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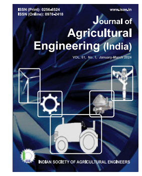

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Reliability of Artificial Intelligence-based Models Compared to Numerical Model for Predicting Groundwater Level under Changing Climate

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ABSTRACT

Groundwater modeling is a crucial tool for simulating groundwater level behavior under climate change scenarios, and for studying the effects of water management strategies on sustainability of groundwater resources. In this study, two types of models, namely, a physical-based numerical model called MODFLOW, and a data-driven model called Genetic Algorithm-based Multilayer Perceptron (MLP-GA), were evaluated for the reliable predictions of groundwater levels in the semi-arid region of the Karnal district, Haryana. Seven hybrid MLP-GA models were developed with different combinations of input variables such as rainfall, crop evapotranspiration, deep percolation, and irrigation water requirement. The numerical model and hybrid MLP-GA models were calibrated and validated using groundwater-level data from the pre-monsoon period. Among the hybrid models, the model M-1 with four input variables (crop evapotranspiration, rainfall, deep percolation, and applied irrigation water) and 4-29-1 (four input nodes, 29 neurons in the hidden layer, and one output node) model architecture performed the best, but the numerical model showed superiority over the MLP-GA models. The numerical model and M-1 model were used to predict future groundwater levels under projected climate change scenario. According to the numerical model, under RCP4.5 scenario, groundwater levels in the study area were projected to decline by 7.7 meters by the year 2039 compared to the reference year of 2015. The M-1 model predicted decline of 5.0 meter by the year 2039. The study concluded that all input variables are essential for accurately simulating groundwater levels using MLP-GA models, and that the numerical model is more reliable for assessing the impact of climate change on groundwater behavior for future periods.

1. INTRODUCTION

Groundwater is a key natural resource on the earth that performs an important role to meet the water demand for different sectors namely, residential, commercial, and agricultural uses. In several areas of the world, groundwater supplies have been over-exploited (Konikow & Kendy, 2005), especially in arid and semi-arid regions where rainfall is highly variable and lower than evapotranspiration. North western region of India, particularly the States of Haryana and Punjab, has reported decline in groundwater levels (0.33 to 0.88 m year^{-1}) in the last few decades due to withdrawal of large quantities of groundwater than the replenishment of the groundwater resources (CGWB, 2006; Narjary *et al.*, 2014). This is mainly due to the intensive cultivation of crops such as rice and wheat, which are primarily irrigated using groundwater (Jalota *et al.*, 2018). Apart from that, subsidization of electric charges by state governments also induces farmers to over-irrigate the

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crops which might be another reason for over-use of groundwater resources. The Intergovernmental Panel on Climate Change (IPCC) has projected an increase in temperature due to global warming (IPCC, 2013). A limited warming (below 2°C) with strong emission reductions is projected under RCP2.6, whereas a moderate warming (1.5°C to 2.5°C) with stabilization efforts is projected under RCP4.5. A higher warming (2°C to 3.5°C) with slower emission declines under RCP6.0 and a severe warming (exceeding 4°C) without mitigation under RCP8.5 pose grave risks to ecosystems and societies. Similarly, rainfall amount and its intensity are also projected to increase in future periods (IPCC, 2013). The impact of temperature rise and often erratic rainfall on water demand and water availability can be explained by two steps related to climate. Firstly, crop evapotranspiration is predicted to increase in the future by feeble to a significant level depending on different climate scenarios due to increases in temperature across the world (Gade & Khedkar, 2023). Secondly, an increase in total rainfall is also expected, however, heatwaves, heavy rainfall, and droughts would be more frequent and intense which would lead to an increase in crop water requirement (Mahmoud *et al*., 2023). However, increasing atmospheric CO_2 concentration can decrease crop evapotranspiration due to a decrease in stomatal conductance (Ficklin *et al*., 2010; Nand *et al.*, 2021). For example, Kumar *et al.* (2023) reported a reduction in rice and wheat crop evapotranspiration under increasing CO_2 concentration scenarios in the semi-arid region of Karnal district. Similar outcomes were reported by other researchers (Yang & Lei, 2022; Lenka. *et al,* 2020; Islam *et al*., 2012). There would be higher runoff yield rather than effective for crops due to erratic and heavy rainfall events (Anonymous, 2017). Thus, more frequent irrigation would be needed in future than in the past. This irrigation water demand could be met by either surface or groundwater resources depending on its availability. In semi-arid region, a large proportion of crop water demand is met by groundwater resources that resulted in the depletion of aquifers and tending to dry because of less replenishment/recharge of groundwater. For example, in the Karnal district which falls in the semi-arid region of the Indo-Gangetic Plain, 514 dry wells were identified (CGWB, 2013). In the Karnal district, the groundwater development is about 140% which indicates groundwater withdrawal exceeded the aquifer recharge and thus whole study area has been categorized as over-exploited (CGWB, 2013). Therefore, there is an urgent need to maintain groundwater sustainability to meet the demands of different sectors, especially for irrigation. It would be a daunting task to maintain groundwater sustainability under existing management practices for decision-makers, water users, managers, and developers. It can be managed to some extent by applying different crop management practices and water storage techniques. Groundwater flow models (i.e., numerical, data-driven, and statistical models) are vital tools for evaluating aquifer yield under different water management scenarios incorporating climate change effects.

