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Prediction of Ground Water Level using SVM-WOA Approach: A Case Study

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Reliable and accurate estimation of Groundwater Level (GWL) fluctuations is essential and vital for sustainable water resources management. Due to uncertainties and interdependencies in hydro-geological processes, GWL prediction is complex by the fact that fluctuation of GWL is extremely nonlinear and non-stationary. Utilising novel methods for accurately predicting GWL is of vital significance in arid regions. In present work, Support Vector Machine (SVM), in combination with Whale Optimisation Algorithm (SVM-WOA), is applied to forecast GWL in Bhubaneswar region (Odisha University of Agricultural Technology). Three quantitative statistical performance assessment indices, coefficient of determination (R^2), Mean Squared Error (MSE), and Wilmott Index (WI), is used to assess model performances. Based on the assessment with conventional SVM and RBFN models, the performance of hybrid SVM-WOA model is preeminent. SVM-WOA is capable of predicting nonlinear behavior of GWLs. Proposed modelling technique can be applied in different regions for proper management of groundwater resources and provides significant information, at a short time scale, to estimate variability in groundwater at local level.

Keywords: Groundwater level, OUAT, RBFN, Wilmott index

Introduction

Due to the ever rising water demand for domestic, industrial, and agricultural requirements, groundwater resource management has been the main concern.[1–6] Specifically, in countries like India, depletion of groundwater has created a sense of distress among engineers. In addition, estimation of GWLs in a basin is of huge significance for sustainable groundwater resource management. Estimation of GWL is extremely nonlinear and very complicated since it relies upon several intricate aspects like evapotranspiration, topography, precipitation, and soil characteristics of a catchment.[7,8] Physical-based and data-driven based models have been utilised in prediction studies in several fields of engineering and sciences.[9–11] For understanding hydrological properties of aquifers and other associated factors of subsurface media, computational modelling of stream and transport has become an effective method.[12,13] Disadvantages with use of numerical models are problems faced during transformation of physical process into mathematical formulations and deficiency of adequate dataset. In last two decades, ML methods have been applied in large numbers to overcome these shortcomings and difficulties.[14–16]

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ANN and SVM were employed to predict GWL variation considering two wells at a coastline aquifer in Korea.[17] Result showed that SVM model's performance is superior compared to ANN. An integration model of RBFN and Autoregressive Integrated Moving Average (ARIMA) was used for predicting monthly GWL in Xi'an city, China.[18] They found that proposed hybrid model provided better GWL predictions. RBFNs and SVM were employed for simulating GWL fluctuations using precipitation, temperature, and evaporation as model inputs.[19] Comparison of outputs showed that SVM had less uncertainty and was more accurate. Least square-SVM prediction model was constructed to forecast future GWL and studied interrelationship between monitoring sites by conducting spatio-temporal analysis. Results revealed that LS-SVM outperformed other considered models, with spatio-temporal analysis as an effective approach.

The accuracy of wavelet-MLR, wavelet-ANN, and wavelet-SVM, were investigated and compared it with classical ANN, MLR, and SVM models in simulating one-month-ahead GWL of Qom plain, Iran.[20] They found that integration of wavelet transform improved the prediction accuracy of conventional models in the specified study region. The predictive capability of ANN, NARX (nonlinear autoregressive with exogenous inputs), and

SVM-RBF algorithm were evaluated to predict daily GWL in a location southeast of USA.[21] RBF-WA, MLP-WA (multilayer perceptron), and Genetic Programming (GP) were applied for predicting GWL.[22] They found that MLP–WA gave best performance among all. A comparison between performance of hybrid SVM-QPSO and SVM-RBF with SVM and ELM models.[23] Outcomes indicated that performances of ELM are better compared to SVM, SVM-QPSO and SVM-RBF. SVM-WOA, SVM-MVO (Multi-Verse Optimiser), and SVM-ALO (Ant Lion Optimiser) were applied for estimating ETo at Algiers and Tlemcen gauging sites located in northern Algeria.[24] Applied hybrid SVM-WOA model was more efficient and appropriate. SVR, GPR (Gaussian process regression), and their amalgamation with WT i.e., W-SVM and W-GPR, were applied to forecast GWL in Semnan plain.[25] Results revealed that W-SVM model provided best GWL forecasting than other models. The objective of this research is to predict GWL through hybrid SVM-WOA approach and compared with conventional SVM.

