the Lagrange multiplier, which is added to ensure the minimum possible estimation error. Once the weights are solved, Eqn (3.10) can be used to estimate $z(x_0)$.

The weights used in kriging involve not only the semivariances between the point to be estimated and the known point but also those between the known points. This differs from the IDW Method, which uses only weights applicable to the point to be estimated and the known points. Another important difference between kriging and other local methods is that kriging produces a variance measure for each estimated point to indicate the reliability of the estimation. The variance estimation can be calculated by:

$$\sigma^2 = \sum_{i=1}^n w_i \gamma(h_{i0}) + \lambda \quad (10)$$

E. Optimization Model

In optimization a measure of spatial accuracy (variance of the error of estimation obtained by kriging, σ^2) are combined in a single model and subjected to minimization. Simulated annealing (SA) was used to find the solution. The proposed methodology consists of two steps; in the first it is necessary to define an objective function to be minimized. The second step of the proposed methodology consists in the application of so-called "simulated annealing", which provides a number of random configurations "driven" by the objective function. This method, implemented by Deutsch and Journal (1992).

1) Objective Function

The objective function (OF) is a quantitative formulation of the feature of the monitoring network to be optimized. In practice, once the problem and the monitoring objectives have been set, the choice of the specific OF depends on the available information. For example, if the optimization problem consists in adding one monitoring point to an existing network and the specific goal is to reduce the estimation uncertainty of a given parameter whose variogram model is a priori known, the Kriging Estimation Variance (KEV) can be a suitable OF.

$$\sigma^2 = \sum_{i=1}^n w_i \gamma(h_{i0}) + \lambda \quad (11)$$

OFs quantify the change of ordinary kriging variance produced by adding or removing a location from the network (D'Agostino et al., 1997; D'Agostino et al., 1998; Barca et al., 2008). The kriging estimation variance is a measure of the estimation accuracy and only depends on the geometric configuration of the data points, and, once a variogram model is defined, it is possible to change data locations and calculate the estimation variance again. The coding of the objective function can be done in Matlab.

2) Simulated Annealing

Simulated annealing is a stochastic global minimization technique. The theory of "simulated annealing" is based on the analogy with the organization of the atom network of a metal when it undergoes a process of temperature change (abrupt heating and slow cooling). Following this process, the atoms of the metal change their arrangement to a configuration of low energetic maintenance cost. In the analogy, the configuration of the atoms corresponds to that of the sampling points while the objective function corresponds to the energy of the system (Pardo-Igúzquiza 1998, Deutsch and Cockerham 1994).

The simulated annealing algorithm simulates the metallurgical process of annealing (when a material undergoes extended heating and is then slowly cooled). There is an imaginary analogy between the disposition of the rain gauges in a given area, and the state of atoms/molecules in a lattice-like physical system. Each configuration of atoms/molecules in the lattice is characterised by a given energy. At high temperatures, thermal vibrations permit a reordering of the atoms/molecules to highly structured lattices of low energy. As temperature decreases slowly, the thermal vibrations attenuate and the system tends to the highest structured (lowest energy) configuration.

In the rain gauge network problem, the energy of each configuration is given by the value of the objective function, and temperature is a fictitious parameter that is calibrated empirically for a given data set. At the beginning of the simulation the temperature must be high enough so as to permit the possibility of any configuration of rain gauges, and the cooling of the system is done following a precise annealing schedule.

In algorithmic terms, with reference to the described metallurgical analogy (Metropolis et al. 1953), assign an initial value to the temperature of the system, then randomly choose a starting configuration from all the possible configurations, and determine the corresponding value of the objective function, which is called energy. The temperature drives the duration of the process and, at every following step it decreases down to zero, which is the final temperature; the slower the cooling the higher the probability of finding the optimal configuration is, while the greater the initial temperature, the higher is the probability that the final configuration matches the absolute optimum that is the absolute minimum for the objective function. The starting configuration is perturbed in a randomised way, varying the position of only one sampling point of the monitoring network at a time, and the corresponding value of the objective function is computed again. If the perturbed configuration is better than the previous one (i.e.: the value of the objective function decreases) it is assumed as a transitory excellent solution; otherwise, the new configuration is not automatically discharged, as would happen with a classical method of optimisation, but it is submitted to a probabilistic criterion of acceptance which compares it again with the transitory optimal configuration. If this probabilistic criterion establishes that the configuration is acceptable, it is accepted according to the probability factor P:

$$P = \exp\left(-\frac{\Delta E}{T_i}\right) \quad (12)$$

where ΔE represents the variation of the objective function, and T_i the current value of the temperature parameter, is smaller than a randomly generated number. This test allows the method to avoid the process of converging to a local optimum rather than the global one.