Numerical models are recommended as an excellent tool to simulate groundwater flow under different crop management practices, groundwater pumping scenarios, and climate scenarios. It allows users to examine the aquifer yield of any region under numerous scenarios, and that plays a vital role in developing water management policies for sustainable management of groundwater resources. These mathematical models are solved by a finite difference/ finite-element approach that is recognized as a standard method to solve partial differential equations (Arendt & Urban, 2023). Numerical models accurately simulate the groundwater system as it consists of fundamental internal flows (Block Centered Flow (BCF) and Layer-Property Flow (LPF)), stresses (groundwater pumping, deep infiltration, evapotranspiration, river, lake, and pond, etc.), and solver packages (Harbaugh, 2005). However, numerical models need huge data sets that are not readily available for some regions because of the huge costs and time involved in data collection. It also demands expert knowledge of hydrologists, extensive computational work, and thus it needs more time to develop a groundwater flow model for any region. In contrast, empirical models need typically less data and less effort as compared to physically based models (Coppola *et al*., 2005; Ware *et al*., 2023; Shahbazi *et al*., 2023). The fundamental benefit of this method is that, unlike numerical models, it does not necessitate describing complexity of the underlying physical systems' processes.

Artificial Neural Network (ANN) models are one such model, which are treated as general approximators and are especially fit for dynamic nonlinear framework displaying (Adisa *et al*., 2019). ANNs are addressed by the beginning capacity, which uses interconnected information handling units to change the input into yield (output) by identifying information, connections, and examples. ANNs are regarded as the best methods of extracting information from imprecise and nonlinear data. The capacity to take in and sum up enough information sets assists ANNs with addressing intricate, enormous-scope issues. A few studies have been conducted on the use of neural networks for groundwater level (GWL) simulation. Mohanty *et al*. (2015) employed a back propagation algorithm to predict GWL at 18 sites and the model performance was found satisfactory during ANN training and validation. Furthermore, Nadiri *et al.* (2019) used several models using fuzzy logic and reported that groundwater table declines by management scenarios, and showed higher effects on groundwater level variations than climatic variations in the study of aquifer use. As well, Chen *et al.* (2020) simulated groundwater dynamics based on a single numerical model and three artificial intelligence (AI) methods and tracked down that the exhibition and precision of the created AI models were fundamentally better compared to that of mathematical models.

However, it was noticed that AI algorithms have drawbacks when dealing with nonlinear and non-stationary systems. Several hybrid modeling approaches incorporating statistical analysis and/or combining various AI techniques have already emerged in recent years to improve the capabilities of AI methods. The development of such models is made more effective by integrating two AI methods at different phases of the modeling process and utilizing efficient approaches for input data pre-processing. Some hybrid modeling approaches such as the grey wolf optimizer algorithm (GWP; Maroufpoor *et al.,* 2019), gravitational search algorithm (GSA; Ghorbani *et al*., 2019), Particle Swarm Optimization (PSO; Kennedy & Eberhart, 1995), Genetic-Algorithms (GA; Jha & Sahoo, 2015), Ant Colony Optimization (ACO; Dorigo *et al*., 1996) include certain data-preprocessing and/or combine AI techniques have also been developed in the recent years to increase the capabilities of the AI methods. In the Konan basin of Japan, Jha and Sahoo (2015) constructed five hybrid ANN-GA models for modeling spatiotemporal GWL. In this study, the GA optimization approach was used to optimize the ANN's inputs and settings to get accurate results.

Kumar *et al*. (2022) reported that pressure on groundwater resources will intensify during future periods in the Karnal district of Northwest India due to reduced recharge and increased withdrawal caused by altered precipitation patterns and higher evapotranspiration rates under projected climate change scenarios. This depletion is expected to have adverse effects on the yield, acreage, and production of grain crops, particularly during the dry winter season when groundwater serves as the primary irrigation source. Even with anticipated precipitation increases in certain regions due to climate change, the expansion of irrigated areas may counterbalance any relief, exacerbating groundwater stress. Numerous studies have been carried out in the Indo-Gangetic Plain of Haryana to simulate groundwater levels, utilizing methods such as MOFLOW, deep learning, and statistical models (Kaur *et al*., 2015; Patle *et al.*, 2016; Kochhar *et al*., 2022; Kumar *et al*., 2020; 2022). However, there remains a gap in the literature regarding the direct comparison between numerical models and AI-based approaches for groundwater level simulation. In the last decade, groundwater simulation studies have been conducted to compare the potential of numerical and AI-based models to predict groundwater behavior (Malekzadeh *et al*., 2019; Chen *et al*., 2020). However, the groundwater level simulation in these studies was mainly limited to short monthly periods (Malekzadeh *et al*., 2019), and for the annual groundwater level (pre/post-monsoon groundwater level), these models need to be validated. With this concern, this study was undertaken to check the performance of AI-based models compared to the process-based numerical models for predicting pre-monsoon groundwater levels over the years. In this study, pre-monsoon groundwater level simulation was compared using the numerical model (MODFLOW) and genetic algorithm-based multilayer perceptron (MLP-GA) models, and predicted pre-monsoon groundwater levels for the future periods (2016-2039) under existing management practices of the region. The aim of this work is therefore: 1) to evaluate the performance of the physical processes-based numerical model (MODFLOW) and different architectures of MLP-GA model for predicting pre-monsoon groundwater level, and 2) to compare the performance of the MODFLOW and MLP-GA model for simulating futuristic groundwater level under projected climate change scenarios.

