*CHAPTER-6*

# GROUNDWATER LEVEL PREDICTION OF ALLUVIAL AQUIFER IN VARANASI USING GENERALIZED INTELLIGENCE HYBRID TECHNIQUE (GHAT)

## 6.1 Introduction

Generally, groundwater management is very crucial to reduce drought effects during climate change. Also, the groundwater level (GWL) refers to the availability of groundwater and the physical properties of the aquifer. However, the prediction and estimation of groundwater levels is a challenging task in water resource management. This chapter cites a prediction model using a proposed innovative generalized intelligence control with a hybrid ant colony African buffalo optimization (GIC with HAC-ABO) approach termed as GHAT. The methodology, data used, results, and discussions are presented in the following sections.

## 6.2 Methodology

The prediction of groundwater level fluctuations is necessary for effective groundwater resource management because it is employed to identify the needs of water resources. Thus, the current research proposed the generalized intelligence control with hybrid ant colony African buffalo optimization (GIC with HAC-ABO) approach to estimate the groundwater level (GWL) fluctuations in Varanasi city wells for both pre-monsoon and post-monsoon periods. In this approach, the yearly groundwater level data from the dataset is used for training and testing that is done with the use of an innovative GIC approach. The following Figure 6.1 and Figure 6.2 depict the block diagram and flow diagram for GIC with HAC-ABO.

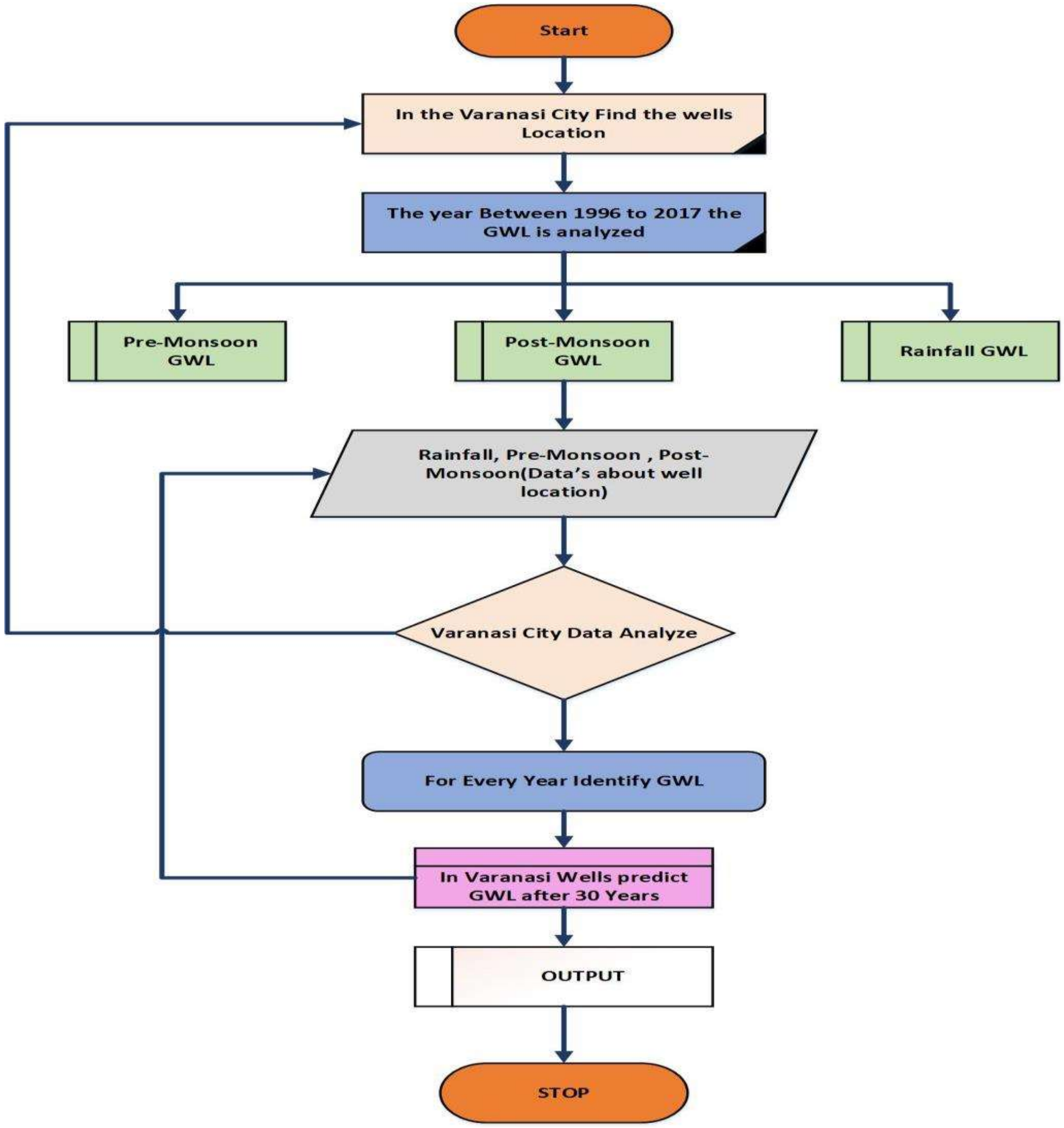


**Figure 6.1 Initial step of the proposed model**

Moreover, the proposed HAC-ABO method utilized to predict the GWL in wells after 30 years in Varanasi city. The GWL prediction is done with the use of MATLAB simulation and calculates the performance parameters like RMSE, MAE, prediction accuracy, and correlation coefficient. Hence, the proposed model attains high performance while validating with existing methods.

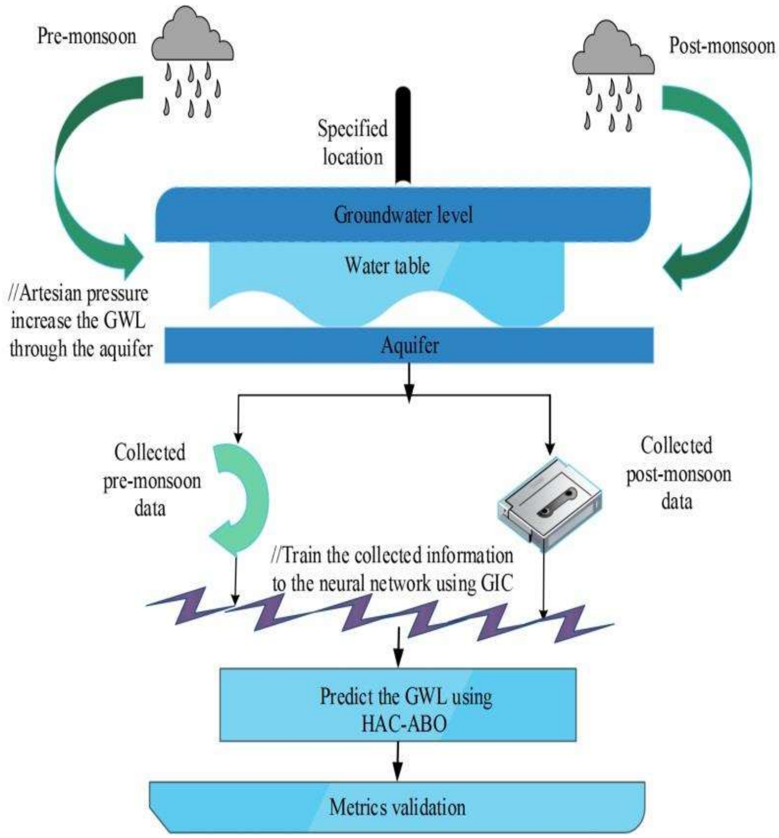


**Figure. 6.2 Proposed methodology flow diagram**

### 6.2.1 Process of GIC with HAC-ABO for predicting GWL

The proposed GIC with HAC-ABO model is employed for predicting the GWL in wells around Varanasi city. Initially, the collected annual data is trained to the system with the use of proposed GIC architecture. GIC is the neuro-fuzzy augmentation learning form; from that, the action selection network (ASN) based method is utilized for the voltage collapse forecasting (Hasda et al. 2020). The main aim of the proposed GIC with HAC-ABO has the following steps.

- The datasets are collected around Varanasi city and these datasets are trained to the MATLAB using GIC.
- Subsequently, the fitness function of HAC-ABO is used in the GIC classification

layer to predict the GWL for pre-monsoon and post-monsoon in Varanasi city wells.

- Consequently, the HAC-ABO method enhances the performance in terms of accuracy, RMSE, MAE, and correlation coefficient.

The input (dataset) is trained to the system using GIC based on the Eqn. (6.1),

$$Dataset = \phi_{i,j}(X) \tag{6.1}$$

where, $\phi$ is the dataset, $i, j$ is a parameter of the dataset and $X$ is the information. The data for GWL is processed and rehabilitated into a time series. Also, the input variables are primarily pre-processed using the GIC layer. Thus, it decomposed the time series as a sum of small number of understandable constituents such as slow-moving tendencies, oscillating elements, and noise. Moreover, the proposed HAC-ABO is the hybrid form of African buffalo optimization (ABO) (Deng et al. 2019) and ant colony optimization (ACO) (Singh et al. 2020). The reason for hybridization is to make the process easier and attaining high prediction outcomes. Also, the simulation of ACO for GWL prediction is attained lower accuracy and ABO attained a little bit higher accuracy than ACO. So, this research combined these two algorithms for achieving high prediction accuracy. In this HAC-ABO model, the fitness function of ABO is combined with ACO that is employed to predict the GWL in wells based on the developed fitness function.