Materials and Methods

Study Area

Khordha district falls between 84°55” to 86°5” E longitudes and 19°40” to 20°25” N latitudes and covers 2813 sq. km. geographical area i.e., almost 1.81% of total area of the Odisha state (Fig. 1). The district is surrounded north by Cuttack, south by Ganjam, east by Puri, and west by Nayagarh districts. The study area in this work is focused on Bhubaneswar region. Bhubaneswar has a tropical savanna climate with an annual rainfall of 1,638 mm. The mean annual temperature is 27.4°C, with summer being hot and humid (March to June), and winter lasts just around 10 weeks (December and January). January is the coldest month, with May being the hottest.

Methodology

RBFN

A RBFN includes three layers: input, hidden, and output layer. Information is collected in input layer, and hidden layer comprises a set of basis function which executes nonlinear transformation of inputs.[26–28] The desired output is obtained in the output layer. As nonlinearity of hidden nodes, gauss function is the most common transformation. The general architecture of RBFNN is represented in Fig. 2. The j-th hidden node’s response to x_i is:

$$h_{ij}(x) = \exp\left(-\alpha \left\| x_i - c_j \right\|^2\right) \quad \ldots (1)$$

where, $\|\ldots\|$- Euclidean norm; c_j- centre of basis function; α- positive constant determining hidden node’s width of symmetric response.

SVM

The SVM model helps to minimise model complexity and estimation error simultaneously.[29] The architecture of simple SVM is depicted in Fig. 3. SVM solves regression and classification problems on the basis of different kernel functions, tacitly converting low-dimensional inputs into a high-dimensional feature space (FS).[30–35] SVM’s regression function is expressed by:

$$f(x) = \omega\varphi(x) + b \quad \ldots (2)$$

where, $\varphi(x)$- high-dimension FS converted from x input vector; b- bias; ω- weight vector.

Regularised risk function is minimized for determining two constraints as expressed below:

$$R(C) = C\frac{1}{n}\sum_{i=1}^{n} L(d_i, y_i) + \frac{1}{2}\|\omega\|^2 \quad \ldots (3)$$

$$L_\varepsilon(d, y) = \begin{Bmatrix} |d-y| - \varepsilon |d-y| \geq \varepsilon \\ 0 \; otherwise \end{Bmatrix}$$

where, C - penalty parameter; $\frac{1}{2}\|\omega\|^2$-regularisation term; d_i-required value; n–number of observations; $C\frac{1}{n}\sum_{i=1}^{n} L(d_i, y_i)$- error; $\mathcal{E}$–SVM’s tube size in L_ε.

Because of good model stability and prediction accuracy, RBF kernel function is applied.

WOA

WOA was introduced based on feeding behaviour and special bubble-net quality of humpback whales.[36] For hunting prey, three steps are performed by the whale: (i) encircling prey; (ii) exploration (search for prey); and (iii) exploitation (bubble-net attack).[37,38] In present work, WOA is utilized for optimizing capacity of SVM (i.e., SVM-WOA).

i. Encircling prey

An individual is represented by a humpback whale, and location of every individual in search space represents a solution. Whale can recognize position of prey and, through echolocation, encircle prey. Updated formula of whale position is given by:

$$X^{t+1} = X_{gbest}^{t} - A \cdot \left| C \cdot X_{gbest}^{t} - X^{t} \right| \quad \ldots (4)$$

