Chapter 9
Impact of Climate Change on Selection of Sites for Lotus Cultivation

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Abstract Lotus (*Nelumbo nucifera*) cultivation provides livelihoods to many people in the tropical and subtropical regions of the world. Lotus is commercially produced in different altitudes. The flower is cultivated in Asia, Australia, North America, and Egypt. Due to demand from the medicinal, fragrance, and culinary industries, as well as from religious sects, cultivation of lotus has become a common source of economic stability due to stable market demand. The harvesting of lotus suffers due to extreme weather patterns, insect attacks, quality degradation of harvesting ponds, and overuse of fertilizers. To ensure optimal production of lotus selection and to control the impact of such inhibitors, the selection of a suitable site is extremely important. That is why farmers invest considerable sums in acquiring ideal ponds for lotus production. Even then, problems still arise: inhabitants of the pond's command area react aggressively to the bad odor produced by rotten tubers, ponds are breeding grounds for mosquitoes, and the rapid spread of lotus stems can prevent local aquatic population from prospering. Thus, the present study was initiated to provide a framework for lotus farmers in which to select a suitable pond to optimize production and maximize profit. The model framework uses neurogenetic models to predict the suitability of a pond for cultivation of the lotus plant.

Keywords Neurogenetic models • Lotus cultivation • Selection mechanism

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9.1 Introduction

Lotus (*Nelumbo* sp.) is an aquatic species in order Proteales and family Nelumbonaceae. The plant has wide floating leaves and bright fragrant flowers. The leaves and flowers of the aquatic Plantae (kingdom) have long stems that contain air spaces that float in water. The root functions of the lotus are carried out by a modified root, rhizomes that fan out horizontally through the mud below the water. The leaves are up to 50 cm in diameter, the flowers are rosy pink with little bits of white shade, and the seeds are hard and dark brown. They can vary in shape from round to oval to oblong. The lotus flower is a morning bloom and is a well-known astringent used in treating kidney, liver, spleen, sleeping, and sexual disorders.

The lotus flower is widely used as a raw material in the fragrance industry. It is an important material for different religious sects. The seeds and stems are edible and used in the culinary industry. The medical industry also makes use of the flowers, stems, seeds, and rhizomes to develop medicines for the treatment of various diseases of the gastroenteric and reproductive systems.

The problems with lotus cultivation can be divided into two major classes:

1. Problems with cultivation methodology
2. Hostility from local inhabitants

Problems with the cultivation methodology include extreme temperature (both high and low temperatures inhibit the growth of the plant), abnormal hydrologic conditions like flood or drought, and the depth of the water body (shallow ponds are not suitable for lotus cultivation). The soil must be humid and moist. The water body must be rich in nutrients, and the pH of the water must be maintained in the neutral zone; acidic water is not suitable for lotus cultivation.

The other class of problems includes opposition from local residents because the rotten stems and roots of lotus generate a pungent odor, and the rapid growth of lotus stems and leaves can engulf an entire pond, which may inhibit the growth of other aquatic creatures. The cultivation of lotus will also attract insects like mosquitoes and can cause an outbreak of malaria or dengue.

Thus the location of lotus ponds is important and ensures optimal production of the flower without being affected by local opposition and other factors related to soil, water depth, and temperature. This investigation tries to estimate the suitability of a pond for lotus cultivation with the help of an artificial neural network and genetic algorithm.

9.1.1 Objective and Scope

The present investigation will try to define the suitability of a pond for cultivation of lotus plants in such a way that the major problems associated with the harvesting procedure can be minimized and maximum profit can be ensured. Because all the problems connected with lotus production are location dependent, the selection of a suitable pond is very important.