After the dataset training, the HAC-ABO function is utilized in the GIC classification layer that is derived based on the searching behavior of African buffalo and pheromonel updates of ants. In general, the ACO mechanism is utilized for identifying the better path depending on the pheromone updates of ants. Moreover, this

ACO behavior is utilized in this approach for analyzing the location of wells in the datasets that are given in eqn. (4).

$$P'_x(Q_x) = \phi_{i,j}(X)[W'_n * Y_n](1-\sigma) \tag{6.2}$$

where, $W'_n$ denotes the current location of the wells $(n = 1,2,3,........,k)$, $Y_n$ denotes the particular year and $\sigma$ represents the evaporation rate. Subsequently, the ABO function is utilized for enhancing the accuracy with the combination of ACO algorithm for predicting the GWL in wells. Also, the groundwater level of wells in the Varanasi city is predicted using Eqn. (5),

$$W'_n(GWL) = P'_x(Q_x) + \{a1(bl*_{\max} - R_n) + a2(bk*_{\max.n} - R_n)\} \tag{6.3}$$

where, $bl*_{\max}$ represented as the actual GWL in Varanasi city wells, $bk*_{\max.n}$ denotes predicted GWL, $a1, a2$ is the learning parameters, and $R_n$ is the noise parameter. Moreover, $bk*$ represents the prediction parameter thus, the GWL has predicted during before monsoon and after monsoon using Eqn. (6),

$$bk*_{\max.n} = bk*\frac{(a1+a2)}{bl*_{\max}} \tag{6.4}$$

Hence, the proposed GIC with HAC-ABO model predicts the GWL in Varanasi wells during pre-monsoon and post-monsoon for the following years, which are detailed in algorithm 1. Finally, the proposed GIC with HAC-ABO methodology providing the best solution for predicting the GWL in Varanasi wells for both post-monsoon and pre-monsoon, which are shown in Fig.6.3

**Algorithm 1: GIC with HAC-ABO**

***Start***

{

***int*** $\phi, i, j$ ***// Initialize the dataset***

$Dataset = \phi_{i,j}(X)$

$X = W'_n + R$ ***// X-information of the dataset***

*well location is denoted as* $W'_n$ *is mentioned in eqn. (4)*

*X attained from 1996 to 2019*

*Analyze* $P'_x(Q_x)$ *in Varanasi city*

***Then***

{

*Analyze* $bl*_{max}$***//actual GWL in wells for post-monsoon and pre-monsoon***

}

***if*** *update* $bk*_{max.n}$ ***then*** ***// Predict the GWL in wells for following years***

*predict GWL using eqn. (5)*

***end if***

*enhance the parameters//* ***performance metrics***

*output best solution//* ***predicted output***

}

***Stop***

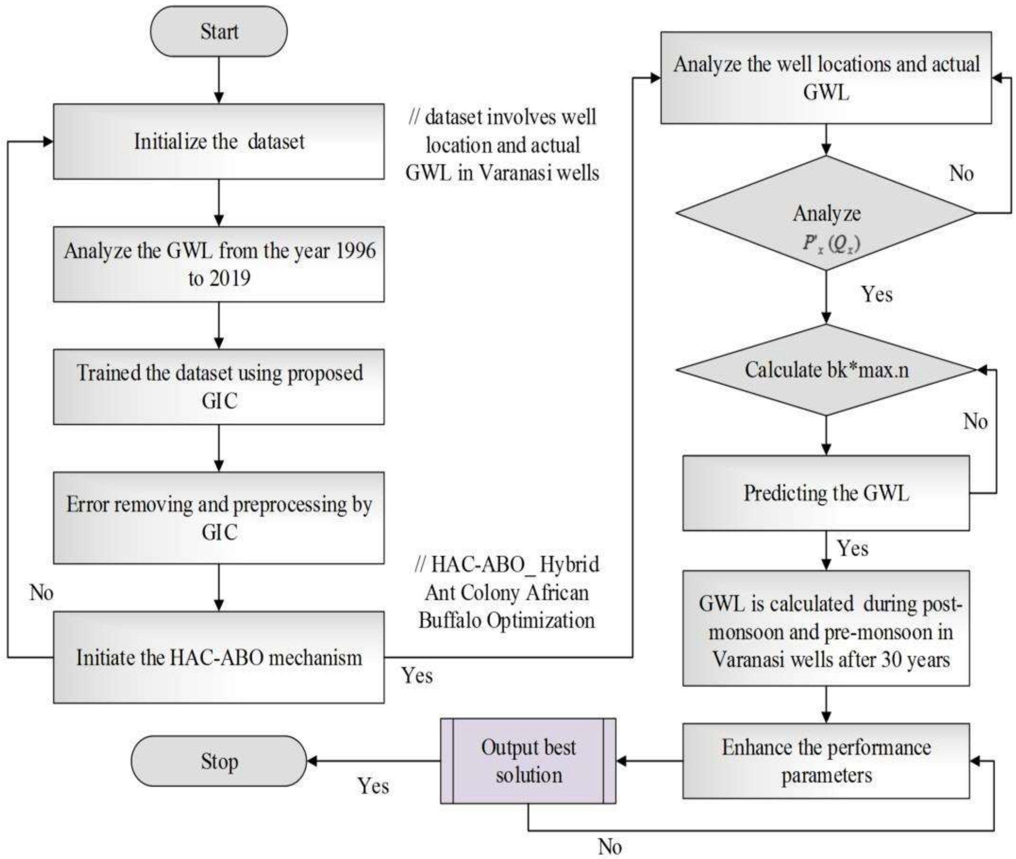


**Figure. 6.3 Processing steps for GIC with HAC-ABO**

The proposed GIC with HAC-ABO approach is to analyze the GWL in the Varanasi wells at U.P. Initially, MATLAB is trained with three categories of datasets that include the well location and GWL in pre-monsoon and post-monsoon for every year. Here, the first two datasets are collected from CGWB, and the third dataset is around the Varanasi city that is trained and tested for forecasting of groundwater level, CGWB1 involves the GWL in wells for both monsoons in the years 1996 to 2004.

- CGWB2 involves the GWL in wells for both monsoons in the years 2005 to 2013.
- Varanasi analyzed data (VAD) involves the GWL in wells for both monsoons in the years 2014 to 2019

Hence, these three datasets have different well locations with actual GWL values for various years. The main goal of the study is to apply the neural network process on the dataset to predict groundwater level for the following years. Initially, the data is converted into the proper format to make implementation. Consequently, the data is analyzed and observed for the variation in groundwater level patterns. Also, the workflow of the proposed approach is shown in Fig. 6.4. Finally, the proposed approach predicts the groundwater level in wells for both pre-monsoon and post-monsoon periods. Also, HAC-ABO is utilized for attaining better accuracy and minimizes error.

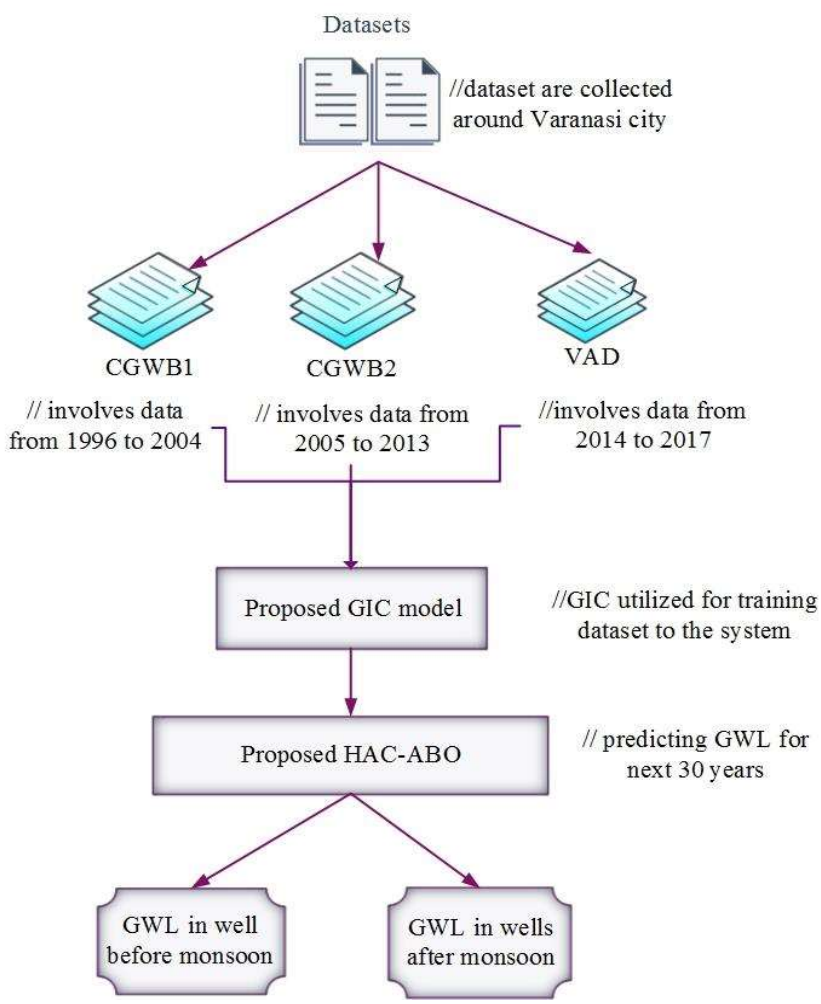


**Figure. 6.4 Workflow diagram using datasets**

### 6.3 Results and Discussion

The simulation results of CGWB1 dataset, CGWB2 dataset, VAD(Varanasi analyzed datasets) and performance metrics of the modeling are presented and discussed in the following sections.