a) Basic Algorithm of simulated annealing

1. Choose a random X_i , select the initial system temperature, and outline the cooling (ie. annealing) schedule.
2. Evaluate $E(X_i)$ using a simulation model
3. Perturb X_i to obtain a neighbouring Design Vector (X_{i+1})
4. Evaluate $E(X_{i+1})$ using a simulation model
5. If $E(X_{i+1}) < E(X_i)$, X_{i+1} is the new current solution
6. If $E(X_{i+1}) > E(X_i)$, then accept X_{i+1} as the new current solution with a probability $e^{(\Delta/T)}$ where $\Delta = E(X_{i+1}) - E(X_i)$.
7. Reduce T according to the cooling schedule.
8. Terminate the algorithm.

where T = System Temperature, E = Objective function

b) Outline of the procedures for upsizing the network

1. Given the k number of points to be added to the existing network formed by n points, the value of the kriging variance must be computed at all unsampled points over the interest area on the basis of information provided by the existing network

2. Find the co-ordinate where the kriging variance value is the maximum
3. The kriging variance must be recomputed at the unsampled points adding to the network the point found at the previous step
4. Repeat points 2) and 3) of the procedure until all k points are added to the existing network.

The Simulated Annealing solver in Matlab optimization tool assumes the objective function will take one input x , where x has as many elements as the number of variables in the problem. The objective function computes the scalar value of the objective and returns it in its single return argument y . To minimize the objective function using the `SIMULANNEALBND` function, need to pass in a function handle to the objective function as well as specifying a start point as the second argument. The first two output arguments returned by `SIMULANNEALBND` are x , the best point found, and $fval$, the function value at the best point. A third output argument, `exitFlag` returns a flag corresponding to the reason `SIMULANNEALBND` stopped. `SIMULANNEALBND` can also return a fourth argument, `output`, which contains information about the performance of the solver.

III. STUDY AREA

The Karuvannur watershed lies between $10^{\circ} 15'$ to $10^{\circ} 40'$ North latitude and $76^{\circ} 00'$ to $76^{\circ} 35'$ East longitude within Thrissur district and shares the Western boundary of Palakkad district of Kerala and thereby covers an area of 1054 km². It is bounded by Thrissur and Chavakkad Taluks of Thrissur district in the North, Mukundapuram and Kodungallur Taluks of Thrissur district in the South, Alathur and Chittor Taluks of Palakkad district in the East and the Arabian Sea in the West.

The Karuvannur River originates from the Western Ghats and is fed by its two main tributaries, viz., the Manali and the Kurumali. The Manali River originates from Ponnemudi in the border of Thrissur and Palakkad districts at an elevation of + 928 m. The Chimony and Muply, the two subtributaries of the Kurumali originate from Pundimudi at an elevation of + 1116 m. The other streams which feed these tributaries include the Chauralaar, Chimonipuzha, Talikuzhi, Mupilipuzha, Idukuparathodu, Sinikuzhithodu, Manaliar, Pullathodu and Kunjirupuzha. Peechi dam constructed across Manali River and Chimmoni dam across Kurumali River help to control the flood and irrigate the land.

The Thrissur district has a tropical humid climate with an oppressive hot season and plentiful seasonal rainfall. The glaring aspect of the land use of the district is that it is blessed with potential resources such as agricultural land and forest. Karuvannur watershed is mainly covered with mixed plantation and forest area. The soil textures of Karuvannur watershed are mainly gravelly clay, clay, loam, sand and gravelly loam. The water penetration depends upon type soil texture. Sand has high water penetration capacity and clay has high water holding capacity than any other soil type.

Karuvannur river basin is one of the major river basins within the district with an actual utilizable water resource of 623 Mm³ of which the net utilizable surface and ground water resources are 519.8 Mm³ and 103.2 Mm³ respectively. Karuvannur river has a drainage area of 1054 km², stream length 48 km, average monsoon flow of 1275 Mm³, average lean flow 55 Mm³ and total flow 1330 Mm³ (Rajagopalan and Sushanth, 2001). The average rainfall in the low land of the river basin was estimated to be 2858 mm, the midland 3011mm and the highland 2851mm. About 60 per cent of the rainfall is received during south west monsoon period, 30 per cent from north east monsoon and 10 per cent in the pre-monsoon period.

