# Chapter 5
# Application of a Genetic Algorithm to Predict the Growth Rate of *Bufo melanostictus* in Urban Forest

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**Abstract** *Bufo melanostictus*, commonly known as the Asian common toad, is widely found in various urban forests and marshy lands. The animal is not endangered (present conservation status: Least Concern) but is under threat of being so due to various issues. One of the major threats to the toad population is the recent rapid scale of urbanization, which is gradually diminishing the common habitat and reproduction places of the species. Like other species of Bufonidae family, toads breed in still and slow-flowing rivers and temporary and permanent ponds. Many rivers have changed their characteristics due to climate change. For this reason many habitats formerly suitable for breeding are now found to be unsuitable. The present study aims to estimate the growth rate of the toad based on its various habitats and on climate patterns along with food availability. The impact from urbanization and deforestation is also considered. Overall the study tries to analyze the impact of urbanization and changes in climate patterns on the Asian common toad using a genetic algorithm technique.

**Keywords** Growth rate • Genetic algorithm • Climate impacts

## 5.1 Introduction

The present scenario of large-scale urbanization and recent changes in climate patterns has impacted on the growth rate of the Asian common toad. Although the species is not under threat of extinction and not even in the class of concern

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according to IUCN Conservation Status Ranking, it may become a member of that class soon if the present trend of habitat loss continues. The role of the toad in ecology is important. Toads actively participate in controlling the insect population. If the population of insects grows out of control, then major losses of crops may occur, creating a threat to the present level of food security of the human population. Unfortunately, human beings are becoming the main threat to toad populations.

This study attempts to predict the growth rate of the toad population with the help of a genetic algorithm (GA). But the main objective of the study is to analyze the impact of urbanization and change in climate on the growth of toad populations. The study may help to visualize future scenarios in which the climate will be different from the current one and the extreme urbanization will have already been implemented. The situation of the toad population at that time will help present-day urban managers to take specific mitigation measures to prevent the decay of the toad population as well as the agro-industry due to their interrelations.

GAs are known to be efficient enough to predict an output variable if a sufficiently large amount of data is fed to the model. The basic methodology of a GA is to create a population of new or mutated traits. The accuracy of a model depends mainly on the efficiency of the GA in replicating new patterns of data.

GAs have been used to predict the growth rate of *Bufo* sp., and a search of the literature revealed that no other algorithm was found to be more satisfactory. Because GAs are problem-independent, data-flexible, nature-based algorithms, there was no problem in applying to the kind of problem considered here.

### *5.1.1* Bufo *sp.*

The Asian common toad (*Duttaphrynus melanostictus*; synonym: *Bufo melanostictus*) is a complex of more than one toad species, widely distributed in South Asia, also known as Asian toad, black-spectacled toad, common Sunda toad, and Javanese toad; it grows to approximately 20 cm long. The species breeds during the monsoon season, and the tadpoles are black. Young toads may be seen in large numbers after monsoons.

Asian common toads can be found in northern Pakistan, Nepal, Bangladesh, India, Sri Lanka, Myanmar, Thailand, Laos, Vietnam, Cambodia, southern China, Taiwan, Hong Kong, Macau, Malaysia, Singapore, and the Indonesian islands of Sumatra, Java, Borneo, Anambas, and Natuna Islands. They are also present on the islands of Bali, Sulawesi, Ambon, and Manokwari and dwell in the northeastern portion of the Vogelkop Peninsula in New Guinea as an exotic species. The Asian common toad has been sighted as high as 1,800 m. The common habitats of the toad include lowland, upper beaches, riverbanks, and agricultural and urban areas. They are rare in closed forests (van Dijk et al. 2004).

The Asian common toad can be identified by its warty skin and distinct bulges on the back of its head, known as the parotid glands; it tends to walk not jump and is covered in obvious warts. It has horizontally slit pupils with yellow/golden brown irises, and its dorsal surface and flanks are a fairly uniform brown/greenish gray; it is light sandy brown in warm weather, has a ventral surface that is dirty white/cream with speckles. It varies in length from 8 cm (male) up to 13 cm (female).

### *5.1.2 Life Cycle of Asian Common Toad*

The life cycle of the Asian common toad is divided into six physiologically distinct stages, which are discussed in detail in what follows.