#### 6.3.1 Simulation results for CGWB1 dataset

The proposed approach utilizes the CGWB1 dataset that involves actual groundwater level in Varanasi wells during the years 1996 to 2004, which is employed to predict the GWL for the next 30 years. Moreover, the CGWB1 dataset has the details about more number of wells around the Varanasi villages and involves GWL during the years 1996 to 2004 that are trained to the system. From that, the eight numbers of wells are utilized for testing to forecast the groundwater level that is measured in terms of meter (m). Here, the tested GWL in wells are identified from Anai, Babatpur, Chobepur, Tahipur, Raja Talab, Kakrahwan, Barwaon, and Rustampur. Subsequently, the actual GWL in wells during pre and post-monsoon values in the CGWB1 dataset is graphically represented in Fig.6.5 and Fig.6.6. This dataset is tested using the proposed GIC with HAC-ABO approach that can predict the groundwater level for both pre-monsoon and post-monsoon periods. Consequently, the GWL in wells after 30 years are predicted for the next 30 years. The predicted GWL outcomes during pre-monsoon in the years 2030, 2040, and 2050 are represented in Fig. 6.7. The predicted GWL during post-monsoon in the years 2030, 2040, and 2050 are represented in Fig. 6.8.

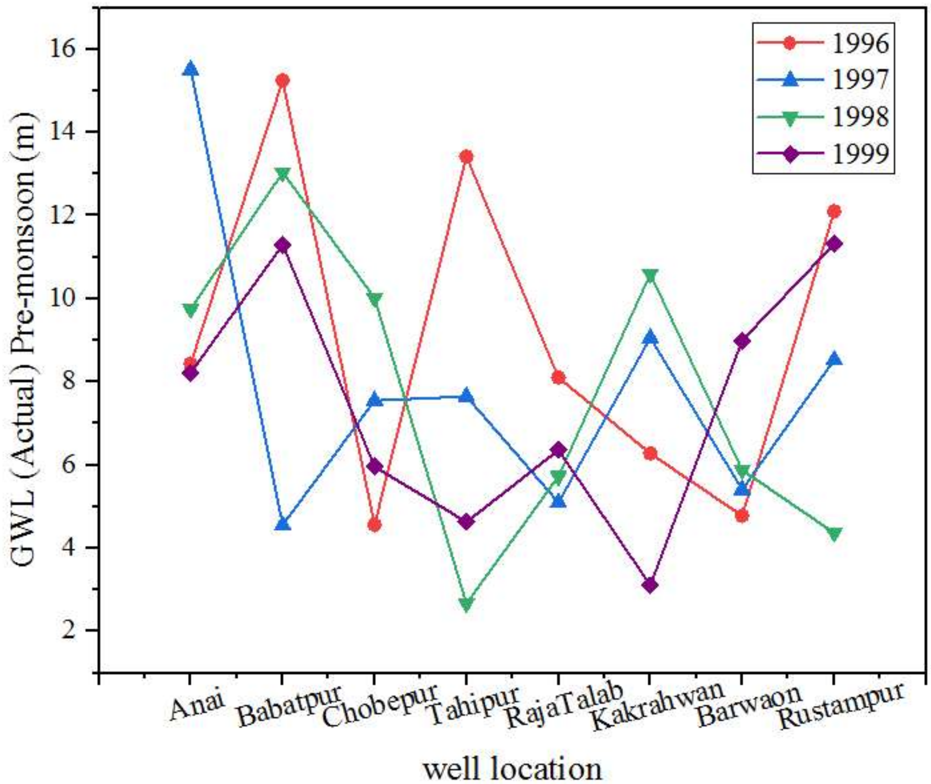


**Figure. 6.5 Actual GWL in wells during pre-monsoon using CGWB1**

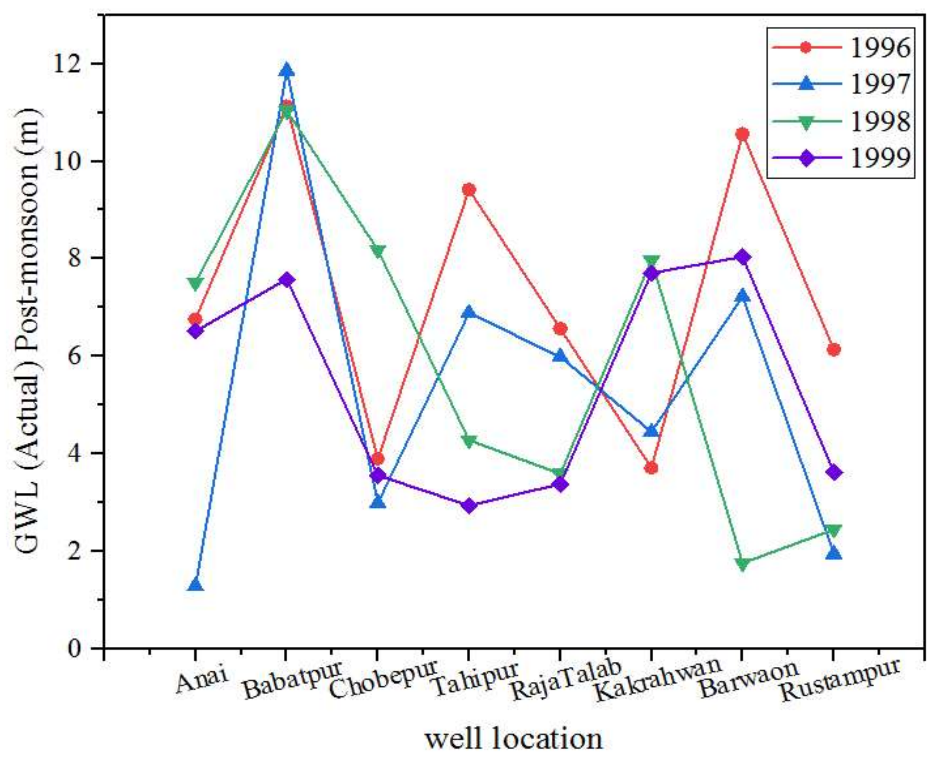


**Figure. 6.6 Actual GWL in wells during post- monsoon using CGWB1**

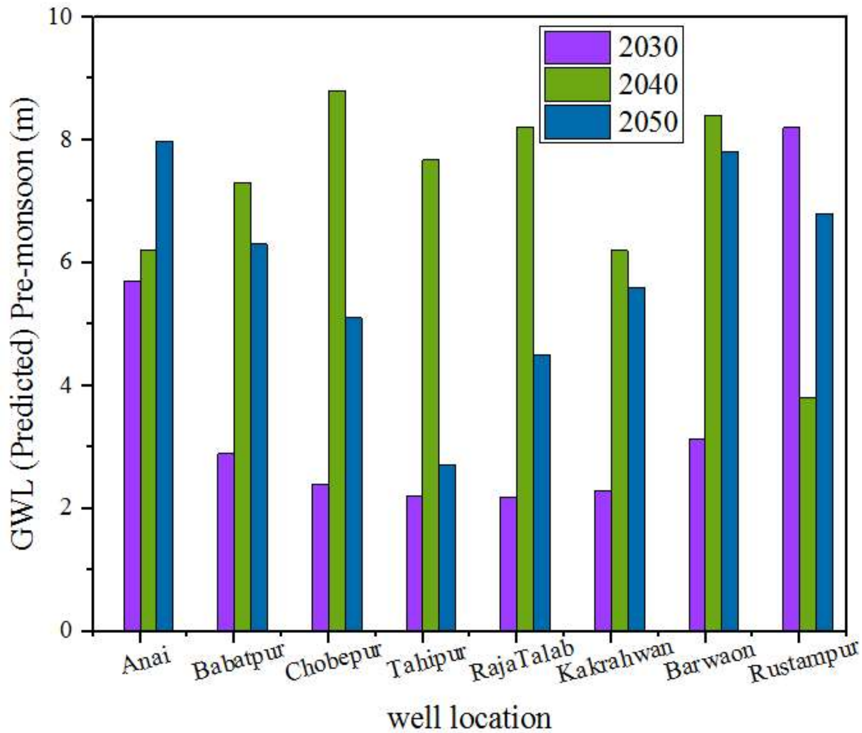


**Figure.6.7 Predicted GWL in wells during pre-monsoon using CGWB1**

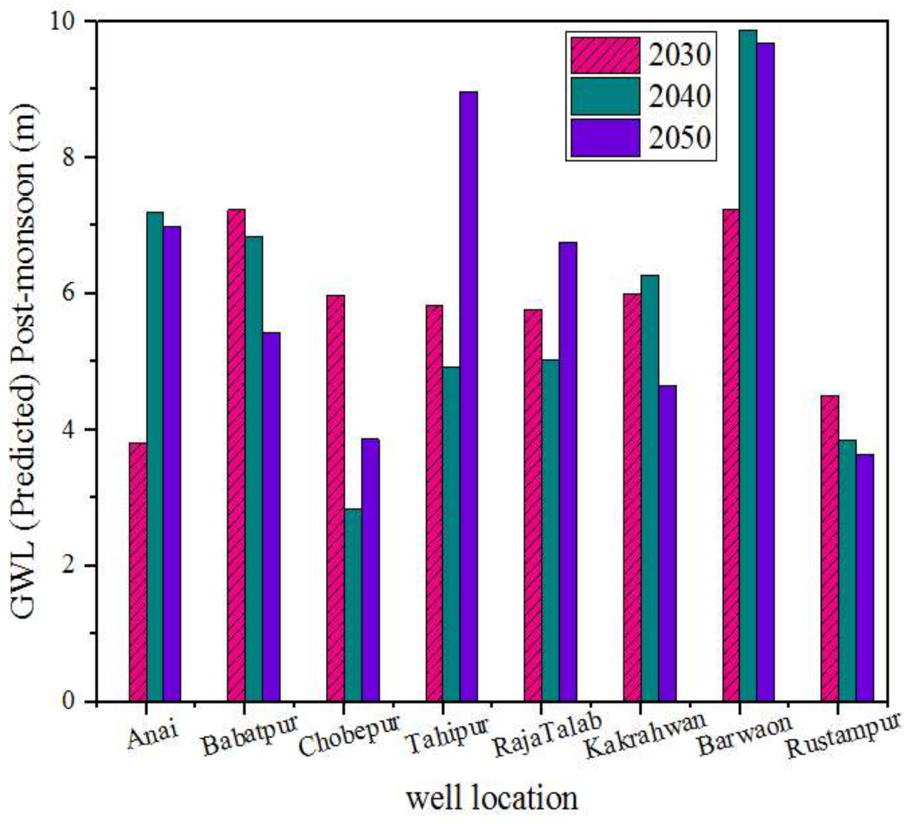