The scope of the study also includes the determination of a scientific methodology for the selection of a pond for lotus culturing. The framework can help agro-based industries

Table 9.1 Input and output variables considered for present neuro-genetic model for prediction of pond suitability

Input	Output
Temperature (T)	Suitability of pond
Humidity (H)	
Concentration of fish (F_c)	
Existing utility of pond (P_u)	
Size of dependant population (P)	
Pond depth (h)	
Pond area (A)	
Bottom soil (S_o)	
Turbidity (Tu) of pond water	
Salinity (S) of pond water	
Dissolved oxygen (DO) of pond water	
Presence of predatory species (Sp)	
Proximity to residential complexes (d_r)	
Proximity to market (d_m)	
Availability of labour (L)	
Availability of fertilizers (F)	
Availability of electricity (E)	
Price in market (C)	

and individual farmers to adjust their location selection procedure according to the model output. The location of the pond will help to minimize local opposition, bring extremes weather and water conditions under control, and help optimize production of lotus flowers by taking advantage of the appropriate local geophysical properties.

9.1.2 Brief Methodology

Table 9.1 shows the variables selected as input and output. The categorized data set of the variables were fed to the model to predict the ideal location. The categorization was performed based on the degree of influence of the variables upon the output variable. The categories were also rated according to their relationship with the cultivation of lotus plants. The ratings were used to estimate a weighted average, which in turn predicted the suitability of a pond for lotus culture (suitability function).

The weights were determined using nonlinear optimization methods as no previous studies were found from related fields. All the input variables were assigned a random weight, which was varied within a predetermined boundary. The boundary condition was determined based on discussions with experts and feedback from farmers. The objective function was the average weighting itself, which was maximized by varying the weighting of each variable. The scale dependency of the weights were removed by normalizing the same. That is why the value of the weighting does not vary above or below 1 and 0, respectively.

After the optimal weighting was determined, the suitability function or average weighting derived from the different combinations of input variables was also categorized and used as output data for the training data set. The function was categorized in such a way that it represents its relationship with the selection of the pond, i.e., the higher the average weighting, the higher the suitability of a pond for lotus cultivation, and, conversely, the lower the average weighting, the lower the pond's suitability for lotus cultivation.

A combinatorial data matrix was then created where all possible combinations of input variables were considered, and the output was estimated with the help of neurogenetic models, which are known for their efficiency in mapping of highly nonlinear relations. The universal data matrix developed earlier was then used for training the neural nets so that the model could learn the inherent nature of the relationships that exist between the deciders and output variables.

If a lotus farmer has picked out several locations as potential lotus ponds, he or she can evaluate the suitability of the water body using the model. Such knowledge-based decisions can yield fruitful results and reduce the risk of incurring losses from the harvest.

9.1.3 Neurogenetic Models

The ability to map nonlinear relationships between input and output variables and the ease with which problems can be conceptualized and simulated have made neurogenetic models one of the most desired algorithms for data mining and simulation objectives. Table 9.2 presents some of the studies that examine the efficiency of neurogenetic models in solving optimization, functional approximation, simulation, prediction, classification, and clusterization problems.

The data dependency and universality in application of neural networks have often incited critics of neural networks to call them black boxes. Neural nets are also plagued with deficiencies like requirements for large data populations, problems associated with topology selection, and weighting of the update algorithm and activation function by trial and error. In addition, ignorance regarding the physical interrelationships between variables has led some critics to charge that the reliability of models developed with the help of neural network algorithms is somehow degraded.

But the introduction of search algorithms like genetic algorithm, ant colony optimization, artificial bee colony algorithm, and particle swarm optimization for the selection of parameters like model topology, activation function, etc., which are generally selected by stochastic methods, has also enriched the application of combined models in complex nonlinear objectives.

In the present study neural network and genetic models were combined to develop an algorithm for accurate and reliable decision making.

9.1.4 Genetic Algorithm

Genetic algorithms (GAs) are popular search algorithms (Table 9.3) that use the theory of natural selection during crossover of genes undergoing meiotic cell division. Phenomena like the introduction of new traits (mutation) in the reproduced population are also mimicked to increase the efficacy of the algorithm.