(a) Spawn (egg-mass)
The male frog fertilizes eggs in female frogs as they are laid in the amplexus or mating position. The eggs are laid in long chains known as spawn or egg mass. At this time, temperature and humidity must be favorable enough for the sustenance of the egg. The eggs at this stage are extremely vulnerable and fragile. Extreme climates, predators, or human interference can ruin the entire mass of eggs.

(b) Egg
Toads as well as frogs lay sufficient numbers of eggs so that even if most of the eggs are unable to survive the hazards between fertilization and full-blown frogness, sufficient numbers of them may still exist to carry the traits of the species to the next generation. When the eggs die, they tend to turn white or opaque.

The mitotic division of the central yolk in the egg forms a mass that is similar to raspberry inside a jelly cup, and soon the embryo starts to look more and more like a tadpole, getting longer and moving around in its egg.

In about 6– 21 days after mating, the egg will hatch. At this time eggs need a clear and calm environment withno climatic, predatorial, or human interference.

(c) Tadpole
Shortly after hatching, the tadpole still feeds on the remaining yolk, which is actually in its gut! The tadpole at this point consists of poorly developed gills, a mouth, and a tail and is extremely fragile. It usually sticks itself to floating weeds or grasses in the water using little sticky organs between its mouth and belly area. Then, 7–10 days after the tadpole has hatched, it will begin to swim around and feed on algae.

After about a month, the gills start to acquire skin, until they eventually disappear. The tadpole gets minuscule teeth that help it grate food, turning it into oxygenated, digestible particles. The long coiled guts of the tadpole help it digest as much nutrients from its meager diet as possible.

(d) Tadpole with legs
Tiny legs start to appear after approximately 6–9 weeks, the head becomes more distinct, and the body elongates. The tadpole's diet will now include larger items like dead insects and even plants.

The arms begin to develop to the point where they will eventually pop out, elbow first.

After approximately 2 months and 1 week, the tadpole begins to look like a frog with a tiny tail on its back.

Tadpoles are a delicacy to many fish, reptiles, birds, and even humans; they can easily be killed by the mere force of turbulent water and cannot survive extreme weather conditions and disruptions in their food supply.

(e) Young Toad
After approximately 3 months, the tadpole has only a tiny stub of a tail and looks like a miniature version of the adult frog. All the common habits and external characteristics of the toad start to appear.

**Table 5.1** Factors affecting growth rate of *Bufo* sp. in different stages of life cycle

| Stage in life of a toad | Factors |
|---|---|
| Egg | Temperature, rainfall, humidity, type of water body, turbulence in water, presence of predators, anthropogenic impacts |
| Tadpole | Rainfall, type of water body, flow in water body, presence of food, presence of predators, and anthropogenic impacts |
| Adult | Temperature, humidity, type of water body, type of landscape, type of forest, presence of food, presence of predators, and anthropogenic impacts |
| Reproduction | Temperature, humidity, type of water body, type of landscape, type of forest, presence of food, presence of predators, presence of proper number of mates, and anthropogenic impacts |

(f) Adult Toad
In approximately 12–16 weeks, depending on water and food supply, the toad can complete its growth cycle and become ready for reproduction.

### *5.1.3 Factors Affecting Growth Rate of Asian Common Toad*

Table 5.1 presents the factors affecting the different stages in the life of a toad. The major contributors to the growth rate of the toad are temperature, rainfall, and type of water body. The presence of predators and anthropogenic impacts play a detrimental role in the life cycle of the Asian common toad.

### *5.1.4 Objective of Study*

The objective of the present study, as already discussed, is to predict the growth rate of the Asian common toad with respect to the climate patterns, habitat, and food sources. The main goal of the study is to analyze the impact of anthropogenic influences and climate change on the growth rate of toad populations, which control insect populations and in turn guarantee our own food sources.

The study employs advances in neurogenetic algorithms in predicting output.