**Figure. 6.8 Predicted GWL in wells during post-monsoon using CGWB1**

### 6.3.2 Simulation results for CGWB2 dataset

Moreover, the CGWB2 dataset involves the data about 106 wells around the Varanasi city in the years 2005 to 2013. In this CGWB2 dataset, the well locations are taken as Araziline, Dindaspur, Gajapur, Gagapur, Jakhani, JansaBaz, Kachnar, and Kashipur in which the actual GWL are utilized for testing. The CGWB2 dataset contains the groundwater level in wells during pre and post-monsoon in the years 2005 to 2013.Also, the GWL in the wells from these locations are analyzed in the year 2005 to 2008 for pre-monsoon is represented in Fig.6.9. Moreover, the GWL in the above wells for post-monsoon in the year 2005 to 2008 is given in Fig.6.10. In the year 2005, the GWL in the Kachnar well had high-level groundwater, while in the year 2008, it had lower GWL. Likewise, the GWL is varied year by year due to the monsoon rainfalls.

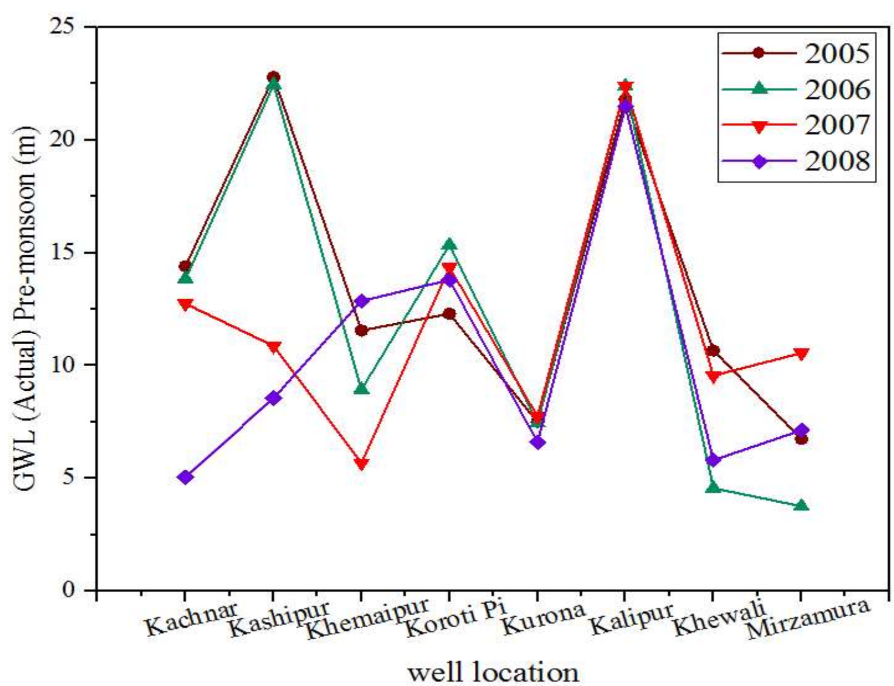


**Figure. 6.9 Actual GWL in wells during pre-monsoon using CGWB2**

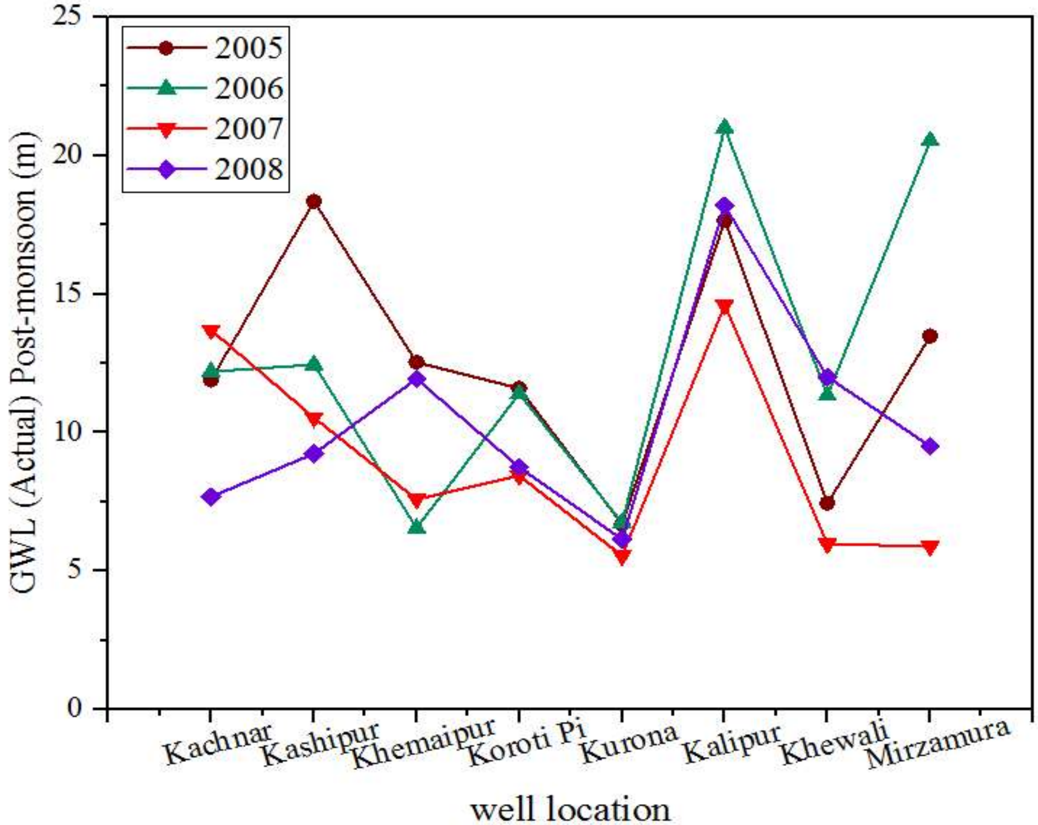


**Figure. 6.10 Actual GWL in wells during post-monsoon using CGWB2**

Accordingly, the GWL in wells after 30 years are predicted using proposed HAC-ABO approach. Here, this HAC-ABO attained the GWL predicted results for the next 30 years. The predicted GWL results during pre-monsoon in the years 2030, 2040, and 2050 using the CGWB2 dataset is represented in Fig.6.11. The predicted GWL outcomes during post-monsoon in the years 2030, 2040, and 2050 are represented in Fig.6.12.

The actual GWL in wells from the Araziline, Dindaspur Gajapur, Gagapur, Jakhani, JansaBaz, Kachnar, and Kashipur locations are analyzed for forecasting the GWL. The developed approach predicts the GWL for both monsoon periods for the above wells in the years 2030, 2040, and 2050.