2. MATERIALS AND METHODS

2.1 Study Area and Data Acquisition

The study was conducted in the Karnal district of north-western India, which has a total geographical area of 2,520 square kilometers (Fig. 1 a). The predominant land use in the area covers 2271.15 square kilometers of agricultural land, followed by built-up areas and water bodies (Fig. 1b). The primary soil type found in the region is loam, with sandy loam being the subsequent soil type (Fig. 1c). Climatologically, the study area is classified as a semi-arid region with mean annual rainfall and evapotranspiration of 740

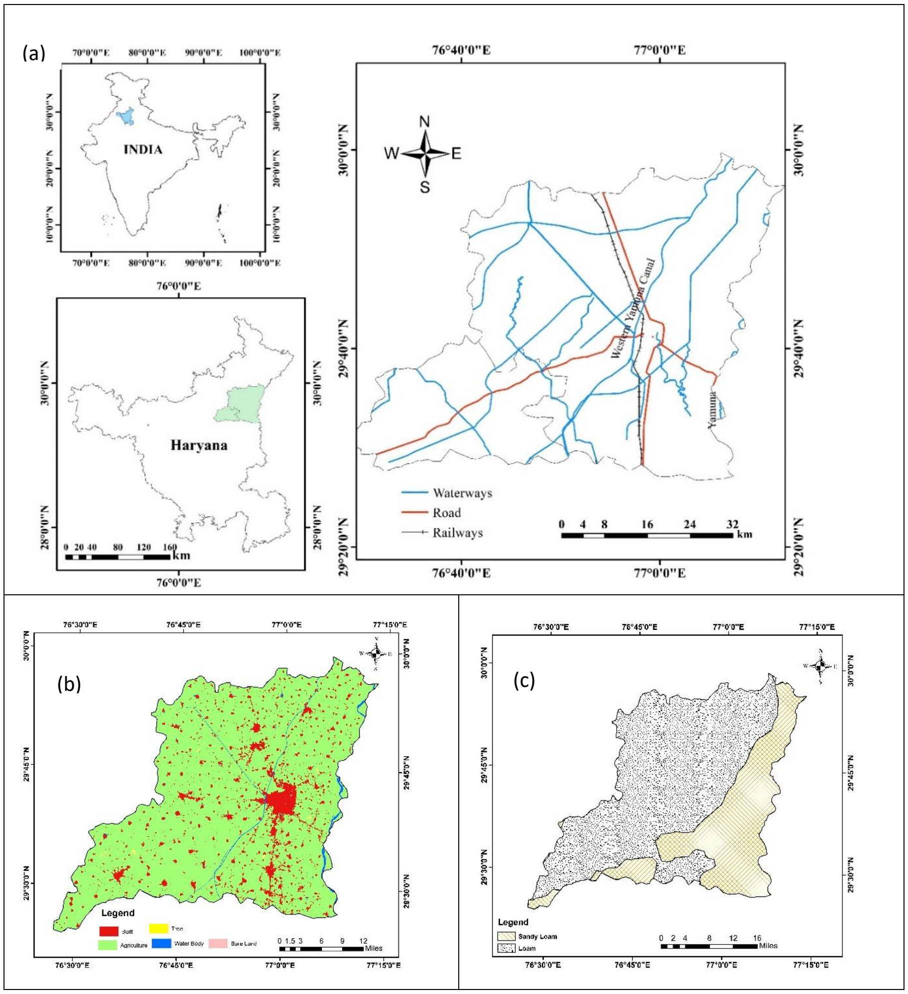


Fig. 1. Thematic map of the study area (a), Land use and land cover map (b), and Soil texture map of the study area (c)

and 1550 mm, respectively. The meteorological data for the 1981-2010 period were collected from a local observatory situated at ICAR- Central Soil Salinity Research Institute (CSSRI), Karnal. The aquifer hydraulic properties and stratigraphy were acquired from the Central Groundwater Board Report (CGWB, 2013). Data on depth of groundwater level were obtained from the District Hydrology Department, Karnal, Haryana for the 2000-2015 periods. The conceptual model for groundwater flow was created using the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) at a resolution of 90 m x 90 m. The Haryana statistical abstract includes information on the population, livestock, cropping method, sowing dates, and other pertinent field data. Consequently, it was applied to calculate the total groundwater pumping for agricultural and urban areas (Statistical Abstract of Haryana, 2000-2015). The IPCC Fifth Assessment Report's climate change projections were used to examine the effect of futuristic climate on groundwater behaviour. The representative concentration pathways (RCP) RCP4.5 climate change scenario was selected for studying climate change impact as it is based on a moderate global emission scenario with mitigating climate change effect (IPCC, 2013) which could be compatible with the current emission scenario and management practices. Bias corrected and spatially disaggregated (BCSD) monthly projections of rainfall and temperature at 0.5^0 x 5^0 resolutions, from the Coupled Model Inter comparison Project phase 5 (CMIP5) multi-model dataset for the period 1950–1999, were used (ftp://gdo-dcp.ucllnl.org/pub/dcp/archive/cmip5/global_mon). More than 20 modeling groups participated in CMIP5, and climate projections were available from a number of GCMs. Further, with different initial conditions, initialization methods, and perturbed physics versions, varying numbers of runs (realizations) per GCM were available. The climate projections were available for different variables (precipitation, Tmax, Tmin, Tav, etc.) and for different simulation periods such as near-time (up to 2035) and long-time (up to 2100). In this study, climate projections of models having long-time simulations (up to 2100) of precipitation, Tmax, Tmin were selected. Accordingly, 61 climate projections from 30 GCM of varying number of runs (Abeysingha *et al*., 2020) were available under RCP4.5 and were used in this study for generating climate change scenarios. The Hybrid-Delta (HD) ensemble method (Islam *et al*., 2012; Tohver *et al*., 2014)) was used to generate a multi-model ensemble climate change projection for the study area. Daily temperature and precipitation were derived for historical (1981-2010, base period) and future (2010-2039) periods.