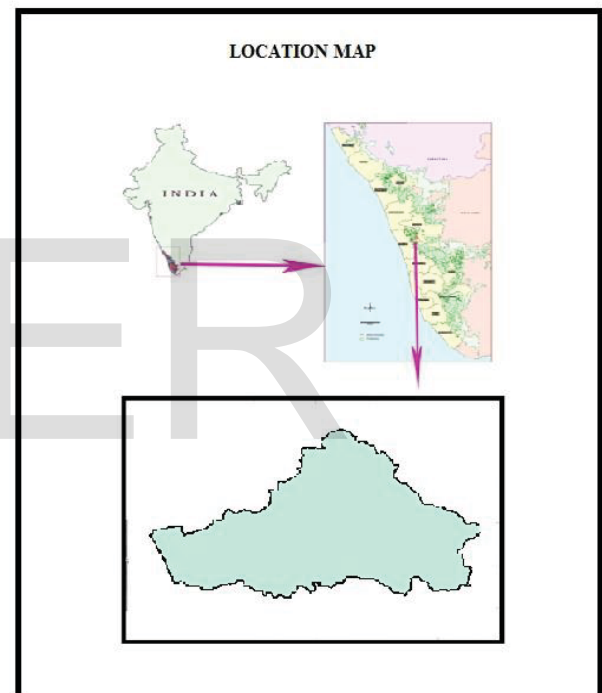


Fig. 3. Location Map of Study Area

IV. DATA DESCRIPTIONS

Data preparation and analysis was carried out using Ms Office excel and ArcGIS 10. ArcGIS 10 provided the GIS platform for visualization, manipulation of data production of maps. The ArcGIS Geostatistical Analyst tool was used for interpolation, production of maps and error plot. The tool provides advanced statistical tools for surface generation, analysis and mapping of continuous datasets.

TABLE 1. DATASET

Dataset	Type	Source	Specification
Rainfall Data	Rain gauge data, Tabular	Hydrology Department	Primary Data
DEM	Elevation (Raster)	http://srtm.csi.cgiar.org/index.asp	Secondary Data(90m Resolution)
Karuvannur Basin Boundary	GIS File	Watershed Atlas of Kerala, KFRI	Secondary Data(Shape file)

A. Rainfall Data

Daily rainfall data for 21 raingauge stations, for the year 2012 were obtained from the Hydrology Department. Out of the same 14 raingauge stations were within the Karuvannur river basin and 7 stations lie around the basin. The heaviest rainfall event of the year 2012 was selected for the augmentation of raingauge network. This is due to the fact that this rainfall event was recorded at all the stations which eliminate the skewness that would be introduced by stations with no rainfall

TABLE 2. RAINGAUGE STATIONS IN KARUVANNUR RIVER BASIN

Station	Longitude	Latitude	Elevation(M)
Peechi	76° 21' 59"	10° 31' 30"	95
Pudukkad	76° 22' 49"	10° 26' 15"	39
Triprayar	76° 07' 18"	10° 23' 45"	8
Echippara	76° 27' 00"	10° 26' 27"	47
Enamakal	76° 06' 30"	10° 30' 30"	-4
Irumpupalam	76° 23' 15"	10° 34' 15"	86
Karikkadavu	76° 26' 47"	10° 22' 16"	76
Mupli	76° 23' 46"	10° 25' 00"	42
Mathilakam	76° 10' 37"	10° 17' 37"	11
Ollukara	76° 16' 00"	10° 32' 00"	29
Pottimada	76° 21' 59"	10° 34' 45"	80
Vaniampara	76° 25' 30"	10° 34' 20"	109
Varandharapilly	76° 20' 40"	10° 25' 20"	24
Panachery	76° 18' 00"	10° 33' 00"	27

TABLE 3. RAINGAUGE STATIONS NEAR TO KARUVANNUR RIVER

vettilappara	76° 32' 00"	10° 17' 30"	88
Parambikulam	76° 46' 00"	10° 23' 00"	576
Pazhayannur	76° 20' 30"	10° 40' 20"	49
Thumburmuzhy	76° 29' 00"	10° 18' 00"	69
Thunakadavu	76° 47' 01"	10° 25' 00"	655
Vynthala	76° 18' 01"	10° 15' 50"	13
Kunnamkulam	76° 04' 00"	10° 38' 45"	24

B. Digital Elevation Model

The Digital Elevation Model (DEM) well define the topography of the area by describing the elevation of any point at a given location and specific spatial resolution as a digital file. The DEM was downloaded from the site, <http://srtm.csi.cgiar.org/index.asp>. Accuracy of DEM is better for SRTM (Shuttle Radar Topography Mission) than ASTER (Advanced Space borne Thermal Emission and Reflection) and hence the same was used in the study, though the spatial resolution of SRTM is 90m and that of ASTER is 30m. The DEM data was loaded into ArcGIS it was projected into one equal area projected coordinate system. Normally, Universal Transverse Mercator (UTM) is used.