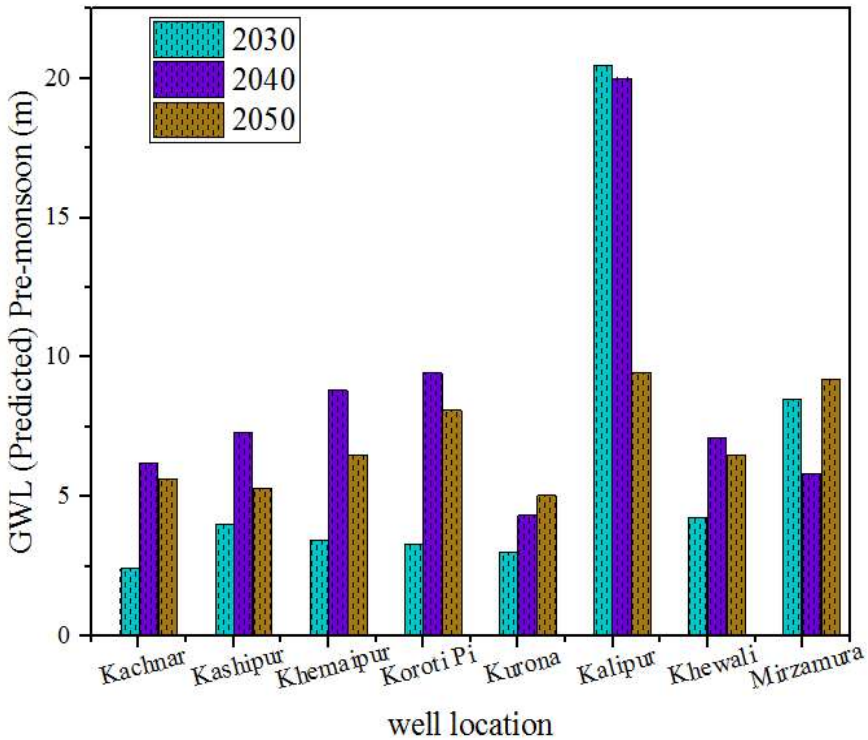


**Figure. 6.11 Predicted GWL in wells during pre-monsoon using CGWB2**

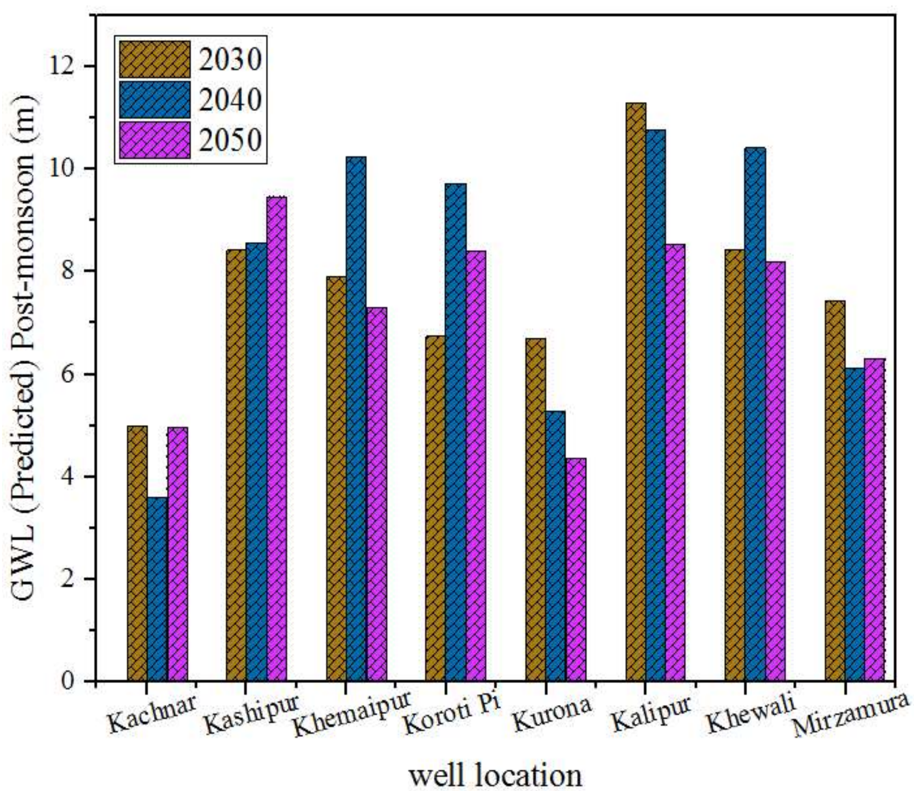


**Figure. 6.12 Predicted GWL in wells during post-monsoon using CGWB2**

### 6.3.3 Simulation results for VAD dataset

This dataset involves the GWL for 20 wells around the Varanasi city during post and pre-monsoon periods in the years 2015 to 2018. This dataset is utilized for training in the system and some of the wells groundwater levels are evaluated and tested. Here, the well locations are considered as Bhagwanpur road, Chittupur road (Dilip lodge), Chittupur road 2, Trauma centre, Samneghat 1, Samneghat 2 (river crossing), Samneghat 3 (sand side), and Vyassaatachakki around the Varanasi. Thus, the actual GWL in wells during pre and post-monsoon values from 2015 to 2018 is graphically represented in Fig.6.13 and Fig.6.14. Subsequently, the GWL in wells after 30 years is predicted using the proposed HAC-ABO approach. Here, this HAC-ABO attained the GWL in wells for both pre-monsoon and post-monsoon for the next 30 years. The predicted GWL during pre-monsoon in the years 2030, 2040, and 2050 using the VAD dataset is symbolized in Fig.6.15. The predicted GWL during post-monsoon in the years 2030, 2040, and 2050 are represented in Fig.6.16.Hence, the GWL is predicted for the upcoming 30 years using the proposed GIC with HAC-ABO approach. Therefore, it attained high prediction accuracy for forecasting the GWL around the Varanasi city wells.