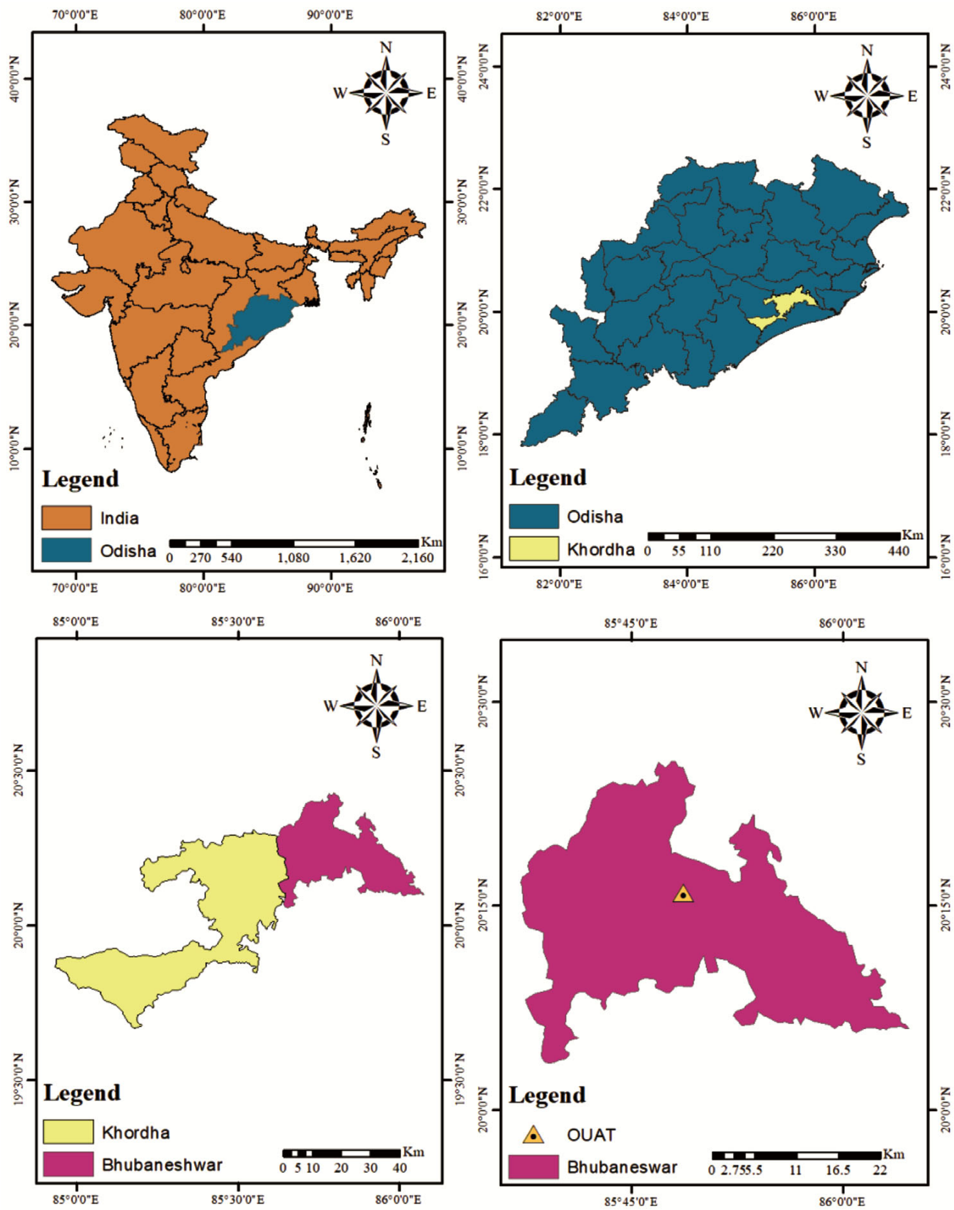

Fig. 1 — Proposed gauge station

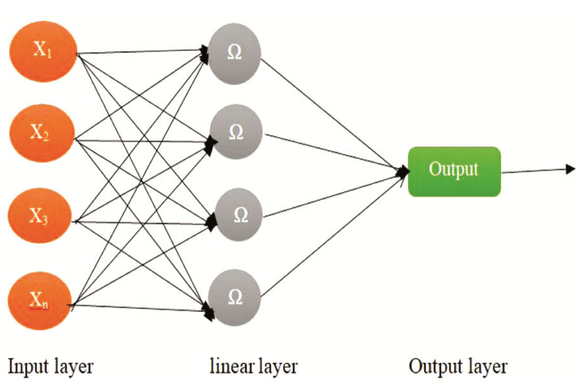

Fig. 2 — Architecture of RBFNN

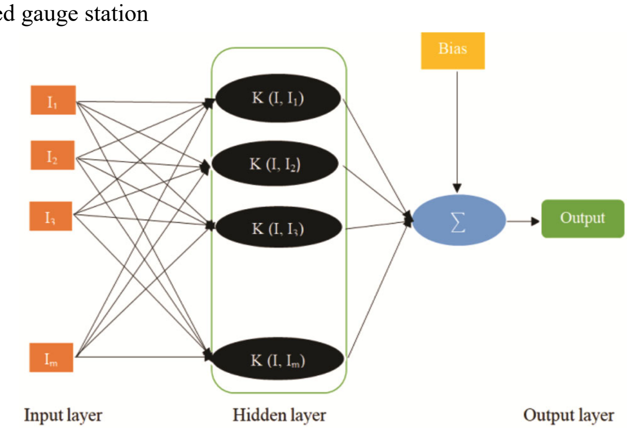

Fig. 3 — Architecture of SVM

where, t- current iteration; X^t- current location vector; X^t_{gbest} = location vector of preeminent solution attained so far; $X^t_{gbest} = X^t_{gbest1}, X^t_{gbest2}, \dots X^t_{gbestD}$; D- vector dimension; $A \cdot |C \cdot X^t_{gbest} - X^t|$-encompassing step-size; A and C- coefficient vectors which are defined by:

$$A = 2a \cdot rand_1 - a$$
$$C = 2 \cdot rand_2$$

where, $rand_1$ and $rand_2$-arbitrary numbers produced by a uniform distribution within $[0, 1]$, a-decreases linearly over course of iterations from 2 to 0.

ii. Bubble-net attacking

Humpback whale swims to the target in a spiral manner of motion during spiral update position, and specified mathematical model is expressed as:

$$X^{t+1} = X^t_{gbest} + D \cdot e^{bl} \cdot \cos(2\pi l) \quad \dots (5)$$

where, $D = |X^t_{gbest} - X^t|$- distance amid prey and whale (preeminent solution attained till now); b-constant to restrict shape of a logarithmic spiral; l-arbitrary number between $[-1, 1]$

The whales swim around the target inside a dwindling circle and simultaneously along a spiral-shaped path which is defined using the following mathematical formula:

$$X^{t+1} = \begin{cases} X^t_{gbest} - A \cdot |C \cdot X^t_{gbest} - X^t|, p < 0.5 \\ X^t_{gbest} + D \cdot e^{bl} \cdot \cos(2\pi l), p \geq 0.5 \end{cases}$$

where, p -arbitrary number between [0,1]. The pseudo code and flow chart of WOA are shown in Fig. 4 and Fig. 5, respectively.

Performance Evaluation Measures

All input and output dataset were normalised in training procedure utilizing maximum (X_{max}) and minimum (X_{min}) values, as described in following equation as normalisation is significant in data pre-processing for eliminating redundancy and ensuring data integrity. After normalization all the values (X) in training and testing phases ranges from 0 and 1. In Eq. (6), X, x_{norm}, represent real value and normalised value, respectively:

$$x_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad \dots (6)$$

The MSE, R^2, and WI metrics were applied to assess performance of applied models. For the best performing model and best fit amid observed and

```
Generate Initial Population (Whales) X_i (i = 1, 2, ... ... . n)
Evaluate each solution in the population
X* = the best search agent
while t < Maximum iteration do
    for each solution do
        Update a, A, C, l and p
        If p < 0.5 then
            If |A| < 1 then
                Update the position of the current search agent by Eq. 9
            else if |A| > 1 then
                Select a random search agent (X_rand)
                Update the position of the current search agent by Eq. 15
        else if p > 0.5 then
            Update the position of the current search agent by Eq. 13
    Check if any search agent goes beyond the search space and amend it
    Calculate the fitness of each search agent
    Update X* if there is better solution
    t = t + 1
Return X*
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Fig. 4 — Pseudo-code of WOA

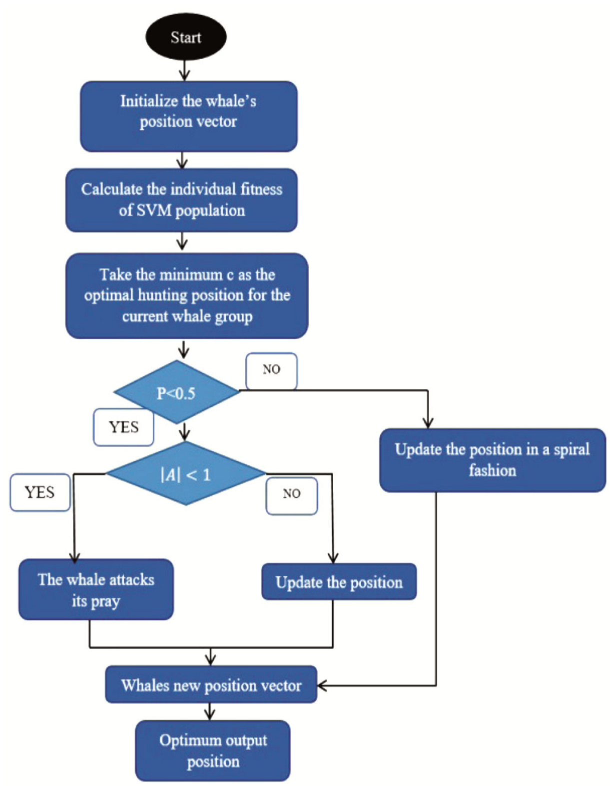

Fig. 5 — Flow chart of SVM-WOA

predicted values, R^2 and WI values must be nearer to 1, and RMSE close to 0. Following equations are used to define the specified metrics:

$$R^2 = \left(\frac{\sum_{k=1}^{N}(Q_i^o-\overline{Q_i^o})(Q_i^p-\overline{Q_i^p})}{\sqrt{\sum_{k=1}^{N}(Q_i^o-\overline{Q_i^o})^2\sum_{k=1}^{N}(Q_i^p-\overline{Q_i^p})^2}}\right)^2 \quad \ldots (7)$$

$$MSE = \frac{1}{N}\sum_{k=1}^{N}\left\|Q_i^p - Q_i^o\right\| \quad \ldots (8)$$

$$WI = 1 - \left[\frac{\sum_{i=1}^{N}\left(Q_i^o-Q_i^p\right)^2}{\sum_{i=1}^{N}(|Q_i^p-\overline{Q_i^o}|+|Q_i^o-\overline{Q_i^o}|)^2}\right] \quad \ldots (9)$$

where, N- number of inputs; Q_i^o and Q_i^p-collected and predicted GWL at the ith time step, respectively; $\overline{Q_i^o}$ and $\overline{Q_i^p}$- mean of collected and predicted GWL, respectively. The inputs considered are presented in Table 1. $P_t, T_{min}, T_{max}, Q_t$ and E_t represents precipitation, minimum and maximum temperature, discharge, and evapotranspiration.