Table 9.2 Sample applications of neurogenetic algorithm in different problem-solving approaches

Reference	Comparative model	Purpose	Input	Remark
Monjezi et al. (2012)	Multivariate regression models	Prediction	Characteristics of rocks	Uniaxial compressive strength was predicted with the help of neurogenetic models and multivariate regression analysis to avoid the cost and time of preparing laboratory samples. The prediction results were compared and according to the performance metrics, coefficient of determination and mean square error, the neurogenetic model was better with respect to the multivariate regression model
Ganesan et al. (2011)	Genetic programming	Optimization	Geophysical and operational constraints	Genetic and neurogenetic algorithms were used for optimization of geologic structure mapping. Minimization of the objective function was performed by GA first separately then combined with a neural network model and results clearly showed the superiority of the latter approach over the former
Singh et al. (2007)	Coactive neuro-fuzzy inference system (CANFIS)	Prediction	Temperature and stress	The creep strain of rock was predicted with the help of neurogenetic and CANFIS models for a comparative analysis
Sahoo and Maity (2007)	None	Prediction	Frequency and strain of structure	Location and amount of damage were estimated with the help of neurogenetic models where the topology of the neural network was identified with the help of a GA. The results encourage further use of such models in prediction problems

Table 9.3 Sample applications of GA in different problem-solving approaches

References	Type of genetic algorithm	Purpose	Input	Remark
Ou (2012)	GA coupled GM model	Forecasting	Agricultural output of Taiwan from 1998 to 2010	GA-coupled GM and individual GM were compared with respect to its prediction of Taiwan's agricultural output. Based on the performance metrics like mean absolute percentage error and the root mean square percentage error, it was concluded that GA-coupled GM was only better than GM for in- and out-sample data sets
Cao et al. (2012)	Boundary-based fast genetic algorithm (BFGA)	Reference point optimization or goal programming or searching for an optimal option nearest to the goal from a set of solutions	Economic, environmental, and ecological benefits, social equity including Gross Domestic Product (GDP), conversion cost, geological suitability, ecological suitability, accessibility, "not in my back yard" (NIMBY) influence, compactness, and compatibility	Land use of Tongzhou Newtown in Beijing, China, was optimized with the help of BFGA, which is a modified form of a sexual GA. The GA model helped to search and identifies the near-optimal solution from the available 10,000 land use plans

Panagopoulos et al. (2012)	Soil water assessment tool (SWAT)-coupled GA algorithm (applied with the help of MATLAB-GA toolbox and SWAT software) attached to an economic function model for cost estimation	Optimization	Changes in livestock, crop, soil, and nutrient application management in alfalfa, corn, and pastureland fields	GA, along with SWAT and an economic model, was used to identify the most optimal pair within a location and the best management plan based on constraints like reduction of diffused pollutants and maintaining an optimal cost-benefit ratio. The result yielded an optimal pair that reduces the pollutants total phosphorus by 45% and nitrogen as nitrates by 25% at a cost of 25 euro/person
Shiri et al. (2012)	Gene expression programming (GEP)	Forecasting	Air temperature, relative humidity, wind speed, and solar radiation	Daily reference evapotranspiration was predicted with help of GEP, adaptive neuro-fuzzy inference system (ANFIS), Priestley–Taylor, and Hargreaves–Samani models. On comparing with different performance metrics it was found that GEP, followed by ANFIS, outclassed all other models
Yun et al. (2010)	Noisy GA based on simple GA	Stochastic optimization	Reservoir inflow	Reservoir inflow was optimized with help of NGA and Monte Carlo method. The optimization results identified the former as a better method for stochastic optimization with respect to the latter model
Ines et al. (2006)	Sexual GA coupled to soil water atmosphere plant (SWAP) and surface energy balance algorithm for land (SEBAL)	Data assimilation and water management optimization	Sowing dates, irrigation practices, soil properties, depth to groundwater, and water quality	Different water management options were optimized with the help of the SWAP and SEBAL generated distributed data set of the input variables on which basis the water management options were optimized with the help of a GA

The methodology of GAs is simple where each input variable has a weighting that is varied randomly to find an optimal solution for a given objective. A fitness function is also used to estimate the accuracy of the solutions. The function is used to identify a population of specific size that yielded the best solution to the given problem. The weightings are referred to as genes. There are two types of genetic algorithm: sexual and asexual. In sexual GAs, the weightings of the best solutions are interchanged and the solutions are evaluated based on the accuracy as determined by the fitness function. As exchanges of genes are conducted, new traits are formed along with an increase in the likelihood of introducing new paths for a quick but efficient problem searching approach.