2.2 Estimation of Input Variables for Numerical and Artificial Intelligence Models

The study area falls under intense agriculture, where a large portion of the land (85%) comes under the rice and wheat cropping system. The canal water accounts for merely 20% of the irrigated crop area and demand for the rest of the agricultural land is accomplished by groundwater (CGWB, 2013). As a result, groundwater is a significant source of water for irrigation sector, particularly for growing rice-wheat systems. The area of major crops such as rice, wheat, and sugarcane are 1758, 1766, and 112 square kilometers, respectively. Estimation of return flow and irrigation requirement (draft) is crucial for predicting groundwater behavior accurately. Therefore, irrigation requirement and return flow from the agricultural land (rice and wheat) were calculated using the previously calibrated and validated water balance model AquaCrop (Raes *et al*., 2009; Kumar *et al.,* 2022). The water demand for the domestic sector was computed using population data (www.census2011.co.in/district.php). In the study area, the majority of forest land is covered by the Eucalyptus plant. Thus, by accounting for the water needs of eucalyptus plants as 1500 mm year^{-1} (Minhas *et al.,* 2015), water loss on forest land was computed. The seepage loss from the canal was calculated using the standard methodology (GEC, 2009) based on canal network details collected from the Haryana Irrigation Department, Karnal. In the case of urban land, it was assumed that return flow would be equal to the difference of rainfall and runoff (rainfall-runoff). Runoff from urban land was estimated using the Soil Conservation Service- Curve Number (SCS-CN) method in Microsoft Excel for a 15-year period (2001-2015) (Soil Conservation Services, 1972). Return flow from the barren land was estimated through Hydrus 1-D model using the parameter validated by Narjary *et al.* (2021) for this region.

2.3 Overview of MODFLOW

Visual MODFLOW Flex 8.0 is a numerical model that offers a user-friendly graphical interface for simulating groundwater flow and pollutant transport. One of the notable features of Visual MODFLOW Flex 8.0 is its built-in Geographic Information System (GIS) interface, which enhances the understanding and ease of creating conceptual models and interpreting model results. The software incorporates components for representing basic internal flow processes such as Block Centered Flow (BCF) and Layer-Property Flow (LPF), as well as various types of stresses like groundwater pumping, deep percolation, evapotranspiration, rivers, lakes, and ponds (Harbaugh, 2005). These packages enable users to construct conceptual models that closely mimic the real physical systems and convert them into numerical models.

At its core, Visual MODFLOW Flex 8.0 is based on the solution of partial differential equations, specifically the Bossinesq equation (Equation 1), using finite or discrete element methods (Javandel & Witherspoon, 1968; 1969; McDonald & Harbaugh, 1988).

The Boussinesq equation governs the behavior of groundwater and is expressed as follows:

$$\frac{\partial}{\partial a}\left(k_x \frac{\partial p}{\partial x}\right) + \frac{\partial}{\partial b}\left(k_y \frac{\partial p}{\partial y}\right) + \frac{\partial}{\partial c}\left(k_z \frac{\partial p}{\partial z}\right) - V = S_a \frac{\partial p}{\partial T} \quad ...(1)$$

where, p is the hydraulic head (m) at a point; S_a is the aquifer storage time that changes with type of aquifer system, in our case it is specific yield (%) as the aquifer is unconfined; , and are the hydraulic conductivity in x, y and z-direction in (m day^{-1}), V is a volumetric flux (m^3 day^{-1}), T is the time (day).

The equation-1 is solved by the finite-element method that work on the principle of continuity in the model. Thus, it is essential that the net flow (outflow-inflow) in each cell must be equal to change in storage of that cell (Harbaugh, 2005). The continuity equation (equation-2) can be written as follows:

$$\sum Q_i = S_a \frac{\Delta p}{\Delta T} \Delta D \quad ...(2)$$

where, Qi is the flux into the cell (m^3 day^{-1}); S_a is the storage time for the unconfined aquifer; ΔD represents the cell area i (m^2), Δp denotes the change in the head (m) in the particular cell and ΔT is the time interval (day).

2.4 Hybrid Artificial Intelligence Model

2.4.1 Model overview

The multilayer perceptron (MLP) neural network is a powerful tool for addressing hydrological processes (McGarry *et al.*, 1999). It consists of input, hidden, and output layers, with adjustable hidden layers to minimize errors. Inputs are processed through the layers via weighted connections, and adjustments are made to minimize errors between calculated and target outputs (Farfani *et al.*, 2015). Various learning algorithms like Levenberg-Marquardt, steepest descent, etc., optimize weights and parameters, often using backpropagation. However, backpropagation has limitations, such as slow convergence and sensitivity to parameters. This study employs a genetic algorithm (GA) to optimize model parameters, including hidden layer count, offering a more robust solution, and the model is referred to as MLP-GA model hereafter.