### *5.1.5 Brief Methodology*

First, the input parameters are selected based on their influence on the growth rate of the toad population. A literature search revealed that the following variables largely control toad populations:

1. Type of water body ($W_t$), depth ($h$)
2. Climate [mainly humidity ($H$) and temperature ($T$)]

3. Plant population ($p$) and type ($p_t$)
4. Presence of food source ($F$), i.e., type and amount of insect population as toads love to eat insects like termites, common flies, and even scorpions
5. Presence of competitive ($C$) and predatory ($P$) species
6. Distance from locality ($d_L$), industry ($d_i$), and forest/plantations ($d_f$): toad generally avoid human populations and settlements. But if food sources are inadequate outside urban regions, toads are forced to enter households to capture easy prey like house flies, spiders, mosquitoes, etc.

The input variables are then categorized and scored based on their effect on the growth rate. The score is directly proportional if the variable improves the population growth rate; if the presence of a variable has a detrimental effect on the growth rate, then the scoring becomes inversely proportional.

For example: the presence of predatory/competitive species has a negative impact on a toad population. Thus, the higher the concentration of predatory species, the lower the score for this category. Again, for the plant population a variable, high concentration of plants will have an incremental effect on the growth rate of the toad population due to the availability of a food source, and thus this factor was given a higher score.

Based on these categorized and scored input variables, an objective function (Eqn. 5.1) is developed such that it becomes directly proportional to the growth rate of the toad population.

$$\text{Sum}\left(W_t, h, H, T, p, p_t, F, C, P, d_L . d_i, d_f\right) \tag{5.1}$$

Various situations, both constructive and destructive, are conceptualized and created by categorizing according to the situation. Then the scenario data set is fed to the trained genetic model for output. Based on the value of the output, the impact on population growth rate due to urbanization and climate change is estimated.

## 5.2 Neural Network and Genetic Algorithm

A neural network is a popular method of nonlinear prediction with hitherto unseen flexibility and simplicity by which it accomplishes its objective with all types of problems from various fields of research ranging from the development of a user-controlled search engine to the prediction of the impact of climate change. The basic methodology of neural networks is to predict output using a function of the weighted sum of all inputs where the weights are used to reduce the difference between the actual and predicted output.

The weights are continuously updated, and the differences between the desired and predicted output are noted until and unless the difference becomes equal to the desired difference or the maximum number of iterations allowed is completed.

The iterations are performed to update the weighting and predicting the output with the new weighted sum. If the error decreases, then the weighting is updated in the earlier pattern or it changes its direction and magnitude. The entire procedure to update the weight for minimization of error is known as training an algorithm. After the model is trained, it is tested with a data set with known output values.

The three most important decisions for improving the accuracy of the network output are as follows.

1. Selection of network topology:
   The methodology of topology selection directly impacts computational power and the duration of the makespan time. A heavy topology will require greater amounts of computational power and time and vice versa. Thus, the selection of the topology is an important aspect for increasing the accuracy of a model. Most commonly the trial-and-error method is used for the selection , but some studies used GAs, particle swarm optimization, or even fuzzy logic to accomplish the same objective. The topology was commonly selected by either exhaustive search method or meta-heuristics like GA.
2. Selection of training algorithm:
   The training algorithm is the iteration method by which an optimal weighting is found by minimization of the difference between the actual and observed output. There are various types of training algorithms like, for example, quick propagation, conjugate gradient descent, back propagation, neurogenetics, genetics, and fuzzy logic.
3. Selection of activation function:
   The activation function is the function of the weighted sum of the inputs. The activation function controls the accuracy of the models and also encourages other researchers to develop new algorithms for templating. The activation function either scales the properties or tries to reduce the noise involved in the signal. An activation function can be, for example, logistic, hyper tan, sinusoidal, or sigmoidal.

Once the model is trained and tested and if satisfactory accuracy can be achieved, it is calibrated and validated with data having known outputs. According to the accuracy of the results, the topology, training algorithm, and activation function can be used for data values that do not have a known output.

### *5.2.1 Genetic Algorithm*

A GA can be defined as a class of adaptive stochastic nature-based heuristic algorithms involving search and optimization. A GA was first used by Holland (1992).

The basic logic behind the algorithm is to mimic a simple picture of natural selection in order to find a good algorithm with the help of mutation or to randomly vary a given collection of sample programs. The second step is to select the optimal population, which is often done by measuring it against a fitness function. The process is repeated until a suitable solution is found.