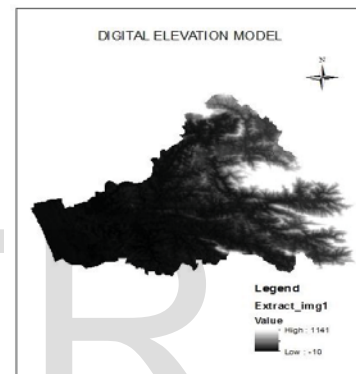


Fig4. DEM of Karuvannur River Basin

C. Karuvannur Basin Boundary

To create the shape file of the Karuvannur river basin boundary, toposheets for the required area was collected from the Kerala Forest Research Institute, Peechi. The basin boundary from the watershed atlas was georeferenced with respect to the mosaiced toposheets which was later digitized to obtain the boundary shapefile. To get the location map of raingauge station, the MS Excel sheet that contain the latitude and longitude of the stations were exported to the ArcGIS platform.

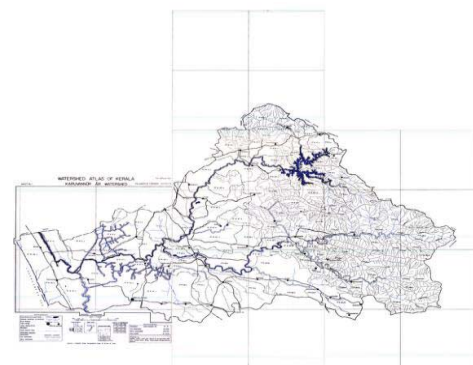


Fig.5 Karuvannur River Basin

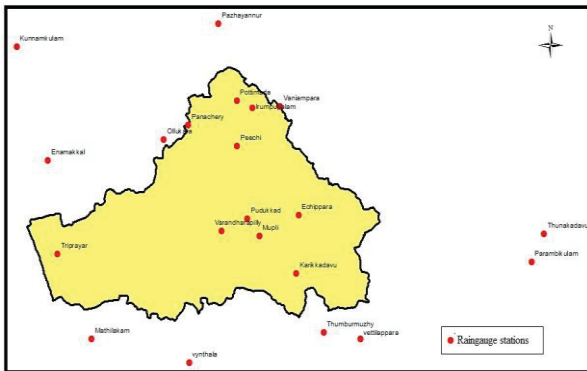


Fig. 5 Location Map of Rain gauge Stations in Karuvannur River Basin

V. RESULT AND DISCUSSIONS

A. Rain gauge Network Augmentation

It is clear that the estimated variance is an important factor for determining the location of rain gauges, the variance depends only on the geometrical location of the rain gauges. Obviously, the choice of variogram model and its parameters is conditioned by the particular set of available data. But once the variogram model is chosen, the variance can be viewed as depending exclusively on the location of the rain gauges. Hence it becomes possible to compute the error variance associated with any set of hypothetical data points without getting actual data at these points.

The estimation variance is thus very suitable objective function for network optimization. The existing network of rain gauges can be replaced or supplemented by the best representative new set of rain gauge at specified locations.

1) Spatial Simulated Annealing

Spatial simulated annealing (SSA) has been applied to the selected Objective Function, namely the Kriging Estimation Variance (KEV). In the initial stage of optimization, variogram model was fitted to data set to get the variogram model parameter. Objective function was generated from the available rainfall data, Coordinates of available rain gauge stations and variogram model parameter.