GA is a search technique based on the principles of natural evolution (Holland, 1975; Li *et al.*, 2011). It is particularly effective for optimizing complex nonlinear models, where finding the global minimum may be possible. The GA begins by generating a random population and then performs a series of operations on the population, guided by the relative fitness of individuals, allowing the population to evolve over multiple generations. Parameters such as population size, mutation probability, and crossover probability need to be carefully tuned through trial and error to obtain the best solution. Works by Lotfi & Akbarzadeh-T. (2014) and Nourani *et al.* (2017) provide detailed explanations of GA, and its flow chart is depicted in Fig. 2. In the initial step of this study, the GA is used to determine the number of neurons in the hidden layer and other model parameters, optimizing the weights in all functions to find the best solution to the problem. For each set of hidden neurons, the network is trained to minimize the mean square error at the output layer. The hyperbolic tangent sigmoid transfer function is found to be the most suitable for transferring the optimized weights from the hidden layer to the output layer during the trial-and-error procedure.

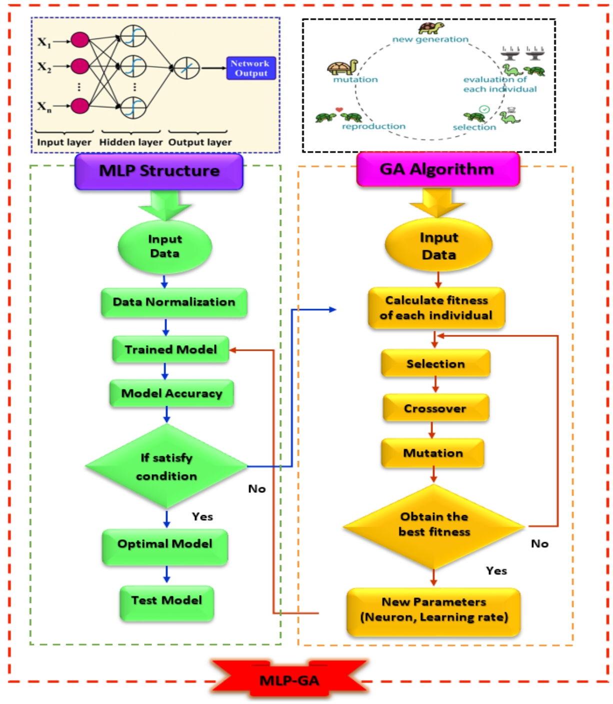


Fig. 2. Flow diagram of hybrid artificial intelligence model (MLP-GA)

2.4.2 Model setup

The study area was equipped with 55 observation wells that monitor groundwater fluctuations across the entire region. Hence, the pre-monsoon groundwater level data from these 55 wells was processed in the model. Based on different combinations of inputs and model architecture, seven different MLP-GA models were formulated (Table 1). In the M-1 model, there are a total of 4 input nodes, 29 neurons in the hidden layer, and one output node representing the pre-monsoon groundwater level data of the 55 observation wells (Table 1). The 4 input nodes correspond to the input parameters: crop evapotranspiration (ET_c), rainfall (PCP), deep percolation (GR), and applied irrigation water (GD). The M-2 and M-4 models have 3 input nodes, 36 and 31 neurons in the hidden layer, respectively. There were 2 (input nodes) in the M-3, M-5, M-6, and M-7 models and 19, 17, 21, and 11 neurons in the hidden layer of the respective models; and groundwater level as output. The architectures of seven developed models were 4-29-1, 3-36-1, 2-19-1, 3-31-1, 2-17-1, 2-21-1, 2-11-1 for M-1, M-2, M-3, M-4, M-5, M-6, and M-7 models, respectively.

Seven hybrid MLP-GA models were trained by different input and output combinations which are depicted

Table 1. Input and output variables of the Genetic Algorithm-based Multilayer Perceptron (MLP-GA) model

Model	INPUT				OUTPUT
	Precipitation	Groundwater recharge	Groundwater draft	Crop evapotranspiration	Groundwater level
M-1	PCP	GWR	GWD	ET_c	GWL
M-2	PCP	GWR	GWD		GWL
M-3		GWR	GWD		GWL
M-4	PCP	GWR		ET_c	GWL
M-5	PCP	GWR			GWL
M-6		GWR	GWD	ET_c	GWL
M-7	PCP	GWR		ET_c	GWL

Note: *PCP-Rainfall; ET_c -Crop evapotranspiration; GWR- Groundwater recharge; and GWD- Groundwater draft; and GWL-Groundwater level*

in Table 1. The combination of input and output parameters was investigated based on the correlation between input i.e., crop evapotranspiration (ET_c), rainfall (PCP), deep percolation (GR), and applied irrigation water (GD), and output i.e., groundwater level (GL) parameters. It was done to check whether two or more input parameters were reasonable to represent entire groundwater variability with relevant periods of observed groundwater level and that can be used for groundwater modeling. The best model was opted in among those models that were chosen based on statistical performance and made a comparison with the numerical model. A 15-year data (10 years for training and 5 years for testing) of all parameters (dependent and independent variables) was used for developing the model.

2.5 Evaluation of Model Performance

The performance of numerical and MLP-GA models was evaluated using different statistical indicators and analyzed to find out which combination of input variables of the model results in the simulation close to the observed data. Statistical indicators can be represented by the following equations (Willmott *et al.*, 2012; Legates & McCabe Jr., 1999):

Percentage bias (Gupta *et al.*, 1999) :

$$\text{PBIAS}\ (\%) = \frac{\sum_{t=1}^{n}\left(GW_p - GW_t\right)}{\sum_{i=1}^{n} GW_t} \times 100 \qquad ...(3)$$

where, GW_t is observed data series, GW_p is predicted data series, n is number of observations.