These exchanges of genes are also referred to as crossover, which mimics the crossover of genes in a human cell.

In an asexual algorithm, the weighting of genes of the same solution is varied within the genes themselves; for example, the first one can become the last one, and vice versa. The generation continues until and unless the output from the fitness function does not improve.

The weighting value at which the fitness function for both algorithms does not change can be identified as the optimal solution and used in achieving the present objective.

GAs are also widely used for the identification of optimal parameters of neural nets, for example, the number of hidden layers or the types of training algorithms to update weightings and activation functions which enhance the reliability of such models. Besides improving the neural net performances, GAs have also been used in various optimization and clusterization problems either separately or with other modeling algorithms.

9.2 Methodology

Table 9.4 presents the inputs selected to predict the suitability of a body of water for the cultivation of lotus plants. The table also shows the categories in which the variables were encoded and their corresponding values in scale of importance, were determined in such a way that the objective function becomes directly proportional to the suitability of the location for lotus cultivation.

A GA, along with quick propagation (QP), was used to identify the optimal topology and weighting that enabled the model to learn the inherent relationships between the input and output variables. The activation function was selected with the help of a logistic function.

The sensitivity, specificity, and precision were selected as performance metrics of the model.

The existing utility of the pond variable represents the use of the pond by the dependent population. If the pond is used for fisheries or any other purpose, then that pond is generally avoided due to the probability of hostility from the dependent population. Thus, the EH category for this variable was given a low rating, whereas the EL category was assigned a high rating. Again, proximity to residential complexes can spur opposition from residents due to the hazards associated with lotus

Table 9.4 Model variables and categories they were encoded in and corresponding ratings

Variable	Category	Crisp Counterpart of Encoded Categories
Temperature (T)	EH,VH,SH,H,N,L,SL,VL,EL	1,2,3,4,5,4,3,2,1
Humidity (H)	EH,VH,SH,H,N,L,SL,VL,EL	1,2,3,4,5,6,7,8,9
Concentration of fish (F_c)	EH,VH,SH,H,N,L,SL,VL,EL	1,2,3,4,5,4,3,2,1
Existing utility of the pond (P_u)	EH,VH,SH,H,N,L,SL,VL,EL	1,2,3,4,5,6,7,8,9
No. of dependant population (P)	EH,VH,SH,H,N,L,SL,VL,EL	1,2,3,4,5,6,7,8,9
Pond depth (h)	EH,VH,SH,H,N,L,SL,VL,EL	1,2,3,4,5,4,3,2,1
Pond area (A)	EH,VH,SH,H,N,L,SL,VL,EL	9,8,7,6,5,4,3,2,1
Bottom soil (S_o)	CLAY,CLAY-HUMOUS,HUMOUS,LOAMY, LOAM-SAND, SAND	1,2,4,3,2,1
Turbidity (Tu) of pond water	EH,VH,SH,H,N,L,SL,VL,EL	1,2,3,4,5,6,7,8,9
Salinity (S) of pond water	EH,VH,SH,H,N,L,SL,VL,EL	1,2,3,4,5,6,7,8,9
Dissolved oxygen (DO) of pond water	EH,VH,SH,H,N,L,SL,VL,EL	1,2,3,4,5,4,3,2,1
Presence of predatory species (Sp)	EH,VH,SH,H,N,L,SL,VL,EL	1,2,3,4,5,6,7,8,9
Proximity to residential complexes (d_r)	EH,VH,SH,H,N,L,SL,VL,EL	9,8,7,6,5,4,3,2,1
Proximity to market (d_m)	EH,VH,SH,H,N,L,SL,VL,EL	1,2,3,4,5,6,7,8,9
Availability of labour (L)	EH,VH,SH,H,N,L,SL,VL,EL	9,8,7,6,5,4,3,2,1
Availability of fertilizers (F)	EH,VH,SH,H,N,L,SL,VL,EL	9,8,7,6,5,4,3,2,1
Availability of electricity (E)	EH,VH,SH,H,N,L,SL,VL,EL	9,8,7,6,5,4,3,2,1
Price in the market (C)	EH,VH,SH,H,N,L,SL,VL,EL	9,8,7,6,5,4,3,2,1