Results and Discussion

For evaluating performance of RBFN, SVM, and SVM-WOA models for forecasting monthly GWL, optimal input arrangements were utilised. The assortment of an appropriate kernel function is the major aspect of an SVM model. In present study, C and γ parameters in RBF kernel can enhance capability of predictive systems and must be determined carefully. Grid-based search approach was used to determine optimum C and γ values as projected by Hsu *et al.* (2003).[39] The similarity between observed and predicted GWL in the form of scatter plots during testing period are compared in Fig. 5. The spread among points of scatter plots for RBFN which is observed to be more scattered can be seen from Fig. 6. In contrast, it is found that for SVM-WOA model the points are less spread which proves better GWL prediction accuracy. Obtained R^2 values from the figure show that best prediction accurateness for RBFN, SVM, and SVM-WOA, are found to be 0.90635, 0.93193, and 0.96729**,** respectively. Results from scatter plot indicate that SVM-WOA is a suitable model for short and long term GWL prediction.

The comparison in a time series plot for a period between Jan 2000–Dec 2021, characterised by marked fluctuations of GWL is shown in Fig. 7. It is observed that a clear periodic trend is followed in GWL fluctuation. Precisely speaking, maximum depth is reached in April, resulting in a groundwater scarcity condition because of the dry season, which has an impact on the area between November and February. After the monsoon season, groundwater reaches its lower depth because of heavy rains, resulting in greater groundwater availability conditions in September. From Table 2, it is clear that SVM-WOA generates satisfactory accurateness in GWL prediction (MSE = 0.8264 to 4.3962), while those obtained from RBFN reveal lowest accurateness (RMSE = 10.925−17.16). Largely, the selected forecasting models affect the predictions significantly, with SVM-WOA showing the best outcomes in present research. The inconsistent positive peak in the dry season appears to be associated primarily with external aspects, e.g., water pumping, as it did not demonstrate a seasonal constituent.