Root mean square error (c) **(**Legates & McCabe Jr., 1999):

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(GW_t - GW_p)^2}{n}} \qquad ...(4)$$

Correlation coefficient (Legates & McCabe Jr., 1999):

$$r = \left[\frac{\sum_{i=1}^{n}\{(GW_t - \overline{GW}_t)(GW_p - \overline{GW}_p)\}}{\sqrt{\sum_{i=1}^{n}(GW_t - \overline{GW}_t)^2}\sqrt{\sum_{i=1}^{n}(GW_p - \overline{GW}_p)^2}}\right] \qquad ...(5)$$

where $\overline{GW}_t$, is average of the observed data series and $\overline{GW}_p$ is average of predicted data series.

Coefficient of efficiency (Legates & McCabe Jr., 1999):

$$CE = 1 - \frac{\sum_{i=1}^{n}\left(GW_t - GW_p\right)^2}{\sum_{i=1}^{n}(GW_t - \overline{GW}_t)^2} \qquad ...(6)$$

Performance index (PI) (Yagiz et al., 2012):

$$PI = \frac{\frac{RMSE}{GW_t}}{1 + \frac{\sum_{i=1}^{n}\{(GW_t - \overline{GW}_t)(GW_p - \overline{GW}_p)\}}{\sqrt{\sum_{i=1}^{n}(GW_t - \overline{GW}_t)^2}\sqrt{\sum_{i=1}^{n}\left(GW_p - \overline{GW}_p\right)^2}}} \qquad ...(7)$$

Willmott's index of agreement (WI) (Legates & McCabe Jr., 1999):

$$WI = 1 - \frac{\sum_{i=1}^{n}\left(GW_t - GW_p\right)^2}{\sum_{i=1}^{n}\left(|GW_p - \overline{GW}_t| + |GW_t - \overline{GW}_t|\right)^2} \qquad ...(8)$$

Legates–McCabe's index (LMI) (Legates & McCabe Jr., 1999):

$$LMI = 1 - \left[\frac{\sum_{i=1}^{n}|GW_p - \overline{GW}_p|}{\sum_{i=1}^{n}|GW_t - \overline{GW}_t|}\right] \qquad ...(9)$$

3. RESULTS AND DISCUSSION

3.1 Calibration and Validation

3.1.1 Numerical model

The groundwater flow model (MODFLOW) was calibrated under transient conditions for a period of 10 years (2001-2010) by comparing the observed and simulated hydraulic head data, which represents the depth of the water table. The calibration process utilized an auto-calibration model PEST (Model Independent Parameter Estimation and Uncertainty Analysis) for parameter estimation, focusing on two key parameters: hydraulic conductivity and specific yield. The hydraulic conductivity values varied across different geographical zones of the study area, ranging from 4 to 300 m day^{-1}, with an average estimated value of 27 m day^{-1} (Fig. 3). Most of the region exhibited hydraulic conductivity values between 20 and 30 m day^{-1}, although a few patches had higher values (up to 300 m day^{-1}). The estimated specific yield ranged between 0.1 and 0.2 (Fig. 4).

The performance of the calibrated model was evaluated using statistical indicators such as PBIAS (Percent Bias), RMSE (Root Mean Square Error), r (correlation coefficient), CE (coefficient of efficiency), PI (peak deviation index), WI (Willmott's Index), and LMI (Legates-McCabe Index) (Willmot *et al.*, 2012; Legates & McCabe Jr., 1999). The comparison between observed and simulated hydraulic head values during the calibration period (2001-2010) demonstrated satisfactory accuracy, as indicated by the statistical indicators: PBIAS (0.07), RMSE (2.36 m), r (0.98), CE (0.96), PI (0.03), WI (0.99), and LMI (0.30) (Table 2 and Fig. 5).

Furthermore, the calibrated model was validated for the subsequent 5-year period (2011-2015) by maintaining the calibrated parameters constant. The statistical indicators for the validation period indicated a good agreement between the observed and simulated hydraulic head values: PBIAS (-0.02), RMSE (1.85 m), r (0.96), CE (0.94), PI (0.05), WI (0.99), and LMI (0.40) (Fig. 5). Overall, the calibration and validation results demonstrate a very good model performance in reproducing the observed hydraulic head data, indicating its reliability in simulating the groundwater system.

3.1.2 Hybrid artificial intelligence models

All the MLP-GA models were calibrated by adjusting the independent parameters to match the observed

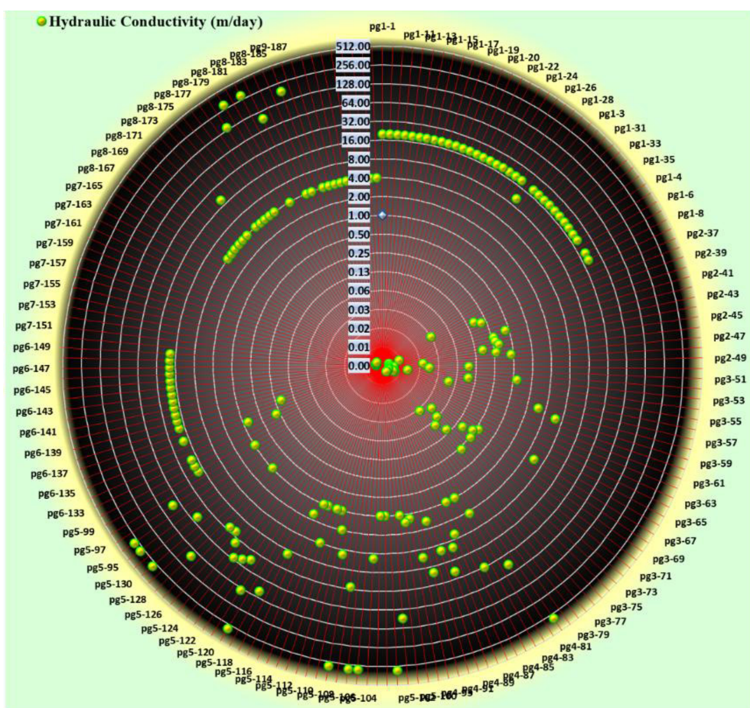


Fig. 3. Scatter radar plot of spatial hydraulic conductivity(K) values over the iterations

