Chapter 15
Rating Irrigation Canals Using Cognitive Indexes

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Abstract The main objective of this investigation was to identify an optimal configuration to enable irrigation canals to withstand future uncertainties from climate change and uncontrolled urbanization. To accomplish this objective, a set of factors was selected based on their influence on the stability and functionality of irrigation canals. The selected factors were of two types: conducive, which increase the efficiency of irrigation canals, and deductive, which decrease it. All the variables were rated with respect to their capacity to increase efficiency on a scale of one to nine, where nine is assigned for efficiency-increasing ability and one is assigned to efficiency-decreasing abilities. All possible combinations one the nine-point scale rating of the factors were created to make a combinatorial data matrix that represents every possible situation that might arise in an irrigation canal. The data set was then clusterized with the help of guided neuroclustering methods (GNCM) and an agglomerative decision tree algorithm (DTA). According to the clusterization and comparison of the two methods, the sample with the optimal configuration that both clustering algorithms had selected within their optimal clusters was identified. The selected combination was recommended in the construction of new canals to increase the canals' longevity. According to the clusterization method, flow volume in the canal can be semihigh, but variation in the flow must be very low. Channel loss and demand from farmers must be semi and extremely low, respectively, and there should be as many buffer ponds as possible and the contribution from groundwater must be maximized. The amount of sedimentation must be minimized. That is, an irrigation canal must be developed in such a way that demand from farmers is highly regulated. A large number of buffer ponds must be created in and around the canal. Preventive measures must be strictly imposed to control inflow volume, channel loss, flow turbulence, and sedimentation. Infrastructure to store excess water must be available so that excess water from extreme events can be stored for

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use in times of high demand. Only canals with the above recommended configurations will be able to withstand the vulnerabilities that will arise in the near future from abrupt changes in climate and uncontrolled growth in urban populations.

Keywords Irrigation canals • Decision tree algorithms • Neuro-clustering

15.1 Introduction

The demand for water from the domestic, agricultural and industrial consumers is increasing due to the rapid scale of urbanization observed in most of the major cities of the World. Keeping in view of the impact of climate change due to global warming and uncontrolled growth in population the quality and quantity of the available water resource is shrinking. As a result of population overgrowth, demand for food is rising which in turn has increased the use of water for irrigation. The large scale industrialization to satisfy the demand from the rising population has also increased the demand for water from the industrial sector. That is why rivers all over the world, especially tributaries and dis-tributaries, which are one of the major sources of water, are under threat of extinction from this ever-rising demand. Large scale industrilization and rapid increase in the urban population has also incremented the pollution content of the water bodies.