cultivation (increased breeding of mosquitoes and other insects, foul odor etc.).Thus the category EH received a low rating, whereas the category EL received a high rating in the case of this variable. As labor, fertilizer, and electricity availability is essential in lotus cultivation the EH, VH, SH, H categories of such variables were given higher ratings than the EL, VL, SL, and L categories. The variable presence of predatory species represents the population of species that were found to threaten the lotus plant (e.g., bacteria, arthropods, and other worms that eat lotus leaves and stems). Naturally, the EH category of this variable was assigned the lowest rating.

The rating of the categories was converted into a percentage by dividing the assigned rating by the maximum rating of the variable. Thus for a certain pond if proximity to market is very high, then the rating of the variable will be the rate assigned to the VH category, which is equal to 2.The percentage of the category will be the assigned rating (i.e., 2) divided by the maximum rating (i.e., 9), or 22.22%. The percentage value was determined to reduce the scale dependency and to introduce uniformity among the ratings of variables.

The objective function or suitability function was mathematically represented as Eq. 9.1, where S is the suitability function of a certain pond, V_i is the ith variable, n_i is the percentage rating of the ith variable, n_{m} is the maximum percentage achieved by a variable among all the considered variables, and i is the total number of variables selected for the present study.

$$S = \frac{\sum_{i=1}^{i} n_i V_i}{n_{\mathrm{m}} \sum_{i=1}^{i} V_i} \tag{9.1}$$

The suitability function was also encoded into nine categories representing the degree of electability of the pond. The higher the suitability function, the higher the electability of the pond for lotus cultivation. That is why the suitability function was categorized into four groups for simplicity [Highly Suitable (HS), Suitable (S), Unsuitable (US), and Highly Unsuitable (HUS)], where the HUS and US group was assigned respectively to suitability functions equal to or less than 0.4 and less than 0.5 but greater than or equal to 0.41. The S and HS category was respectively assigned to suitability values of less than 0.75 but greater than or equal to 0.51 and greater than or equal to 0.76, respectively.

In the second step a combinatorial data matrix was prepared where all possible combinations of the input and output variables were generated. The data were then used to train a neurogenetic model that would predict the suitability of a pond based on the category of the input variables for a given pond location.

9.3 Results and Discussion

The result of the model training and testing along with other performance metrics is given in Table 9.5. According to the model performance the kappa index of agreement between the actual and predicted results was found to be equal to 90.58%, which is commendable in view of the conservative approach of kappa measure of agreement.

Table 9.5 Characteristics of model parameters and adopted performance metrics

Model parameter	Value
Genetic algorithm parameters	
Population size	60
Number of generations	50
Crossover rate	0.80
Mutation rate	0.20
Neural network parameters	
Network topology	18-1-1
Network weight	19
Training algorithm selected	Quick propagation (QP)
QP coefficient	1.75
Learning rate	0.20
Generalization loss allowed	50.00%
Correct classification rate (CCR) desired	98.00%
Number of training iterations allowed	1,000,000
Number of retrains	10
Training CCR	98.34%
Testing CCR	99.46%
KAPPA index of agreement	90.58%

The Levenberg-Merquardt (LM) algorithm was also used, but, due to the high scale loss in generalization, the latter algorithm was rejected in favor of training the model. On the other hand, a QP algorithm was found to have training and testing CCRs of 98.34 and 99.46%, respectively, which were much better than those (72.16 and 72.09%) of LM. The kappa for LM was found to be equal to zero. The value of the agreement index clearly indicates that when trained with LM the neurogenetic model was totally unable to learn the inherent relationship between the input and output variables.

Based on the model performance metrics, the suitability of a pond for lotus cultivation was analyzed with the help of a QP-trained neurogenetic model.

After the model was developed, it was applied to predict some real-life scenarios derived from the case studies conducted on lotus cultivation. The presence and absence of urban populations and changes in the normal climate were found to be the two main factors to impact the suitability of a pond for lotus cultivation. Based on the study results five types of scenario were conceptualized.