2) Variogram model Fitting

Variogram model of data set was estimated in Arc GIS. Fig. 7 shows the Experimental semivariogram cloud. It is then binned and averaged. Spherical semivariogram model was fitted to the averaged semivariance as shown in Fig. 8

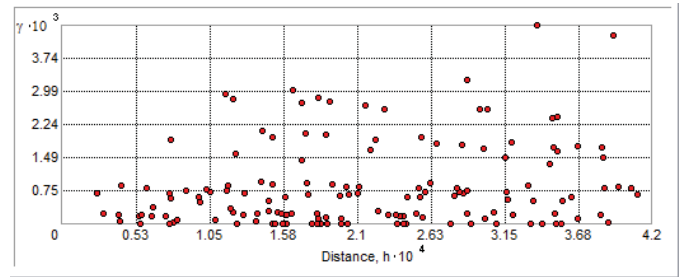


Fig. 7 Experimental semivariogram cloud

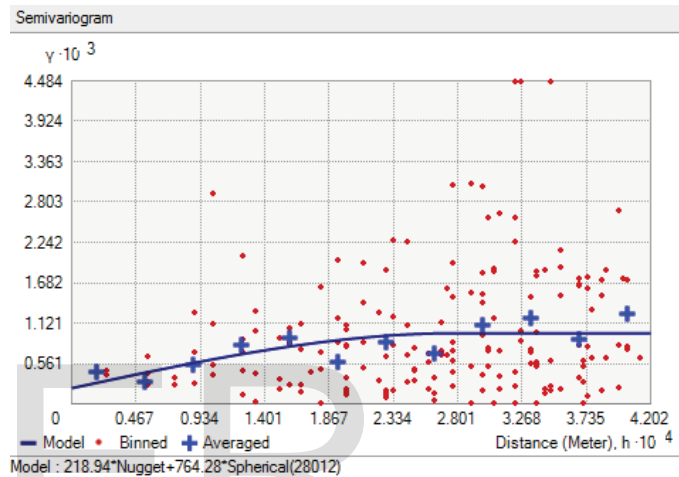


Fig. 8 Fitted Spherical Semivariogram

TABLE 4. VARIOGRAM MODEL PARAMETERS.

Model Type	Nugget	Sill	Range
Spherical	218.94	983.2158	28012

When the simulated annealing solver starts running for the selected objective function and specified annealing parameter, it performing a number of iterations depending on the specific optimization setting, and stops when a suitable criterion was met. Stopping criteria was selected as Function tolerance ie, If the OF value, for a long run of iterations, does not change significantly with respect a tolerance value given by the user, the run stops.

During the whole execution, simulated annealing optimization tool allows the user to follow the optimization evolution by means of a specific graphical interface. Finally, once terminated the simulation, it provide a comprehensive report of optimization results. For each run gauges were added at sites with large estimation variance, and the process was repeated until the average prediction error could not be reduced further. The sites that resulted in the most significant reduction of estimation error were identified as place for new precipitation gauges.

Fig. 9 shows the result of the optimization simulation performed with the simulated annealing tool in Matlab.

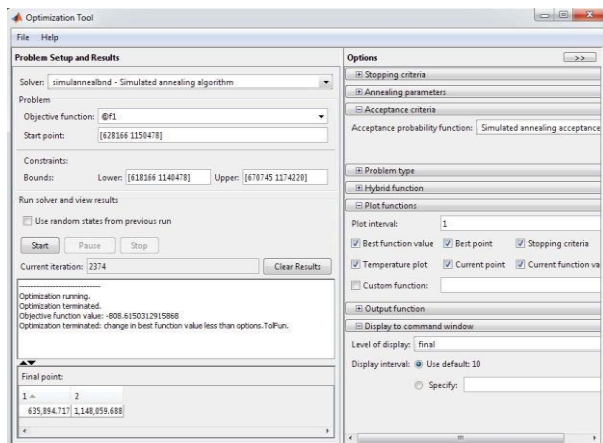


Fig. 9 Simulated Annealing Solver in Optimization Toolbox

Fig. 10 shows the graphical interface of the simulated annealing solver in the optimization toolbox.

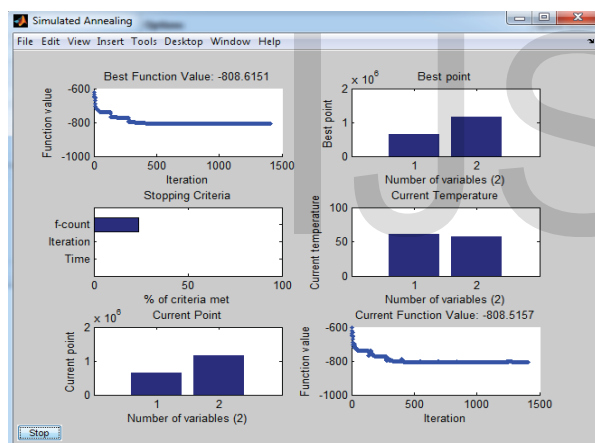


Fig. 10 Plot Function of Simulated Annealing Run

TABLE 5. RECOMMENDED ADDITIONAL GAUGE LOCATIONS AND ELEVATIONS

Stations	Easting (x)	Northing (y)	Elevation (m)
New station 1	635894.203	1148066.836	-1
New station 2	638602.029	1156043.253	10
New station 3	644661.95	1159162.093	56
New station 4	670518.589	1155401.9	867