Indexes are now widely used for qualitative as well as quantitative, but logical, decision making. For example, Sheng et al. (1997) used a geographic information system (GIS) for classification of watersheds in developing countries. Hajeka and Boyd (1994) attempted to design an index to select suitable sites for aquaculture ponds. The methodology was similar to that developed for systems used in the evaluation of soil for irrigation, road construction, waste disposal, and residential development. The potential impact of agriculture drainage on quality of water of receiving streams was evaluated by Brenner and Mondok (1995) with the help of a watershed delivery factor, animal nutrient factor, management factors that were actually indices with fecal coliform and phosphorus as the influential parameters, and a groundwater delivery factor where nitrate concentration of the streams was found to be most the influential determinant. Heathwaite et al. (2000) developed an index to identify the sources and transport pathways that control phosphorus and nitrogen transport. According to the index, P loss was found to be maximum in well-defined areas of watershed, whereas nitrate loss was observed mainly upstream of the watershed. Wanqa et al. (1997) conceptualized the index of biotic integrity (IBI) to determine the relationship between biotic richness and urbanization of a watershed. The index was found to be directly correlated with forest cover but indirectly related to agricultural land, which is again proportional to the amount of urbanization. From the study it was concluded that more than 10–20% urbanization is not good for biotic integrity. Indices also were used in site selection for shrimp farming. Slope, land-use type, soil thickness, elevation, soil type, soil texture, soil pH, distance to sea, distance to roads, local markets, and hatcheries were selected as deciding parameters. Areas that were not allowed to be used for shrimp farming were excluded. A series of GIS models was employed to identify and prioritize the suitable areas for shrimp farming. Only 31% of the land of the study area (in Hiphong) was found to be optimal for shrimp farming. Karthika et al. (2005) used a land-use index to identify suitable sites for brackish water aquaculture in Thane districts of Maharashtra, India. Stagnitti and Austin (1998) developed an independent software tool for the selection of new aquaculture facilities. Principal component clusterization was performed to classify watersheds for environmental flow predictions based on spatial characteristics. The method included 56 parameters to form 5 representative groups of watersheds. The study was conducted by Alcázar and Palau (2010) for the Mediterranean countries. Shaw and Cooper (2008) developed an index that represents the relationship between watershed, stream reaches, and plant type. A study was conducted by Falcone et al. (2010) to compare indices representing the relative severity of human disturbance in watersheds. According to the results, indices composed of many variables performed better than those with single variables. A "threshold method of scoring using six uncorrelated variables: housing unit density, road density, pesticide application, dam storage, land cover along a mainstream buffer, and distance to nearest canal/pipeline" was found to be best representative of anthropogenic disturbances of the watersheds. Jacobs et al. (2010) developed an index of wetland conditions with the help of hydrogeomorphic variables. The index was applied to classify the wetlands of Nanticoke River watersheds. The variables were scored with respect to "range check, responsiveness and metric redundancy." Water quality, evapotranspiration, runoff, species diversity, species health, and stakeholder participation were used by He et al. (2000) to develop an ecological indicator for the assessment of the conditions of altered watersheds. The fuzzy set models were used to prioritize watersheds with respect to the scope of fisheries and abatement of non-point-source pollution by Wenger et al. (1990). Both stream use and stream conditions were utilized to develop the indices for application in the Kewaunee River Basin in Wisconsin, USA. Wang et al. (2010) proposed a framework to evaluate the impacts on watershed ecosystems caused by hydropower development. Watershed ecosystem services were classified into four categories – provisioning, regulating, cultural services, and supporting services – with the help of 21 indicators. Various evaluation techniques (market value method, opportunity cost approach, project restoration method, travel cost method, and contingent valuation method) were used for the calibration of the models. The models helped to identify the key impacts of hydropower development on watershed ecology, like on biodiversity; water quality was found to be negatively impacted by development; the average environmental cost per unit of electricity was derived to be three times the on-grid power tariff, and overall the degradation in watersheds was found to be compensated adequately by extracting maximum utility from the hydropower plant. Zhang and Barten developed an information system for the analysis of the impact of watershed degradation on water yield. The Watershed Forest Management Information System has three submodules. The first module has to do with the prioritization of watersheds based on conservation and restoration requirement. The second module, Forest Road Evaluation System, is concerned with impact analysis of road networks on forest cover. The last module, Harvest Schedule Review System, was developed for the evaluation of multiyear and multiunit forest harvesting, which will assist in reducing the impact of these factors on water yield and associated changes in water quality.

The success of the indices in the identification, delineation, or representation of a decision with respect to related parameters encouraged the authors to create indices for the irrigation canals to rate them according to their ability to suppress ever-increasing demand and number of extreme events.

15.2 Artificial Neural Network

An artificial neural network (ANN) can be defined as a network of complex interactive signal processing networks that mimics the human nervous system while transporting an error signal. The methodology for the development of neural networks for practical problem solving comprises three major steps: building, training, and testing the network. The neural network topology i.e. number of hidden layers necessary to yield accurate results are first identified by the applications of trial and error or any search algorithms. The next step is to train the model for identification of optimal values of weightage with the help of available dataset (referred as training dataset) of the present problem. This goal is achieved by the use of various training algorithms like Quick Propagation, Conjugate Gradient Descent, Batch Back Propagation etc which continuously generates values of weightage and the corresponding predictions are compared with the outputs given in the training data set. In the last phase, the model is tested with a set of dataset which are not used in the training dataset but output of them is known. This step is necessary for verifying the model for its accuracy with datasets that are not utilized in the training data (i.e., dataset with which the model has learned the problem). The model predictions are verified with the help of common performance metrics like Root Mean Square Error, Correlation, Covariance etc. and until and unless the desired accuracy is achieved the model is not allowed for prediction of unknown situations.