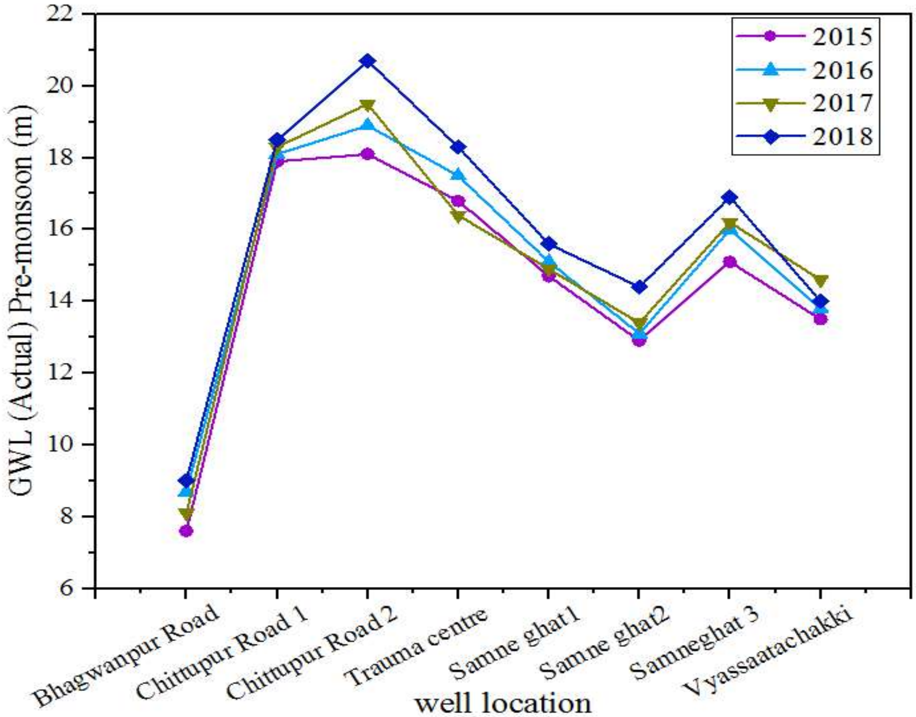


**Figure. 6.13 Actual GWL in wells during pre-monsoon using VAD**

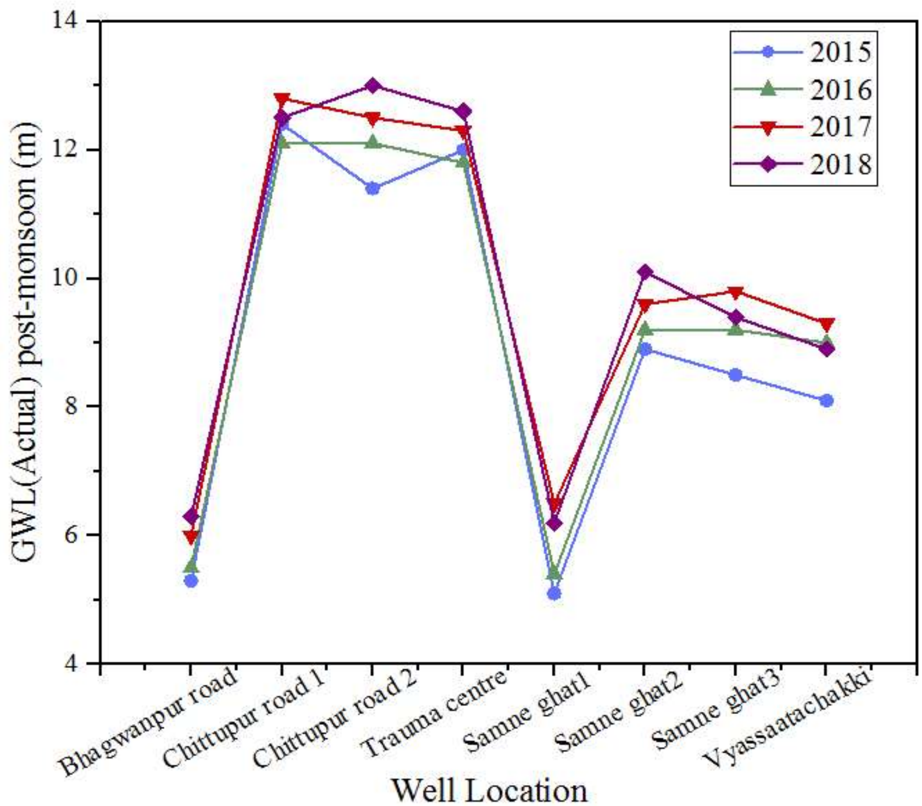


**Figure. 6.14 Actual GWL in wells during post-monsoon using VAD**

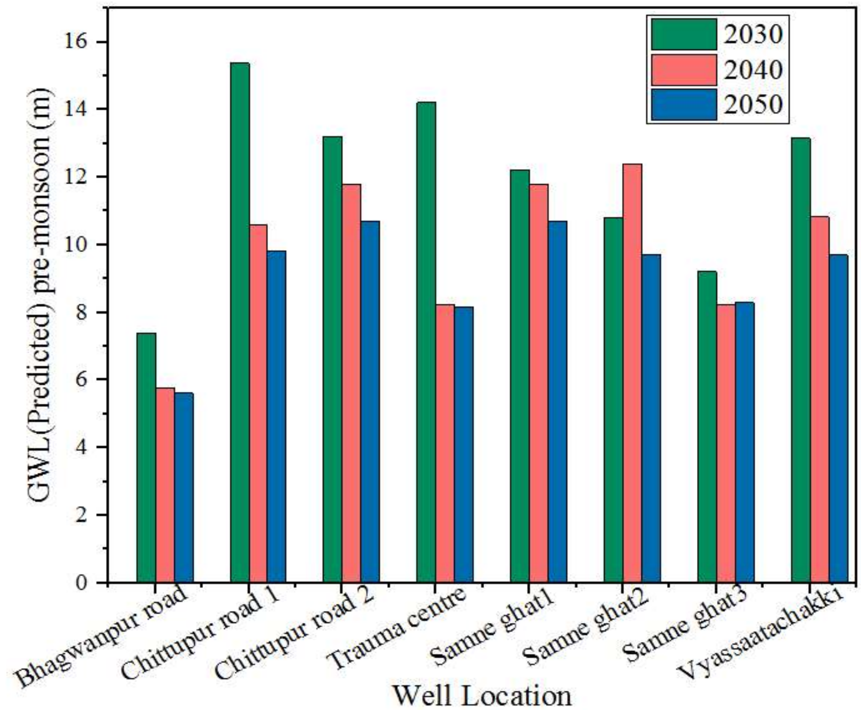


Figure. 6.15 Predicted GWL in wells during pre-monsoon using VAD

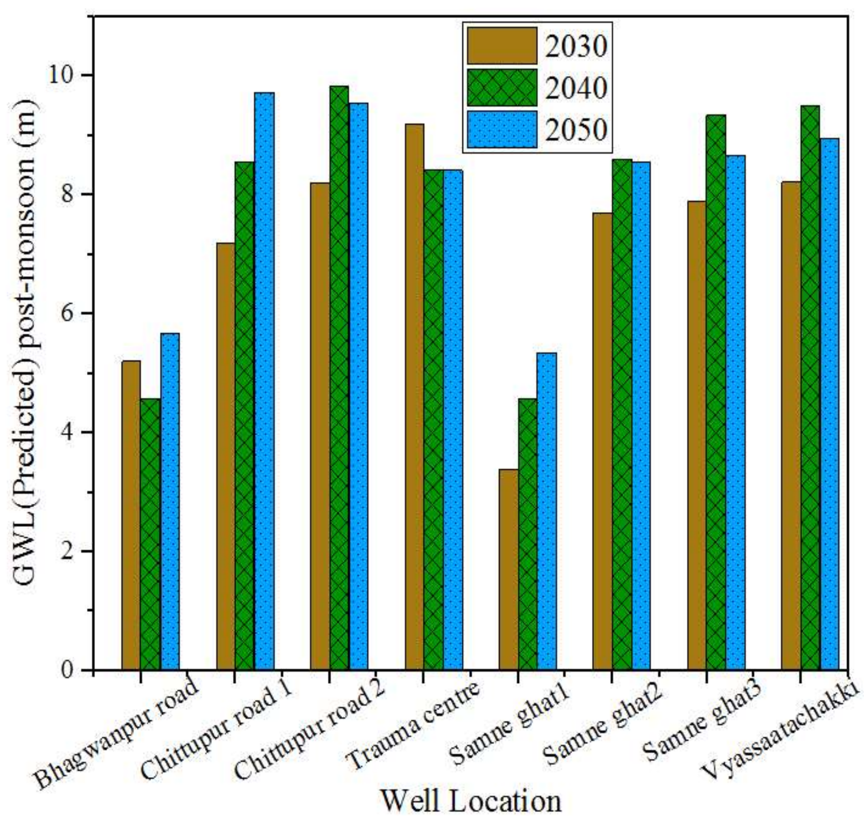


Figure. 6.16 Predicted GWL in wells during post-monsoon using VAD

### 6.3.4 Performance Metrics

The collected statistics are trained to the system by GIC with HAC-ABO model to predict the GWL for post and pre-monsoon periods. The GWL is calculated in the Varanasi city wells during pre-monsoon and post-monsoon, which is identified as the variation of water level for both monsoon periods. Here, the groundwater level is varied from place to place with the depth of the water table that is analyzed by GIC with HAC-ABO model. Finally, the performance metrics are calculated and the efficiency of the proposed method is validated with the use of existing approaches.

The proposed GIC with HAC-ABO method utilized for predicting GWL in wells for the next 30 years, which is implemented using MATLAB R2018b. Also, it is measured the performance metrics like prediction accuracy, correlation coefficient, RMSE, and MAE. In this research, the fitness function of HAC-ABO model is combined with the GIC mechanism for attaining high performance. Moreover, the attained results are compared with existing methods like MLR with ANN (Sahoo and Jha 2013), RBF-WA (Banadkooki et al. 2020), MLP-WA (Banadkooki et al. 2020), and wavelet–SAELM (Yosefvand and Shabanlou 2020).

The prediction accuracy is calculated for identifying how effectively the proposed method predicts the GWL that is computed using eqn. (6.5).

$$Acc = (TP + TN)/(TP + TN + FP + FN) \tag{6.5}$$

where, TP-true positive, TN-true negative, FP-false positive, and FN-false negative. Here, TP is the outcome where the proposed approach properly predicts the GWL wells and TN is the result where the proposed approach properly predicts the GWL of an inaccurate way. Moreover, FP is the result where the proposed method incorrectly predicts the GWL as a proper way and FN is the outcome where the proposed method incorrectly predicts the GWL in wells. The proposed approach evaluated with existing methods such as MLR with ANN, MLP-WA, RBF-WA, and wavelet–SAELM for identifying the effectiveness of the proposed technique. Also, the comparison of prediction accuracy is detailed in Table 6.1 and represented in Fig.6.17. In this, the existing methods like MLR with ANN and wavelet–SAELM have achieved almost 87% and 83% prediction accuracy. Moreover, the methods MLP-WA and RBF-WA have attained nearly 92% and 95% prediction accuracy. Therefore, the proposed GIC based HAC-ABO model attained high performance in prediction accuracy as 96.2 % than other models.

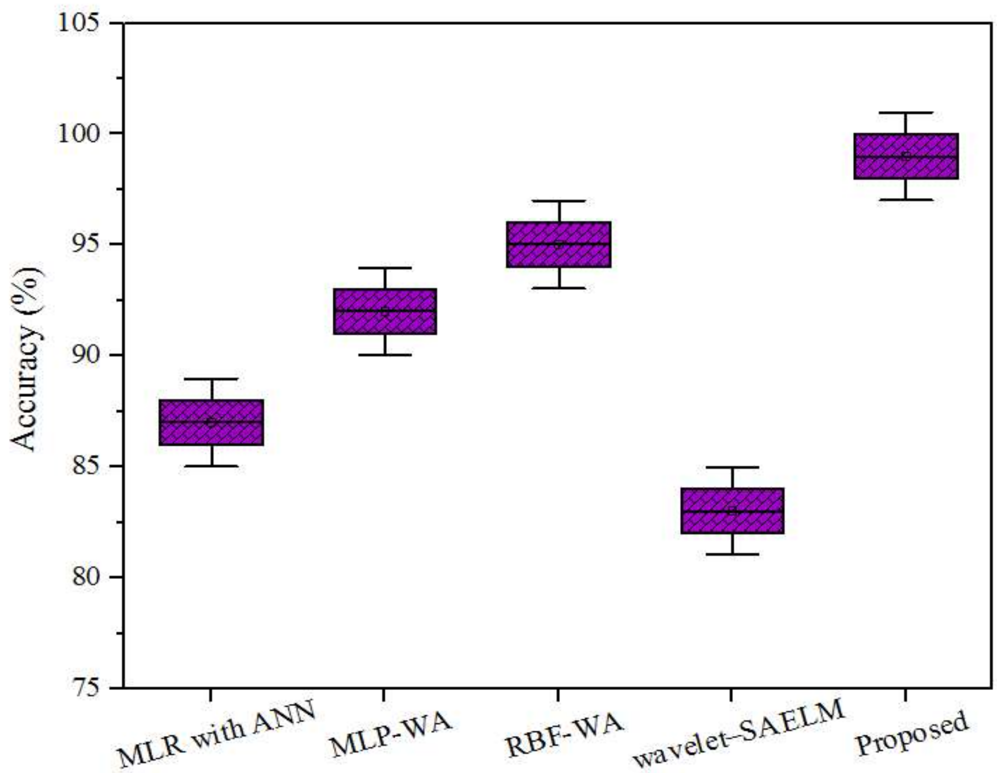


**Figure. 6.17 Comparison of prediction accuracy**

**Table 6.1 Comparison of Prediction accuracy**

| Techniques | Prediction Accuracy[1] (%) |
|---|---|
| MLR with ANN | 87% |
| MLP-WA | 92% |
| RBF-WA | 95% |
| wavelet–SAELM | 83% |
| GIC with HAC-ABO (proposed) | 96.2% |