Scenario 1: *Large-Scale Increase in Population but Climate Normal*
Scenario 2: *Medium-Scale Increase in Population but Climate Normal*
Scenario 3: *Small-Scale Increase in Population but Climate Normal*
Scenario 4: *Large-Scale Increase in Population and Change in Climate* (*IPCC A2*)
Scenario 5: *Medium-Scale Increase in Population and Change in Climate* (*IPCC B2*)

Scenarios 4 and 5 mimic the climate change scenario as proposed in the IPCC Fourth Assessment Report (2007). The other three scenarios try to represent large-, medium-, and small-scale urbanization that is already taking place in many developing countries.

Table 9.6 shows the categories assigned to the input variables to represent Scenarios 1–5.

Analysis of the model results shows that, except for Scenario 4, the model predicted suitability for all the scenarios. In representations of the scenarios using the input variables, the same category was assigned to the Bottom Soil input variable because the nature of the input mainly depends on location, not on climate or population, although it was assumed that even under population and climate change the pond would not change its geophysical characteristics. Regarding the pond depth and area variables, the category assigned to represent all the scenarios except Scenario 4 is the same because a change in population cannot change the dimensions of a pond, but climatic uncertainty can impose change in the storage capacity of the pond. Thus, in the case of Scenario 4, pond area and depth were assigned a category of VL, which represents the impact of using the water bodies for deposition of waste produced by the uncontrolled population as conceptualized by the IPCC under the A2 scenario.

An increase in population would impose scarcity on basic natural resources like land and water. Thus, most of the land area will be converted to either residential complexes or agricultural zones so that the excess population can be accommodated and a stable food supply ensured. To represent this situation, input variables like existing utility of the pond, dependent population, and proximity to residential complexes, all of which represent the existing demand for land and water resources, were assigned either EH or VH respectively for Scenarios 1 and 4 or Scenario 2. An increase in population increases the demand for land and food, but this change in turn increases requirement for labor and electricity. As demand for food is also increased, fertilizers will mostly be used for field irrigation. Thus, labor, fertilizer, and electricity were all assigned the EL category in Scenario 1.

The scarcity of electricity, labor, or fertilizers will diminish when a medium- or small-scale change in the total population takes place. In the case of a medium-scale change, there will be adequate population to cultivate lotus as well as for construction purposes. The amount of fertilizers will also be properly distributed when demand for it is regulated. The category assigned to the same three variables represents the toned-down situation of Scenarios 2, 3, and 5.

The chemical properties of a water body change according to the use of its catchment area. If the watershed is used mostly for agriculture, then the surface runoff will carry loose soil, dry grains, and inorganic fertilizers that, when deposited in a water body, increase its turbidity and decrease the dissolved oxygen (DO) level. As in the case of Scenarios 1 and 4 the watersheds will be used for agriculture, the turbidity level will certainly be higher than in any other situation, whereas the level of DO will also be reduced. Accordingly, the category of the variables representing the chemical properties of the pond was adjusted as per the scenario.

The model prediction found that only under the A2 and Large-Scale Increase in Population scenarios does the pond become unsuitable. That means, except when both climate and population change in such a way that natural resources become extremely scarce, the suitability decision for a pond with respect to lotus cultivation will not change.

Table 9.6 Representation of considered scenarios and decision predicted by neurogenetic model

Input variable	Category assigned
Scenario 1	
Temperature (*T*)	N
Humidity (*H*)	N
Concentration of fish (F_c)	L
Existing utility of pond (P_u)	EH
Size of dependent population (*P*)	EH
Pond depth (*h*)	N
Pond area (*A*)	N
Bottom soil (S_o)	Humous
Turbidity (Tu) of pond water	VH
Salinity (*S*) of pond water	VH
Dissolved oxygen (DO) of pond water	N
Presence of predatory species (Sp)	H
Proximity to residential complexes (d_r)	EH
Proximity to market (d_m)	VH
Availability of labor (*L*)	EL
Availability of fertilizers (*F*)	EL
Availability of electricity (*E*)	EL
Market price (*C*)	VH
Pond suitability	**S**
Scenario 2	
Temperature (*T*)	N
Humidity (*H*)	N
Concentration of fish (F_c)	N
Existing utility of the pond (P_u)	VH
Size of dependent population (*P*)	H
Pond depth (*h*)	N
Pond area (*A*)	N
Bottom soil (S_o)	Humous
Turbidity (Tu) of pond water	H
Salinity (*S*) of pond water	H
Dissolved oxygen (DO) of pond water	N
Presence of predatory species (Sp)	N
Proximity to residential complexes (d_r)	VH
Proximity to market (d_m)	H
Availability of labor (*L*)	H
Availability of fertilizers (*F*)	VH
Availability of electricity (*E*)	N
Market price (*C*)	H
Pond suitability	**S**
Scenario 3	
Temperature (*T*)	N
Humidity (*H*)	N
Concentration of fish (F_c)	H
Existing utility of the pond (P_u)	N