Neural networks can be classified based on their topology, error path followed, and activation function used. A network can contain input, output, and hidden layers. Hidden layers are simply a set of pseudo-input layers that creates an additional set of input layers so that the entire error reduction procedure is followed twice before the prediction of the output. The objective problem determines the configuration of the network topology along with the error achieved. Generally, trial and error is followed, but scientists nowadays use specialized search algorithms to find the optimal configuration of neural networks.

The neural network is a topology that the error signals of a problem follow to reduce errors. According to the path followed by the error signal, neural networks can be grouped into feedforward and feedback network systems. The names followed in a feedforward neural network error always propagate to the forward layer of the network, and in the case of feedback the same signal will follow the back path based on a comparative analysis to evaluate the existing accuracy.

In the case of training algorithms, perceptron algorithms (Rosenblatt 1957), gradient descent (Snyman 2005), and batch back-propagation (Bryson and Ho 1969) algorithms are the most popular. During a training session the main objective of the network is to reduce error by applying different algorithms to solve the problem. Many authors have tried to achieve different objectives and solve complex problems through simple or modified versions of neural models. Below is an overview (Table 15.1):

Table 15.1 Relevant studies related to application of neural networks in clusterizing a representative data set

References	Type of neural network applied	Study objective	Remarks
Raju et al. (2006)		Sustainable irrigation planning	
Rodriguez and Martos (2010)		Surface irrigation parameter identification	
Chavez and Kojiri (2007)	Stochastic fuzzy neural network	Maximum water use and improvements to water quality	
Yang et al. (2009)	Generalized regression neural network	Prediction of leaf area index, green leaf chlorophyll density of rice based on reflectance, and its three different transformations: first-derivative reflectance, second-derivative reflectance, and log-transformed reflectance	
Gautam et al. (2004)	Back-propagation algorithm	Effect of bridge construction on spatial variation of groundwater level	
Torfs and Wójcik (2001)	Local probabilistic neural networks	Analyzing effectiveness of a new ANN algorithm that tries to prove that when inputs are lagged, accuracy is maximized in the case of inputs near the actual value. A case study of predicting discharge for a small watershed was used to substantiate the above objective	
Filho and Santos (2006)	Three-layer feedforward ANN trained with linear least-squares simplex training algorithm	Flood wave simulation with rainfall, stage level, or stream flow as input	
Yoon et al. (2011)	Back-propagation algorithm	Predicted groundwater level with past groundwater level, tide level, and precipitation as input	
Wu and Chau (2011)	Modular artificial neural network (MANN) and data preprocessing by singular spectrum analysis (SSA)	This paper aims to eliminate the lag effect of ANN models in rainfall–runoff models	
Mougiakakou et al. (2005)	Classic NN modified using genetic algorithms	This paper classified the land use pictures of 106 different locations, divided into common, normal, and distinctive classes, with respect to their scenic beauty	

15.3 Decision Tree Algorithm (DTA)

In statistics and data mining, decision tree learning is used to categorize data sets according to predetermined attributes. The learning algorithm of a DTA uses a decision tree "as a predictive model which maps observations about an item to conclusions about the item's target values". The DTA is also known as classification trees or regression trees where leaves represent classifications and branches represent conjunctions of features that lead to those classifications.

DTAs are known to be useful for classification purposes. Although they have been used rarely, they are popular for their well-known classification ability. Some examples are listed below:

(a) Release rule configuration of a flood-control reservoir (Wei and Hsu 2009)
(b) Water quality analysis (Litaor et al. 2010)
(c) Reconstruction of missing daily data (Kim and Pachepsky 2010)
(d) Change detection analysis (Pilloni et al. 2010)
(e) Image classification (Yang et al. 2003)
(f) Topological classification (Simon et al. 2007) and in many other decision-making approaches.