There are many types of GA. The steps involving mutation, application of crossover techniques, and testing for fitness can be customized based on the objective of the problem. GAs, like neural networks, are prone to getting stuck in a local maximum of the fitness function, but they have the advantage that they do not require the fitness function to be very smooth since a random search is performed instead of following the path of least resistance, although the success of a GA depends on the linear relationship between program parameters and the fitness function (Rowland and Weisstein 2012).

### 5.2.2 *Recent Application of Genetic Algorithm to Practical Problem Solving*

Table 5.2 shows some recent applications of GAs along with many other algorithms for solving different types of problems from various fields of research. The objective and the success rate achieved are also discussed.

## 5.3 Methodology

In the first stage of development, variables that could affect the growth rate was identified and categorized into different groups according to their degree of influence on the objective.

Table 5.3 presents the categories into which each of the input variables is divided. Based on the categories, each value of the input variables was rated and the total value of the function was determined. Each category was encoded in such a way that the total rating of the inputs becomes directly proportional to the growth rate.

The threshold values for the division were extracted from various studies and governmental reports. The categorized data was scored with the help of the analytical hierarchy process (AHP), and the total rating of each variable was used to estimate the growth rate function. After categorization of the data set a combinatorial data matrix was developed considering every possible combination that could be created within the input and output categories.

Table 5.3 shows the input variables, categories into which they were divided, and their corresponding rank with respect to their influence on growth rate of Bufo Sp. population. The rating or scoring of the variables was determined using Eq. 5.2:

$$R = \left(\left(1 - \mathrm{Rank}\right) / 10\right) \tag{5.2}$$

where R is the score or rating assigned to a variable with respect to its category.

**Table 5.2** Recent application of genetic algorithm to different decision-making problems

| Authors | Type of GA | Objective | Success rate |
|---|---|---|---|
| Ooka et al. (2008) | Multiobjective genetic algorithm (MOGA) | "Comfortable outdoor thermal urban environment" as a function of landscape, outdoor thermal environment, and economy | Successful at obtaining a pareto-optimal data set representing the optimal outdoor environment |
| Kardani-Moghaddam et al. (2012) | Hybrid genetic algorithm and variable neighborhood search | "To reduce overall cost of task executions without noticeable increment in system makespan" where task execution cost is inversely proportional to makespan time of market grid | The hybrid GA and variable neighborhood search were found to be better than other algorithms applied to solve similar problems |
| Galan et al. (2011) | Genetic algorithm | The influence of the forest canopy (tree density, volume of wood, Hart-Becking index, etc.) along with position dilution of precision (PDOP), the signal-to-noise ratio, and the number of satellites on the accuracy of the measurements performed by global positioning systems (GPS) receivers | The influence of forest-canopy-related variables was found to have the greatest influence on the accuracy of the GPS result |
| Gaafar et al. (2008) | Simple genetic algorithm and modified genetic algorithm by particle swarm optimization (PSO) | To minimize the makespan of a single flexible machine followed by multiple identical assembly stations. The potential of PSO in improving the performance of GAs was also analyzed by comparing the output with other heuristic algorithms | Results show that the regular GA outperforms the heuristic algorithms in many instances of the manufacturing process of shorter schedules, and PSO-optimized GA surpasses the regular GA by 3.6% in many instances |
| Ines and Honda (2005) | Genetic algorithm | To estimate the number of agriculture and water management practices from low-spatial-resolution remotely sensed imageries under mixed pixel environment based on the sowing dates, area fractions of agricultural land uses in the pixel, and their corresponding water management practices | Results indicate that information about agriculture and water management practices can be extracted from low-spatial-resolution remotely sensed images |

| | | | |
|---|---|---|---|
| Chikumbo and Nicholas (2011) | Multiobjective stand-level optimization island model of genetic algorithm based on selected pareto-optimal data set | To estimate a set of the most efficient thinning regime for Eucalyptus fastigata to maximize value of sawlog harvesting and volume of pulp production | The GA was found to be successfully identify the efficient thinning regime or an pareto-optimal condition |
| Coillie et al. (2007) | Genetic algorithm connected neural network | To update Flemish Forest Map using IKONOS imagery where GA was used for feature selection and neural network was applied to classifying the imagery | Algorithm that considers feature selection was found to be outperform the performance of models that do not consider feature selection as per the kappa index of agreement calculated from the results |