(continued)

Table 9.6 (continued)

Input variable	Category assigned
Size of dependent population (*P*)	N
Pond depth (*h*)	N
Pond area (*A*)	N
Bottom soil (S_o)	Humous
Turbidity (Tu) of pond water	N
Salinity (*S*) of pond water	N
Dissolved oxygen (DO) of pond water	H
Presence of predatory species (Sp)	N
Proximity to residential complexes (d_r)	N
Proximity to market (d_m)	N
Availability of labor (*L*)	N
Availability of fertilizers (*F*)	VH
Availability of electricity (*E*)	H
Market price (*C*)	N
Pond suitability	**S**
Scenario 4	
Temperature (*T*)	EH
Humidity (*H*)	EL
Concentration of fish (F_c)	L
Existing utility of the pond (P_u)	EH
Size of dependent population (*P*)	EH
Pond depth (*h*)	VL
Pond area (*A*)	VL
Bottom soil (S_o)	Humous
Turbidity (Tu) of pond water	EH
Salinity (*S*) of pond water	EH
Dissolved oxygen (DO) of pond water	EL
Presence of predatory species (Sp)	EH
Proximity to residential complexes (d_r)	EH
Proximity to market (d_m)	N
Availability of labor (*L*)	EL
Availability of fertilizers (*F*)	EL
Availability of electricity (*E*)	EL
Market price (*C*)	N
Pond suitability	**US**
Scenario 5	
Temperature (*T*)	H
Humidity (*H*)	L
Concentration of fish (F_c)	N
Existing utility of the pond (P_u)	N
Size of dependent population (*P*)	H
Pond depth (*h*)	N
Pond area (*A*)	N
Bottom soil (S_o)	Humous

(continued)

Table 9.6 (continued)

Input variable	Category assigned
Turbidity (Tu) of pond water	N
Salinity (*S*) of pond water	N
Dissolved oxygen (DO) of pond water	H
Presence of predatory species (Sp)	L
Proximity to residential complexes (d_r)	N
Proximity to market (d_m)	H
Availability of labor (*L*)	H
Availability of fertilizers (*F*)	N
Availability of electricity (*E*)	H
Market price (*C*)	H
Pond suitability	**S**

9.4 Conclusion

The present investigation tried to develop a modeling methodology in selecting a pond for lotus cultivation using neurogenetic models. Five scenarios were also conceptualized to analyze the impact of both climate and population change on such decisions. According to the model results, only when both climate and population change in a negative direction is the decision over pond suitability affected. In any other scenario where medium or small changes in population are observed under normal climate conditions, the model prediction for pond suitability remains unchanged. The developed model can become a tool for farmers selecting a pond for lotus cultivation. The results from the software will help farmers select the optimal pond where the probability of disturbance will be minimum. Although the model decision was found to be in agreement with actual scenarios (as found from the kappa index of agreement between the actual and predicted decisions), because the variables are represented as categories, small changes in the variables at levels below the considered range will become inconsequential for the decision. But the categorization was done in such a way that recognizable changes will only be considered in the model decision. Changes with minimum or no impact on the output variables were ignored by considering the ranges of the categories after consulting the latest scientific studies. Pond suitability can also be predicted with the help of neuro-fuzzy or neuro-swarm techniques. A comparative study could be undertaken to determine what models were available to achieve the present objective.

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