15.4 Methodology

The problem of developing an index lies in the selection of its independent parameters upon which a decision about the ratings could be undertaken. Volume of flow, annual variation of flow, channel loss, storage capacity, groundwater contribution, demand from farms, presence of buffer ponds, and sedimentation were considered as independent parameters of incident that are also merely correlated with each other. The justification for the selection of these parameters is given below:

1. *Volume of flow (Q)*: one of the most important parameters of irrigation canal design is volume of flow. The Dimensional properties of the hydraulic structure is estimated based on the volume of flow.
2. *Annual variation of flow (Q_v)*: the distribution pattern of the annual variation in monthly water discharge represents the maximum and minimum amount of flow in the canal. Design of canals for highly varied flow is prone to errors and often is the main cause of overflow and submergence of agricultural lands at a buffer. But for a steady flow the canal faces less uncertainty, making the task for designers easy.
3. *Channel loss (L)*: the loss of water from a canal can be determined as the amount of water that has either infiltrated or evaporated during the time of flow through the canal. This parameter also represents the canal efficiency when loss and water withdrawn are deducted from the volume of inflow and divided by only inflow. The more water is lost, the less able it will be to withstand uncertainty and stress from extreme events.

4. *Storage capacity (S)*: the capacity of a canal to store water. The higher the storage, the lower will be the chance of overflow. The hydraulic structure of the canal will determine its storage capacity. The storage capacity of a canal can be calculated with the help of the hydraulic radius and depth along with the length of the river canal.
5. *Groundwater contribution (G)*: Irrigation canals are generally fed by groundwater during the summer season, and groundwater is recharged by the canal during the monsoon season. This effluence and affluence relationship between the canal and groundwater helps to maintain the water level so that adequate water can be available for harvesting.
6. *Demand from farms (D)*: The demand of water from adjacent agricultural land depends upon the type and frequency of crop harvested, where hydrophilic crops create more demand and hydrophobic crops have lesser requirements for water. But as most cash crops are of the hydrophilic type, demand for water is generally high from the buffering irrigation fields, which again increases the stress on the canal and, often due to the overuse of the canal, creates water scarcity. Again multicrop practices will entail higher demand than monocrop agro lands. The method of water withdrawal from agro-fields will also influence the demand for water from the canal. A sprinkler-irrigated field will demand more water but lose less water than drip irrigation, which will have lower demand but greater loss of water. The type of irrigation practice will also depend on the type of crops being harvested. Thus, such parameters were not considered explicitly. The method of withdrawal of water will also influence the amount of water required. If pumps are used, then large amounts of water will be withdrawn per cycle, but if withdrawal is done by collectors or tube wells, then the amount of water withdrawn per cycle will be less than pump-controlled irrigation.
7. *Presence of buffer ponds (B)*: buffer ponds are generally made to store water in times of scarcity. During summer or in the absence of rain for a long duration such ponds are used by farmers. The presence of buffer ponds greatly reduces the stress on canals. Thus, the more ponds there are, the higher will be the canals' ability to sustain uncertain periods.
8. *Sedimentation (V_s)*: the amount of sedimentation will impact the amount of water that can be carried or stored within the canal. A heavily silted canal will not be able to withstand high volumes of water during positive extreme events like floods.

The classification work was performed by a neural network due to its pattern identification ability as observed and discussed in many scientific studies. The factors were fed to the model as input parameters. The networks' categorization ability was utilized to estimate the cluster of the data sets. At first a training data set was fed to the model so that the characteristics of individual clusters could be identified. Based on the characteristics of clusters the new data set representing situations of uncertainty was fed to the model. This new data set was clusterized, and, because the characteristics of the clusters were already known, the decision-making process about the ability of the canal to sustain uncertainty could easily be estimated.

The same data set was again classified with respect to the DTA. The threshold values were determined with the help of the Euclidean distance from the mean.

Before the data were fed for clustering, the entire data set was rated on a scale of 1–9, where the higher limit was given to the conducive data set and the lower limit was fixed for the deductive data set. That means the rating was inversely proportional to the suitability of canals to withstand abnormal climate conditions.