**Table 5.3** Categories and corresponding ranks of input variables

| Name of input variable | Categories considered and their corresponding rank |
|---|---|
| Water body type | Small Pond (1), Pond (2), Lake (3), Reservoir (4) |
| Water body depth | EH (5),VH (4), SH (3), H (2), M (1), L (2), SL (3), VL (4), EL (5) |
| Temperature | EH (5), VH (4), SH (3), H (2), M (1) , L (2) , SL (3), VL (4), EL (5) |
| Humidity | EH (5), VH (4), SH (3), H (2), M (1), L (2), SL (3), VL (4), EL (5) |
| Soil type | Loam (1), Silt (2), Silty-Loam (3), Clay (4), Silty-Clay (5), Loamy-Sand (6), Sandy-Clay (7), Sandy-Loam (9), Sand (9), |
| Type of flora | Shrubs (1), Herbs (2), Tree (3), Orchids (4) |
| Concentration | EH (5),VH (4), SH (3), H (2), M (1), L (2), SL (3), VL (4), EL (5) |
| Presence of predators | EH (9), VH (8), SH (7), H (6), M (5), L (4), SL (3), VL (2), EL (1) |
| Presence of food | EH (1), VH (2), SH (3), H (4), M (5), L (6), SL (7), VL (8), EL (9) |
| Presence of competitive species | EH (9), VH (8), SH (7), H (6), M (5), L (4), SL (3), VL (2), EL (1) |
| Distance from locality | EH (1), VH (2), SH (3), H (4), M (5), L (6), SL (7), VL (8), EL (9) |
| Dist_Tree cover | EH (9), VH (8), SH (7), H (6), M (5), L (4), SL (3), VL (2), EL (1) |
| Dist_Industry | EH (1), VH (2), SH (3), H (4), M (5), L (6), SL (7), VL (8), EL (9) |

The value of the objective or growth rate function was determined with the help of the scores assigned to each of the variable. The neurogenetic algorithm was now used to understand the relationship and predict the output for a combination not included in the data set. But because the study had considered a combinatorial data matrix, each and every possible combination within the inputs was considered, so the model accuracy for any combination would be predetermined, and thus the reliability of a given prediction would already be estimated.

## 5.4 Results and Discussion

The parameters for the GA algorithm are presented in Table 5.4. In application of the GA, two different sets of parameters were used and compared. Both of these parameter sets population size and number of generations were varied and the results were compared to determine the better model among the two different models. The topology identified with the two sets of model parameters was named as GA1 and GA2.

**Table 5.4** Parameter values selected for search iterations of present neural network model

| Parameters | Value 1 | Value 2 |
|---|---|---|
| Population size | 40 | 60 |
| Number of generations | 50 | 40 |
| Network size penalty | 5 | 5 |
| Crossover rate | 0.8 | 0.8 |
| Mutation rate | 0.2 | 0.2 |

**Table 5.5** Performance metrics of GA1 and GA2 models

| GA1 | GA2 |
|---|---|
| 0.388 | 0.333 |
| 0.990 | 0.995 |
| 0.918 | 0.995 |

The GA1 model was trained with Levenberg-Merquadart (LM), conjugate gradient descent (CGD), and quick propagation (QP) algorithms. The training precision or correct classification rate (CCR) and testing precision were found to be equal to 96.08, 92.45, and 87.56% and 91.67, 67.02, and 64.57%, respectively, for LM, CGD, and QP, respectively.

As the training and testing CCR was better in the LM algorithm, the neural network trained with LM was selected to predict the growth rate of *Bufo* sp. The network topology as selected by the GA was found to be equal to 14-1-11-1.

The GA2 network was trained only with the LM algorithm following the result of the GA1 model. The training and testing CCR for the latter model was found to be equal to 94.12 and 100%, respectively.

The sensitivity, specificity, and precision values of the GA1 and GA2 models were also calculated to identify the better of the two models.

According to the considered performance metrics, the specificity and precision of the GA2 model clearly indicated that compared to GA1 it had much better accuracy. The abstractness of the sensitivity value might be attributed to the uniformity of the data set with which the model was trained.

The results also clearly highlighted the impact of the model parameters of the GA on the accuracy of a neurogenetic modeling platform. It also indicated that population size must be greater than the number of generations so that the searching algorithm can search through a wider domain.