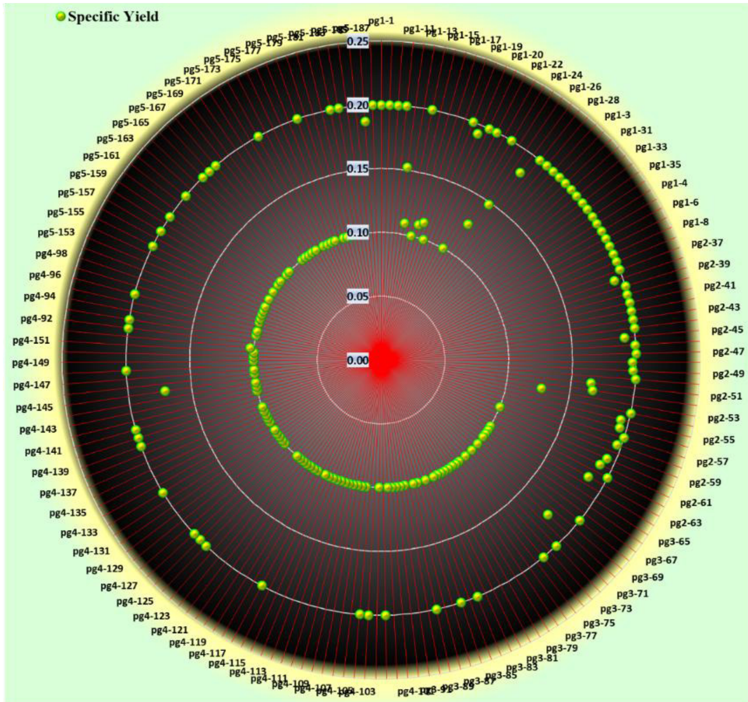


Fig. 4. Scatter radar plot of spatial specific yield (S_y) values over the iterations

Table 2. Performance of Genetic Algorithm-based Multilayer Perceptron (MLP-GA) models and numerical model (MODFLOW) during training/calibration and testing/validation period

Performance indicators	Numerical model	MLP-GA models (Model architecture)						
		M-1 (4-29-1)	M-2 (3-36-1)	M-3 (2-19-1)	M-4 (3-31-1)	M-5 (2-17-1)	M-6 (2-21-1)	M-7 (2-11-1)
Training/ Calibration Period								
PBIAS (%)	0.07	-1.53	0.23	-0.89	-0.13	1.56	0	-0.04
RMSE (m)	2.36	1.28	1.51	2.5	2.02	2.63	3.64	3.75
r	0.98	0.96	0.94	0.83	0.89	0.81	0.59	0.56
CE	0.96	0.92	0.89	0.69	0.8	0.66	0.35	0.31
PI	0.03	0.05	0.06	0.1	0.08	0.1	0.14	0.15
WI	0.99	0.98	0.97	0.89	0.94	0.87	0.54	0.46
LMI	0.3	0.37	0.38	0.49	0.45	0.52	0.6	0.62
Testing/Validation period								
PBIAS (%)	-0.02	11.38	8.76	10.31	-10.2	15.38	11.35	-1.83
RMSE (m)	1.85	3.45	3.17	3.91	3.73	4.04	4.69	5.24
r	0.96	0.84	0.86	0.78	0.82	0.81	0.66	0.62
CE	0.94	0.97	0.97	0.96	0.96	0.96	0.94	0.93
PI	0.05	0.09	0.09	0.11	0.11	0.11	0.13	0.15
WI	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.98
LMI	0.4	0.63	0.61	0.6	0.59	0.67	0.6	0.54

Note: *PBIAS (Percentage bias), RMSE (Root mean square error), r (Correlation coefficient), CE (Coefficient of efficiency), PI (Performance index), WI (Willmott's index of agreement), LMI (Legates–McCabe's index)*