15.5 Results and Discussion

The clustering of the available sample was performed with the help of neural networks with 11 inputs, 1 output, a log-sigmoid activation function, 1,000 iterations, and 0.3 initial weight, and the clustering radius was kept at 30%. There are a total of 1,138 data samples. The data set for training consisted of 9 rows of data, which clearly portrays the characteristics desired in the nine clusters. Cluster 1 was found to include the most suitable combinations of input factors where the canals could withstand prevailing climate uncertainties. Table 15.2 presents the maximum and minimum values of the factors for each cluster of the training data set. Clearly, Cluster 1 will contain the combination of factors by which a canal will be able to withstand the uncertainties of climate change and urbanization.

Figure 15.1 depicts the weight profile or distribution of clusters within the sample data set, where of 1,138 samples 10.82% were found to be most suitable and 11.43% least suitable to withstand abnormalities in climate and human population changes.

Analysis of the cluster characteristics revealed that Clusters 1 and 9 did not represent the most and least suitable irrigation canals. For example, sample locations that had high sedimentation, low concentration of buffer ponds, low storage capacity, high variation of flow, and high channel loss were also grouped into Cluster 1. But samples with a high storage capacity and moderate groundwater contribution and frequency of buffer ponds were grouped into Cluster 9.

That is why the neuroclustering method was found to be error-prone and did not represent the true situation of the samples.

In addition, a guided neuroclustering method (GNCM) was followed where a summation of all the factor ratings of the conducive factors were divided by the summation of all the deductive factors and the normalized results of the same were added as an input variable and the samples were re-clustered:

$$\text{Objective Function}\left(\text{Obj}\right) = \left(\text{QXSXGXB}\right) / \left(\text{Q}_{\text{v}}\text{XLXDXV}_{\text{s}}\right) \tag{15.1}$$

For each of the samples, *Eq. 15.1 was calculated and normalized according to Eq. 15.2:*

$$\text{Obj Normalized} = \left(\text{Obj of the present sample} - \text{maximum of all Obj}\right) / \left(\text{maximum of all Obj} - \text{minimum of all Obj}\right) \tag{15.2}$$

Figure 15.2 depicts the output of the guided clustering procedure.

Table 15.2 Clusterization of training data

Volume of flow	Annual variation of flow	Channel loss	Storage capacity	Groundwater contribution	Demand from agricultural fields	Presence of buffer ponds	Sedimentation	Clusters
9	1	1	9	9	1	9	1	Cluster 1 minimum
8	2	2	8	8	2	8	2	Cluster 2 minimum
7	3	3	7	7	3	7	3	Cluster 3 minimum
6	4	4	6	6	4	6	4	Cluster 4 minimum
5	5	5	5	5	5	5	5	Cluster 5 minimum
4	6	6	4	4	6	4	6	Cluster 6 minimum
3	7	7	3	3	7	3	7	Cluster 7 minimum
2	8	8	2	2	8	2	8	Cluster 8 minimum
1	9	9	1	1	9	1	9	Cluster 9 minimum
9	1	1	9	9	1	9	1	Cluster 1 maximum
8	2	2	8	8	2	8	2	Cluster 2 maximum
7	3	3	7	7	3	7	3	Cluster 3 maximum
6	4	4	6	6	4	6	4	Cluster 4 maximum
5	5	5	5	5	5	5	5	Cluster 5 maximum
4	6	6	4	4	6	4	6	Cluster 6 maximum
3	7	7	3	3	7	3	7	Cluster 7 maximum
2	8	8	2	2	8	2	8	Cluster 8 maximum
1	9	9	1	1	9	1	9	Cluster 9 maximum