In addition, one of the important features of GWL predictive models is maintaining statistics of observed and predicted GWL, like the minimum, maximum, median, mean, and lower and upper quartiles. Box-plot shown in Fig. 8 reveals that all the proposed

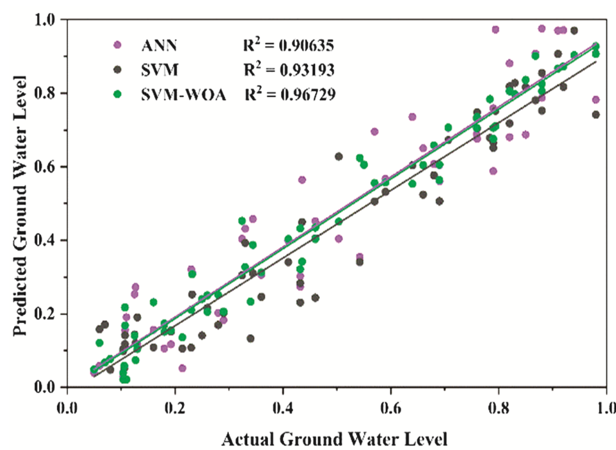

Fig. 6 — Scatter plot of actual vs. predicted GWL values

Table 1 — Models with different input combination

Scenario	Input	ANN	SVM	SVM-ALO
I	P_t	ANN@I	SVM@I	SVM-WOA@I
II	P_t, T_{min}	ANN@II	SVM@II	SVM-WOA@II
III	P_t, T_{min}, T_{max}	ANN@III	SVM@III	SVM-WOA@III
IV	$P_t, T_{min}, T_{max}, Q_t$	ANN@IV	SVM@IV	SVM-WOA@IV
V	$P_t, T_{min}, T_{max}, Q_t, E_t$	ANN@V	SVM@V	SVM-WOA@V

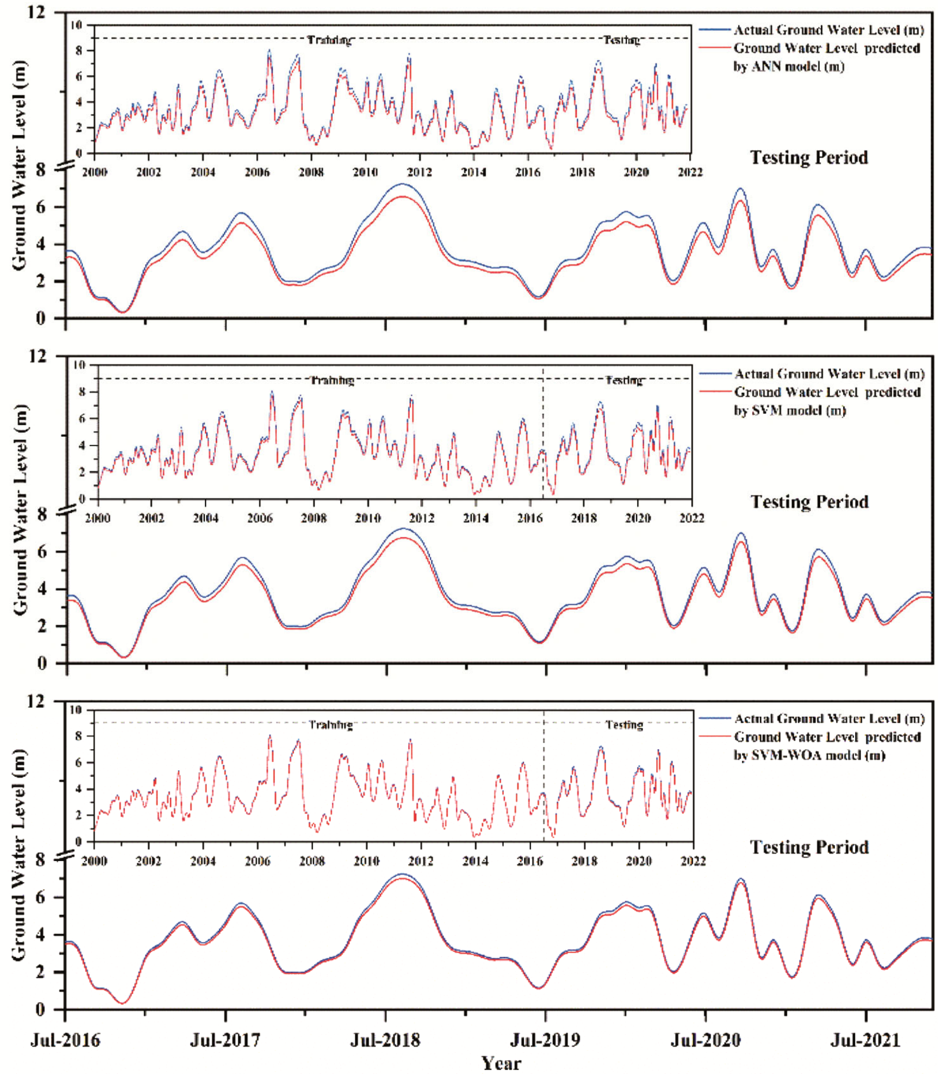

Fig. 7 — Time-series plot comparison between actual and predicted values

Table 2 — Performance assessment results for the proposed models

Technique	Scenario	R^2		WI		MSE	
		Training	Testing	Training	Testing	Training	Testing
RBFN	I	0.91747	0.90057	0.92283	0.90534	13.111	17.16
	II	0.9195	0.90174	0.9244	0.9065	12.9	16.7833
	III	0.92109	0.9028	0.92601	0.90809	12.034	14.202
	IV	0.923	0.90442	0.9285	0.9101	11.4377	13.9904
	V	0.92434	0.90635	0.929	0.91236	10.925	13.58
SVM	I	0.9511	0.9268	0.955	0.93007	8.3393	10.0065
	II	0.95202	0.92811	0.95776	0.93205	7.97	9.49
	III	0.95364	0.92957	0.9581	0.93408	7.7948	9.1184
	IV	0.9557	0.9304	0.95909	0.93592	7.5593	8.902
	V	0.956	0.93193	0.9604	0.9366	7.21	8.566
SVM-WOA	I	0.9796	0.9601	0.98312	0.96447	4.0035	6.2288
	II	0.98007	0.96205	0.9859	0.966	2.6679	5.73
	III	0.981	0.96333	0.98604	0.96815	1.937	5.2901
	IV	0.98281	0.9656	0.987	0.9697	1.38	4.886
	V	0.9834	0.96729	0.98837	0.97202	0.8264	4.3962

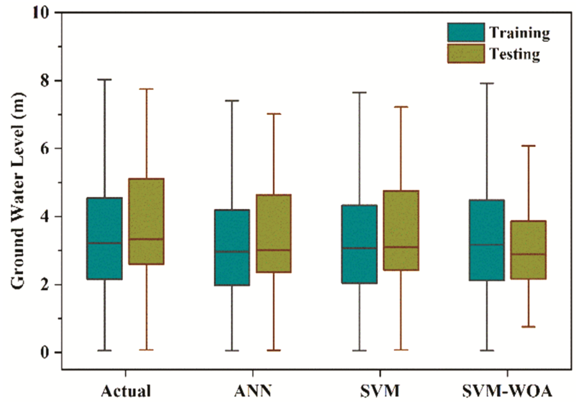

Fig. 8 — Box plot of ANN, SVM and SVM-WOA during both phases

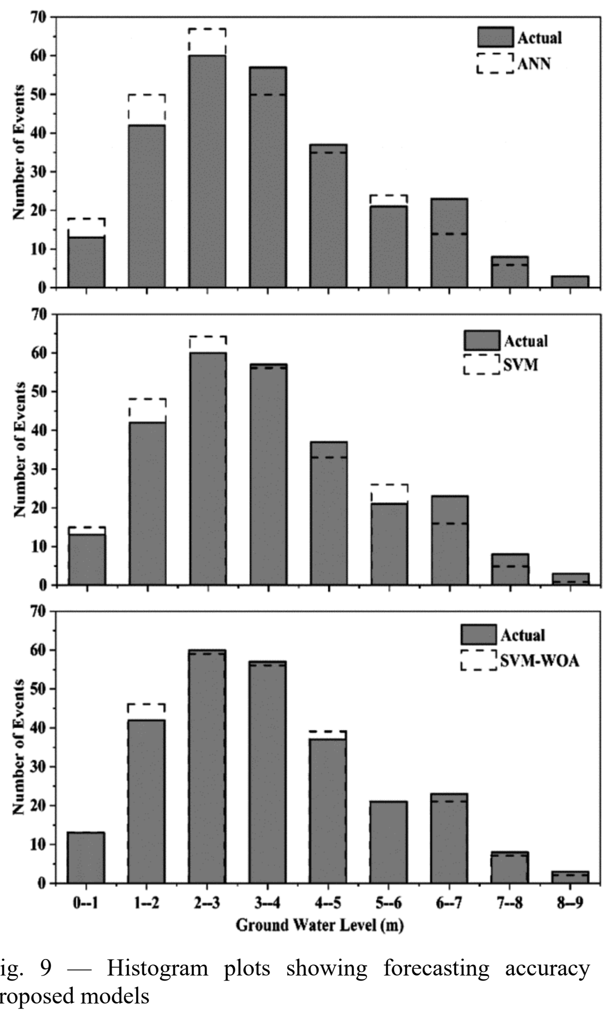

Fig. 9 — Histogram plots showing forecasting accuracy of proposed models