The low sensitivity value can be attributed to the rarity of the output categories, i.e., within the nine categories of the output SH was present 65 times and SL (Semi Low) three times but all the other categories had a frequency of 2 or 1 out of 74 rows of data.

The nonversatility of the output resulted in a low value of sensitivity for both models (GA1 and GA2). GA1 and GA2 were found to have sensitivities of 38.88 and 33.33%, respectively (Table 5.5).

Table 5.6 shows the categories of input variables assigned to create the scenarios representing climate change and the impact of urbanization.

**Table 5.6** Category and corresponding rank of input variables

| Name of input variable | Categories considered |
|---|---|
| Scenario: Climate change: A2 (IPCC) | |
| Water body type | Small pond |
| Water body depth | EL |
| Temperature | VH |
| Humidity | VH |
| Soil type | Sand |
| Type of flora | Shrub |
| Concentration | VL |
| Presence of predators | VH |
| Presence of food | VL |
| Presence of competitive species | M |
| Distance from locality | EL |
| Dist_Tree cover | EH |
| Dist_Industry | EL |
| Scenario: Climate change: B2 (IPCC) | |
| Water body type | Lake |
| Water body depth | SH |
| Temperature | M |
| Humidity | M |
| Soil type | Loam |
| Type of flora | Tree |
| Concentration | VH |
| Presence of predators | EH |
| Presence of food | VH |
| Presence of competitive species | SH |
| Distance from locality | EH |
| Dist_Tree cover | EL |
| Dist_Industry | EH |
| Scenario: Urbanization: Large-scale urbanization | |
| Water body type | Small pond |
| Water body depth | EL |
| Temperature | SH |
| Humidity | SH |
| Soil type | Sand |
| Type of flora | Shrub |
| Concentration | EL |
| Presence of predators | VH |
| Presence of food | M |
| Presence of competitive species | M |
| Distance from locality | EL |
| Dist_Tree cover | EH |
| Dist_Industry | EL |

(continued)

**Table 5.6** (continued)

| Name of input variable | Categories considered |
|---|---|
| Scenario: Urbanization: Mid-scale urbanization | |
| Water body type | Pond |
| Water body depth | SL |
| Temperature | SH |
| Humidity | SH |
| Soil type | Silt |
| Type of flora | Herb |
| Concentration | M |
| Presence of predators | VH |
| Presence of food | H |
| Presence of competitive species | H |
| Distance from locality | M |
| Dist_Tree cover | M |
| Dist_Industry | M |
| Scenario: Urbanization: Low-scale urbanization | |
| Water body type | Lake |
| Water body depth | SH |
| Temperature | SH |
| Humidity | SH |
| Soil type | Loam |
| Type of flora | Tree |
| Concentration | VH |
| Presence of predators | EH |
| Presence of food | VH |
| Presence of competitive species | SH |
| Distance from locality | EH |
| Dist_Tree cover | EL |
| Dist_Industry | EH |

The climatic scenarios were simulated with the help of the recommendations taken from the description of the IPCC A2 and B2 scenarios conceptualized to represent two kinds of climatic impacts: in one scenario, industry was prioritized, and in the other environmental sustainability was given a heavier weighting.

Accordingly (Table 5.6), in the present study, temperature and humidity were assigned a category of VH. The category to represent the presence of a body of water and its depth is also presented as per the A2 scenario. Because industrial concerns would be given priority, the number of trees would be close to zero and mostly shrubs would prevail over other types of flora. Also, frogs would have to stay near an industrial plant or a residential complex because these would be present in high concentrations since industry was to be given priority over environmental sustainability. If tree cover were reduced, the presence of predators and competitive species would also decrease.

However, new kinds of predators like birds, city snakes, etc. could harm frog populations. Thus, the category of VH (Very High) was assigned to the factor (Presence of predators). Similarly, species like lizards, large spiders, and some domesticated carnivores would share the frogs' food source. Thus, the category for the presence of competitive species was assigned an M (Medium or Neither High Nor Low).