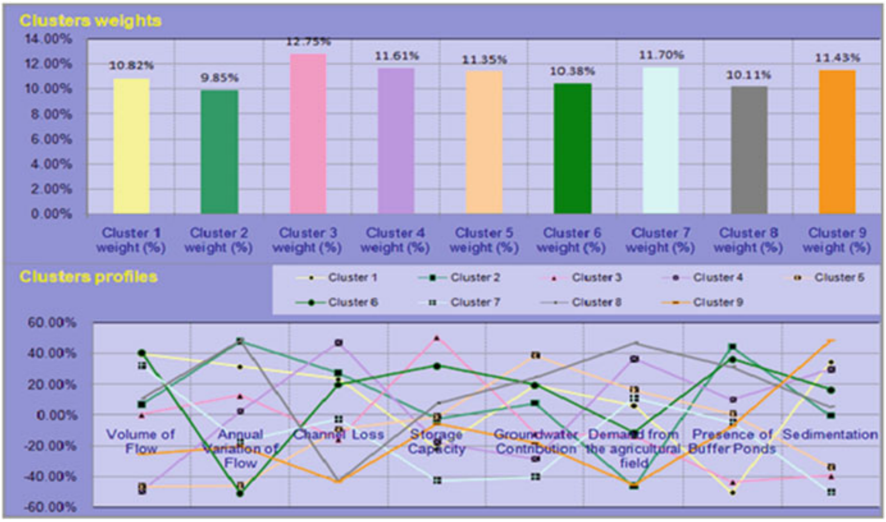

Fig. 15.1 Cluster weights and profiles for available sample data set according to neuroclustering methods

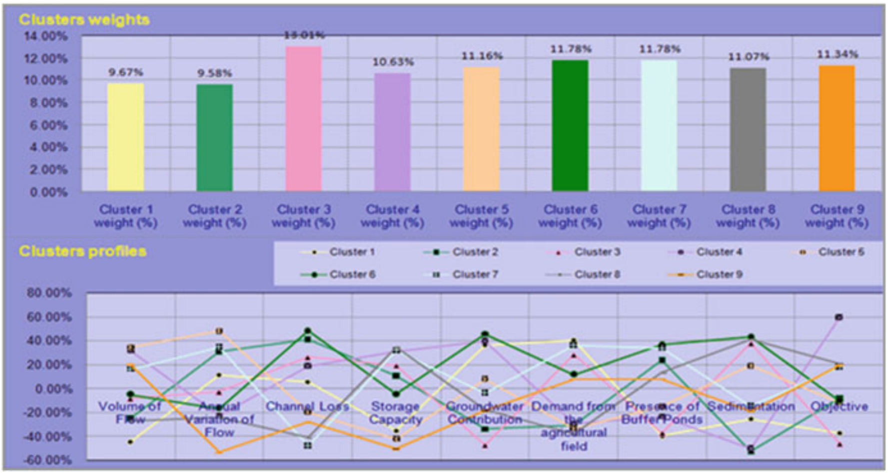

Fig. 15.2 Cluster weights and profiles for available sample data set according to guided neuro-clustering method (GNCM)

In the case of the GNCM method, Cluster 4 was found to represent the most suitable canals with a high volume of flow, low annual flow variation, high channel loss, very high storage capacity, moderate concentration of buffer ponds, very low sedimentation, and low demand from farmers. Although the channel loss was higher in the cluster, it was mitigated by the high storage capacity and low demand from farmers.

From the cluster weight it was found that only 10.63% of the sample population had the characteristic of Cluster 4 and was suitable for withstanding uncertainties from climate change and rapid urbanization. Cluster 3 was found to have the least suitable canals, but within the sample nearly 13.01% of the total population had the characteristics of the Cluster 3 canals.

The sample population was prepared considering every possible combination. In the case of climate change, any canal would face high volume and variation in flow along with high loss of water and deposition of sedimentation. The demand from farmers would be greater due to excess demand from the dependent population. The clusterization procedure revealed that only 10.63% of the total samples that include the impact of climate change and urbanization could mitigate the abnormalities. The remaining combinations would be unable to withstand the uncertainties imposed on them. That is why if the characteristics of Cluster 4 canals were followed in developing new canals, then those canals would not be vulnerable to climatic abnormalities as well as urbanization impacts.