models were capable of maintaining the statistics of observed as well as predicted GWL data. According to Fig. 9, it can be understood that SVM-WOA model performed best in maintaining the statistics of observed GWL.

Recently, Odisha has been facing a problem of deterioration in GWL because prevailing groundwater reserves are quickly being used up due to disparity in supply and demand of groundwater. The extreme intake of groundwater in Bhubaneswar led to lesser GWL. These conditions call for the application of SVM-WOA for accurate forecasting about GWL variations and permitting developed administration of water reserves in Bhubaneswar in addition to providing appropriate tools to formulate operational policies. The integration of GIS techniques and SVM-WOA, if appropriately done, can help developers and other experts related to water management for obtaining precise outcomes. Because of restricted global assets of water and massive water demand for industrial, agricultural, and other purposes, accurate prediction of GWLs has become extremely significant.

Conclusions

This paper aims at applying a DD framework for developing a GWL prediction model. The prediction model was developed utilising SVM-WOA, and time-series analysis was conducted. Two state-of-the-arts ML algorithms which includes classical SVM and RBFN, have been compared against SVM-WOA. Computational outcomes validated the best performance by SVM-WOA via quantitative statistical performance measures and graphical interpretations. The proposed hybrid model in present work discovers the dynamic vibrational regulation of GWL simply based on historical GWL monitoring data. SVM-WOA is a remarkable model for GWL prediction and simulation because of its easily available information and easy computation. Also, it can deliver a consistent base for rational utilization, development, planning, and management of regional groundwater resources. Moreover, this modelling framework can be utilised as a base for a real-time groundwater monitoring system, which allows study of bedrock aquifer, agricultural water supply, and other hydro-geological issues.

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