In the case of large-scale urbanization, the scenario was simulated by assigning the same categories to the input variables except that the climate parameters were put in the SH (Semi High) category representing the typical weather of tropical countries. Also, small ponds are generally frequently found in large urbanized areas. Thus, the type of body of water was given as Small Pond and, like the city ponds, their depth was categorized as EL (Extremely Low).

For B2 and low urbanized cityscape temperature and humidity will be M or Medium i.e. neither high nor low. The type of water body will be lake or reservoir as such geographical features would be protected by strict laws. Predators, food, and competitive species would be pervasive because this type of environment would be conducive to their presence.

As the environment would be conserved, a sufficient amount of protection and cover could be provided to frog species. The category EL was thus assigned to distance from tree cover, but distance from industry and locality has a adverse effect on the toad population so the highest category of the factor is assigned to be EH was given the highest category of the opposite, i.e., EH.

The difference between B2 and low urbanization was the category of climate variable where the latter was assigned a category representing typical tropical climates.

In case of mid-scale urbanization, the climate parameters were given the same category as the other urbanization situations, but all the other variables were adjusted with respect to a mid-scale urbanized city like Nasik or Haridwar of India.

That is why distance from industry, locality, and tree cover was assigned a category of M, which represents the exact situation of a mid-urbanized city. As is characteristic of all semiurbanized landscapes, the presence of predators and competitive species of the common toad was high as the impact of total urbanization was not as high as in a large-scale urbanized city. The soil pattern also changed to silt as such soil is generally observed in semieroded land features common to landscapes likely to be found in full-blown cityscapes.

Table 5.7 shows the categories of output as predicted by the selected neurogenetic models. The output was also explained and compared with real-time scenarios.

## 5.5 Conclusion

The present investigation tried to predict the growth rate of the Asian common toad using the power of neurogenetic models. The role of GA parameters in enhancing model performance was also examined. After training and testing of the model and selecting the better of two models, predictions were made on the basis of five scenarios representing climate impacts and urbanization situations. According to the model output a semi-low growth rate would be observed if industry and urban extension were given the highest weighting. The opposite situation would hold if environmental laws were strictly enforced; in this scenario, a semi-high growth rate was predicted.

**Table 5.7** Scenarios representing different situations due to urbanization and climate change that can effect the Asian common toad population

| Scenario | Output | Remarks |
|---|---|---|
| Climate change: A2 (IPCC) | SL | The increase in temperature and humidity and impact of industry have resulted in the given output from the model. As the presence of food is VL and the distance from and concentration of tree cover will be scarce, the toad will have no place to reproduce or survive. But the only positive of this scenario is the not-so-high concentration of predators and competitive species. Thus, a semi-high growth rate was predicted instead of extremely low growth rate |
| Climate change: B2 (IPCC) | SH | The strict conservation of the environment will provide a high concentration of tree cover both in amount and frequency. An adequate amount of water bodies like lakes will be conserved. The species distribution will also be under control. Industry and domesticated spaces will be concentrated in certain locations, and thus the toad will have enough freedom to reproduce and survive. Thus, a growth rate of SH was predicted by the model |
| Urbanization: large-scale urbanization | SL | The model prediction can be justified by the remarks given for the A2 climate change scenario. The only difference is the temperature and humidity. As far as the model simulation is concerned, neither of the variables has a noticeable influence on output. But if the parameter category were EL or VL, it might have an impact on the growth rate of the toad population |
| Urbanization: mid-scale urbanization | SH | The situation with large- and mid-scale landscapes was very similar, the only difference was that the impact of urbanization was not as intense as for large-scale urbanization. As the food source, presence of tree cover, water bodies, and their concentration were moderate, the output of the model predicted a semi-high growth rate for the toad population |
| Urbanization: small-scale urbanization | SH | The impact of urbanization was minimum in this scenario. The presence of predators reduced the growth rate to SH. If predators and competitive species (M) are scarce, the growth rate may be EH or VH |

The output from the model indicated that the presence of predators and competitive species had a noticeable influence on the growth of Asian common toad population. The distance from tree cover and industrial plants and residential complexes was also important to the growth rate of the toad. The study highlighted the scope of increasing toad population by identifying the harmful elements that would hinder the rate of growth if proper compensatory measures were not taken. On the other hand, the GA that was used was found to perform better if the number of generations was less than the amount of data population. Although the GAs were found to be very slow with heavy data set.

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