After the application of GNCM the DTA was applied to the same sample population with the help of the following rule:

If the objective function is greater than 85% and less than 100%,
Then assign the canal to Cluster 1
Else
If the objective function is greater than 75% and less than 84%,
Then assign the canal to Cluster 2
Else
If the objective function is greater than 65% and less than 74%,
Then assign the canal to Cluster 3
Else
If the objective function is greater than 55% and less than 64%,
Then assign the canal to Cluster 4
Else
If the objective function is greater than 45% and less than 54%,,
Then assign the canal to Cluster 5
Else
If the objective function is greater than 35% and less than 44%,
Then assign the canal to Cluster 6
Else
If the objective function is greater than 25% and less than 34%,,
Then assign the canal to Cluster 7
Else
If the objective function is greater than 15% and less than 24%,,
Then assign the canal to Cluster 8
Else
Assign the canal to Cluster 9

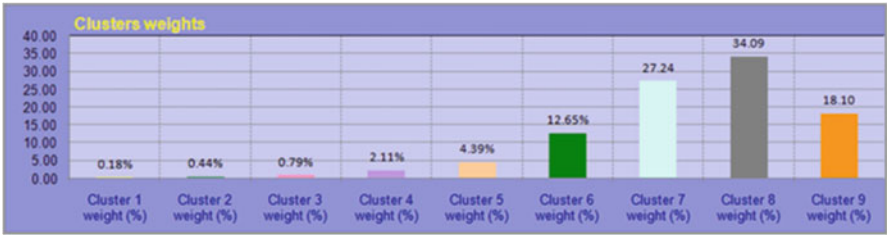

Fig. 15.3 Cluster weights for available sample data set according to guided DTA method

Table 15.3 Optimal configuration of irrigation canals for withstanding future uncertainties (*blue*: conducive variables; *black*: deductive variables)

Volume of flow	Annual variation of flow	Channel loss	Storage capacity	Groundwater contribution	Demand from the agricultural field	Presence of buffer ponds	Sedimentation
7/9	2/9	3/9	8/9	6/9	1/9	9/9	3/9

After the DTA was applied to the sample data set, it was found that Cluster 1 of the DTA was similar to Cluster 9 and 4 of GNCM and Cluster 9 of the DTA was comparable to all clusters of GNCM except Cluster 4.

That is why Cluster 4 is the only cluster that represents channel configurations that can withstand future uncertainties. In the case of the DTA it was found that only 0.17% of the total sample was predicted to have an optimal Cluster 1 whereas 18.10% of the population was found to have rejected Cluster 9 (Fig. 15.3).

As both the DTA and GNCM selected the L191 sample within the optimal cluster [DTA assigned Cluster 1 to the sample whereas GNCM assigned the same sample to Cluster 4; the cluster profile (Fig. 15.2) also supported the selection] the characteristics of L191 were selected as the optimal configuration for a canal to withstand the onslaught of climate and anthropogenic events (Table 15.3).

15.6 Conclusion

The present investigation tried to classify different characteristics of irrigation canals to identify features of a canal that would be able to withstand climatic and urbanization impacts. DTA and GNCM neural networks were applied to clusterize every possible combination of the inputs if all of them were rated on a scale of one to nine according to their impact on canal suitability. The scale was configured in such a way that the suitability of canals was enhanced when the conducive variables increased toward nine and deductive ones decreased towards 1. After the GNCM was applied, it was found that the characteristics of Cluster 4 canals could be identified as a standard for future canal design. But application of DTA revealed that Cluster 1 had the characteristics that engineers should follow to make canals feasible for uncertain situations. It was also found that canals having Cluster 1 in DTA had acquired all the Cluster 4 and 9 characteristics in GNCA but canals having Cluster 9 in DTA had achieved all the Clusters except 4 in GNCA. The sample L191 was found to have configurations that GNCM had assigned to Cluster 4 and DTA had grouped it under Cluster 1. That is why it was concluded that because both GNCM and DTA indicate those canals with the most suitable characteristics to counter future uncertainties, that configuration of the canal may be recommended when new canals are developed in the future. Thus, the ideal irrigation canal in the future must have the characteristics presented in Table 15.3 to make prepare them for the looming changes in climate and human populations.

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