[1]calculated for identifying the effectiveness of the proposed model

The correlation coefficient (CR) is a calculation of the strength of the relationship between the relative movements of two output variables, which is calculated using Eqn. (6.6).

$$CR = \frac{\sum_{i=1}^{X} \left(bl*_{\max} - A'_i\right)\left(bk*_{\max.n} - P'_i\right)}{\sqrt{\sum_{i=1}^{X} \left(bl*_{\max} - A'_i\right)^2 \sum_{i=1}^{X} \left(bk*_{\max.n} - P'_i\right)^2}} \tag{6.6}$$

where, $i$ denotes the number of datasets, $bl*_{\max}$ is the actual GWL, $bk*_{\max.n}$ represents the predicted GWL, $A'_i$ is the mean of actual GWL in $i^{th}$ dataset, and $P'_i$ denotes the mean of predicted GWL in $i^{th}$ dataset.

The proposed model has the CR value as 0.05 that is validated with existing methods, which is shown in Fig.6.18. Here, the approaches MLR with ANN and wavelet–SAELM attained nearly 0.9 higher CR value. Also, the approaches MLP-WA and RBF-WA has the CR value as almost 0.3 and 0.4. Thus, the proposed GIC with HAC-ABO achieved a lower correlation coefficient as 0.05 than other methods that are detailed in Table 6.2.

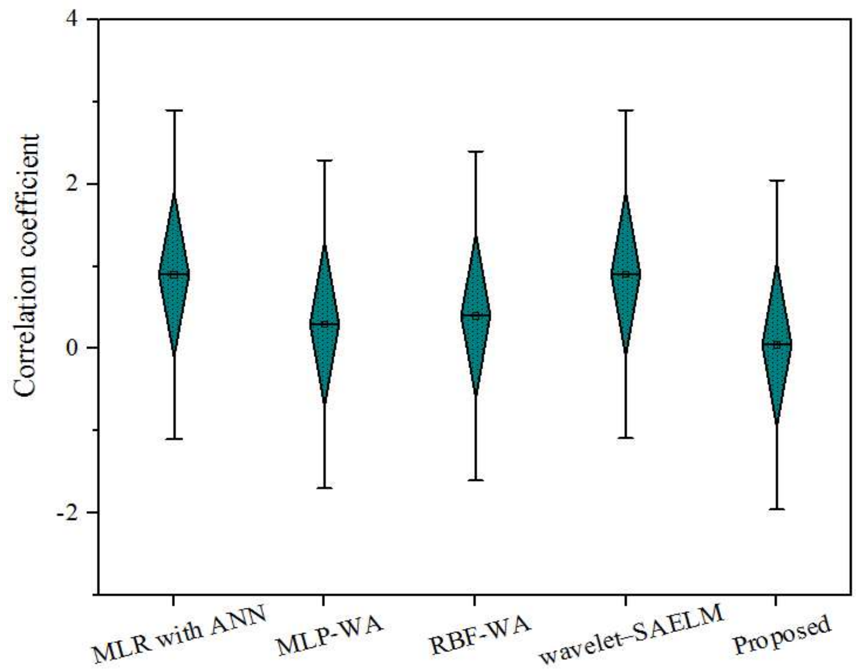


**Figure. 6.18 Comparison of correlation coefficient**

**Table 6.2 Comparison of CR**

| Techniques | Correlation coefficient (CR[1]) |
|---|---|
| MLR with ANN | 0.9 |
| MLP-WA | 0.3 |
| RBF-WA | 0.4 |
| wavelet–SAELM | 0.907 |
| GIC with HAC-ABO (proposed) | 0.05 |

[1]measurement of the strength between the relative movements of the output variables

The RMSE is utilized for calculating error in the GWL prediction that can be assisting to identify how effectively the proposed approach predicts the GWL in wells during monsoons, which is measured using eqn. (6.7).

$$RMSE = \sqrt{\frac{1}{X}\sum_{i=1}^{X}\left(bl*_{\max} - bk*_{\max.n}\right)^2} \quad (6.7)$$

The RMSE value of the proposed model is compared with prevailing techniques and attained lower error that is illustrated in Fig. 6.19. Also, the existing methods like MLR with ANN, MLP-WA, RBF-WA, and wavelet–SAELM are attained high RMSE value that is reduced by proposed method. Thus, the developed GIC with HAC-ABO mechanism attained 0.032 lower RMSE values that are elaborated in Table 6.3.

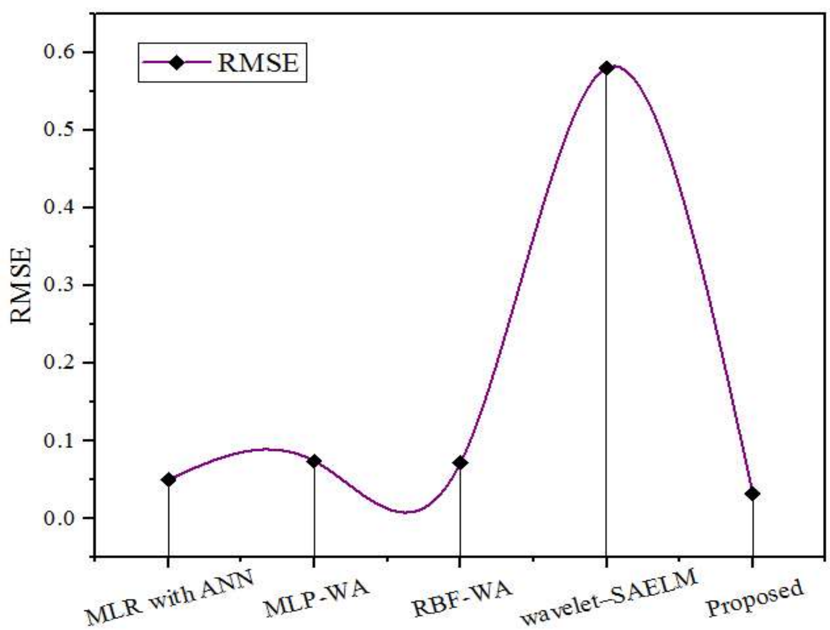


**Figure. 6.19 Comparison of RMSE**

**Table 6.3 Comparison of RMSE**

| Techniques | RMSE[1] |
|---|---|
| MLR with ANN | 0.05 |
| MLP-WA | 0.074 |
| RBF-WA | 0.072 |
| wavelet–SAELM | 0.58 |
| GIC with HAC-ABO (proposed) | 0.032 |

[1]utilized to calculate the error

Mean absolute error (MAE) is utilized for reducing large errors in the prediction process. If the error is presented when forecasting the GWL that is calculated by MAE using eqn. (6.8),

$$MAE = \frac{1}{X}\sum_{i=1}^{X}\left|bl*_{\max} - bk*_{\max.n}\right| \tag{6.8}$$

The MAE is calculated in the proposed approach and evaluated with prevailing methods that are demonstrated in Fig. 6.20. Also, the proposed method attained a lower MAE as 0.02 than other models, which is mentioned in Table 6.4. Consequently, the developed GIC with HAC-ABO method has achieved high performance.