New station 5	647259.746	1144478.28	22
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Fig. 11 shows the location map of rain gauge stations. Black dots in the figure are those already existing stations and Red dots are those added to the existing monitoring network as requested.

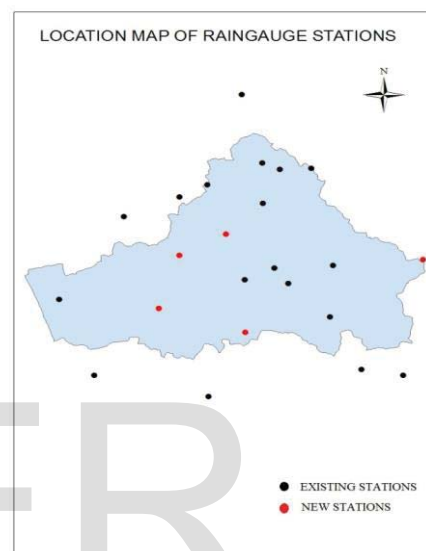


Fig. 11 Location map of existing and new stations

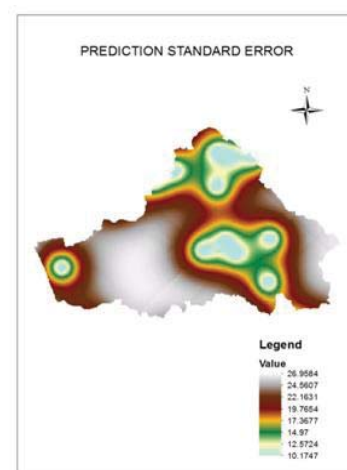


Fig. 12 Prediction Standard Error before Augmentation

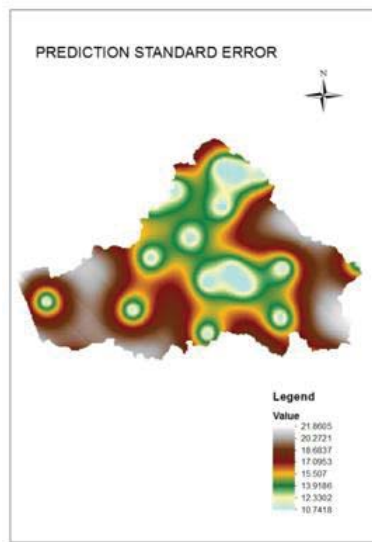


Fig. 13 Prediction Standard Error after Augmentation

In Fig. 14, the plot of average prediction error versus the number of samples is shown. The error of estimation decreases with the optimal location of additional points.

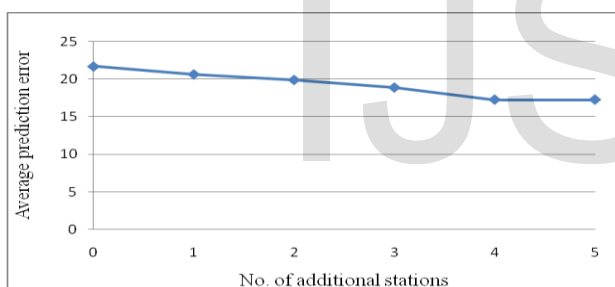


Fig. 14 Average prediction error of estimation versus the number of samples in the augmentation.

VI. CONCLUSIONS

The Spatial Simulated Annealing (SSA) can be applied to the selected Objective Function (OF), namely the Kriging Estimation Variance (KEV) to augment the raingauge network. The algorithm always converges towards the global optimum or very near the global optimum and it is easy to implement as well as being economic in computer terms. The result of the simulated annealing run defines the UTM co-ordinates of the optimal locations where the 5 new raingauge stations should be placed. Gauges were added at sites with large estimation variance, and the process was repeated until the average prediction error could not be reduced further. The sites that resulted in the most significant reduction of estimation error were identified as place for new precipitation gauges.

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