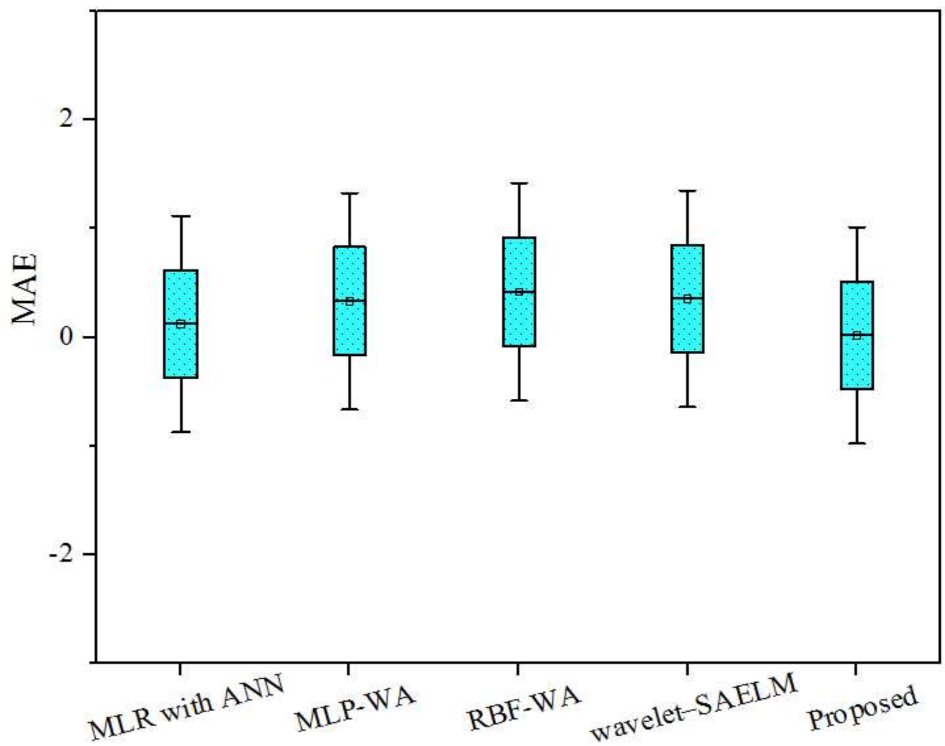


**Figure. 6.20 Comparison of MAE**

**Table 6.4 Comparison of MAE**

| Techniques | MAE[1] |
|---|---|
| MLR with ANN | 0.122 |
| MLP-WA | 0.337 |
| RBF-WA | 0.42 |
| wavelet–SAELM | 0.36 |
| GIC with HAC-ABO (proposed) | 0.02 |

[1]identifying errors while doing the prediction process

Hence, the proposed GIC with HAC-ABO model is compared with recent optimization algorithms like ACO (Li and Hilton 2007), ABO (AHMED 2019), ALO (Banadkooki et al. 2020), and GA (Roshni et al. 2020). The existing optimization methods attained lower accuracy and lower performance for forecasting the groundwater level.

Thus, the proposed model provides high efficiency than other methods which is represented in Fig. 6.21, and the attained values are mentioned in Table 6.5. The single forecasting approaches attained lower prediction accuracy but the proposed hybrid model achieved high prediction accuracy and efficiency. Here, the ACO and ABO approaches attained almost 78% and 86% lower accuracy for predicting GWL. Thus, the proposed hybrid model attained 96.2 % high prediction accuracy for forecasting the groundwater level.

Here, the groundwater level varies due to rainfall, pre-monsoon and post-monsoon climate variability. Therefore, the proposed GIC with HAB-ACO model will predict the GWL in wells during the pre-monsoon and post-monsoon seasons for the next 30 years. Furthermore, the comparative value demonstrates the performance of the proposed model.

The proposed GIC with HAC-ABO model is simulated in MATLAB and attained high performance than other approaches. This method predicts the GWL in Varanasi city wells during pre-monsoon and post-monsoon periods. The GWL is predicted after 30 years in the Varanasi city wells that are analyzed using the dataset, which involved GWL for past and present years for various wells. Thus, the proposed model attained 96.2% high prediction accuracy for predicting GWL in Varanasi city wells. From this result assessment, it is proved that the proposed model is efficient and applicable in GWL prediction.

Primarily, three kinds of GWL statistics datasets are trained to the system. Consequently, a novel optimized generalized based intelligent approach is designed effectively to predict the groundwater level in Varanasi city. Here, the generalized approach is enhanced with the fitness function of ant and African buffalo model. Thus, it has accomplished a high exactness measure in groundwater level prediction. Finally, this model has achieved less error rate as 0.02 MAE and 0.032 RMSE, which is lower than other existing associated works.

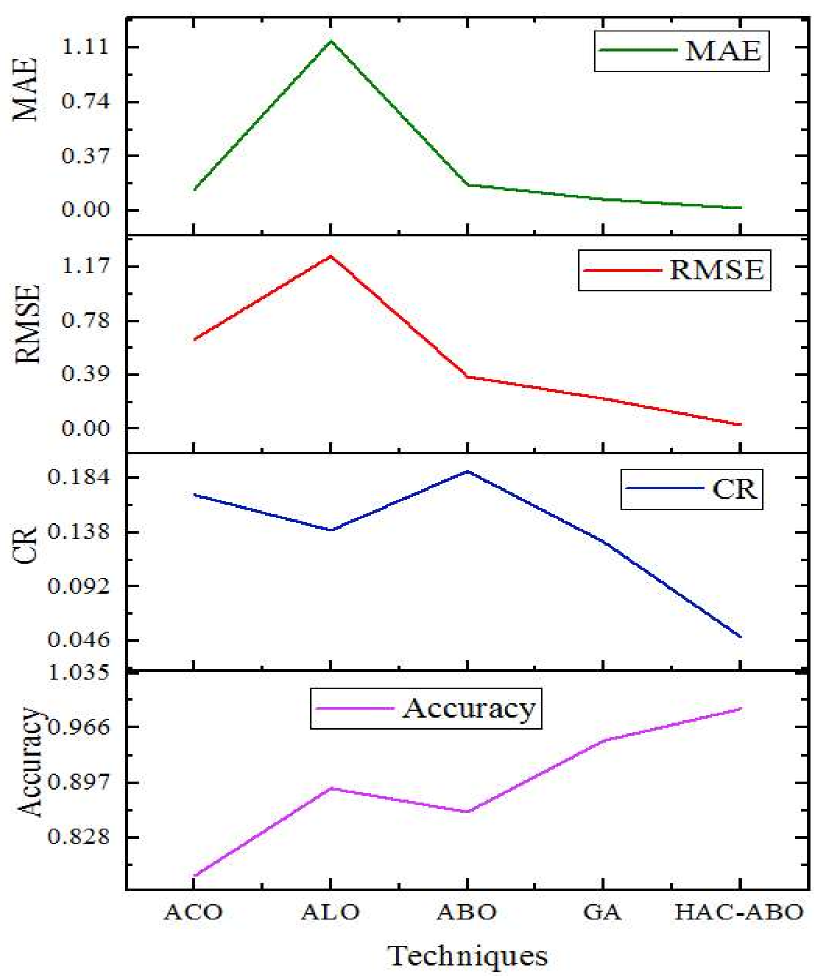


**Figure. 6.21 Comparison of parameters with optimization models**

**Table 6.5 Comparison of proposed hybrid approach with single forecasting methods**

| Techniques | Accuracy (%) | Correlation coefficient (CR) | RMSE[1] | MAE |
|---|---|---|---|---|
| ACO[1] | 78% | 0.17 | 0.65 | 0.15 |
| ALO[2] | 89% | 0.14 | 1.25 | 1.16 |
| ABO[3] | 86% | 0.19 | 0.38 | 0.18 |
| GA | 95% | 0.13 | 0.22 | 0.08 |
| HAC-ABO (proposed) | 96.2% | 0.05 | 0.032 | 0.02 |

[1]Ant colony optimization

[2]Ant lion optimization

[3]African buffalo optimization

The proposed GIC with HAC-ABO model is simulated in MATLAB and attained high performance than other approaches. This method predicts the GWL in Varanasi city wells during pre-monsoon and post-monsoon periods. The GWL is predicted after 30 years in the Varanasi city wells that are analyzed using the dataset, which involved GWL for past and present years for various wells. Thus, the proposed model attained 96.2% high prediction accuracy for predicting GWL in Varanasi city wells. From this result assessment, it is proved that the proposed model is efficient and applicable in GWL prediction.

Primarily, three kinds of GWL statistics datasets are trained to the system. Consequently, a novel optimized generalized based intelligent approach is designed effectively to predict the groundwater level in Varanasi city. Here, the generalized approach is enhanced with the fitness function of ant and African buffalo model. Thus, it has accomplished a high exactness measure in groundwater level prediction. Finally, this model has achieved less error rate as 0.02 MAE and 0.032 RMSE, which is lower than other existing associated models.

## 6.4 Conclusions

Undoubtedly, groundwater management plays a significant role in meeting water needs in society. Due to limited water resources, the demand for more and more groundwater is growing rapidly. Keeping this aspect in view, the level of groundwater should be analyzed for efficient groundwater management to identify groundwater usages. In the present research, the GWL of the observational well located in the Varanasi, Uttar Pradesh was modeled for very first time by an innovative machine learning and hybrid optimization method. The introduced GIC with HAC-ABO approach is employed to predict groundwater level in Varanasi city wells for post and pre-monsoon periods. Development of ground water modeling utilized three categories of datasets that involves well locations and actual GWL around the Varanasi city. In this, the first two datasets have been attained from CGWB that are utilized for training and testing to forecasting the groundwater level. Also in the third dataset, the well locations are identified using a Differential Global Positioning System around the Varanasi and the GWL is measured using graduated steel tape for post-monsoon and pre-monsoon periods. Hence, the system is trained with datasets by the proposed GIC model, the GWL is predicted using the HAC-ABO approach. This model calculates the groundwater level in Varanasi city wells for next 30 years during pre-monsoon and post-monsoon. Thus, the proposed method attained 99% high prediction accuracy, 0.02 MAE, and 0.032 lower RMSE. Also, the achieved results have been validated with other techniques that proved the effectiveness of the proposed method. Hence, it improved the 6.75% prediction accuracy than other existing methods. It is suggested to forecast the groundwater level based on temperature of the city and droughts in the future. Also, clear measurement of wells depth, and the water evaporation can be employed to predict the groundwater level.