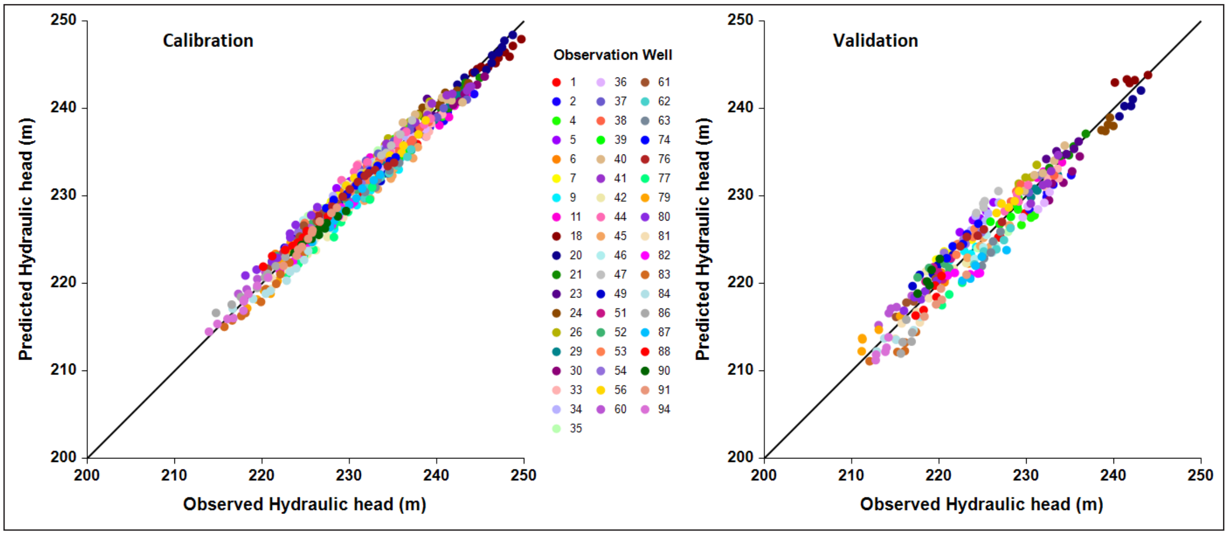
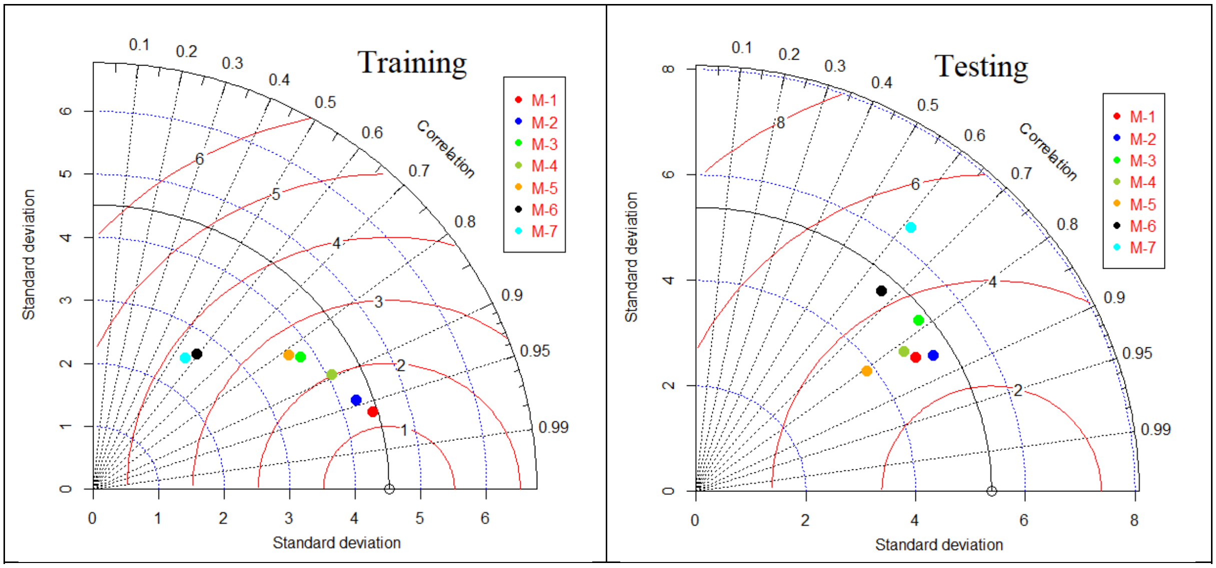


Fig. 5. Observed and simulated hydraulic head during calibration and validation period

groundwater level. The results of the models for the training period are presented in Table 2 and Fig. 6a. The performance indicators of the M-1 and M-2 models, including PBIAS, RMSE, r, CE, PI, WI, and LMI, indicated a satisfactory agreement between the observed and simulated groundwater levels. The values for these indicators were PBIAS (-1.52 and 0.22), RMSE (1.28 m and 1.50 m), r (0.96 and 0.94), CE (0.91 and 0.8), PI (0.049 and 0.06), WI (0.97 and 0.96), and LMI (0.37 and 0.45), respectively.

On the other hand, the performance indicators of the M-6 and M-7 models showed a poor agreement between the simulated and observed groundwater levels. The statistical indicators of PBIAS (0.001 and 0.037), RMSE (3.63 m and 3.74 m), r (0.59 and 0.55), CE (0.35 and 0.31), PI (0.14 and 0.15), WI (0.53 and 0.46), and LMI (0.60 and 0.62), indicated a poorer performance of these models. The results in Table 2 also demonstrate that the M-3, M-4, and M-5 models provided only marginally adequate results. However, since their RMSE values were greater than 2 m, these models cannot be considered reliable for estimating future groundwater levels. Among the seven hybrid MLP-GA models, the M-1 model performed reasonably well despite having more input parameters compared to the other models. This suggests that adding more model inputs can be beneficial for accurately building the groundwater flow model.

Model validation is the essential process to check the simulation accuracy of the calibrated model. Results of the model validation for period (2011-2015) given in (Table 2 and Fig. 6b). The performance indicators of M-1 and M-2 and M-4 model were PBIAS (11.38,8.75 and -10), RMSE (3.44 m, 3.16 m and 3.72 m), r(0.84,0.85 and 0.81), CE (0.96,0.97 and 0.0.96), PI(0.09,0.08 and 0.10), WI(0.99) and LMI(0.63,0.61 and 0.59), respectively. Results indicated that Models M-1, M-2, and M-4 had RMSE values of more than 3 m, but other statistical evaluating parameters were within the acceptable range. While the model's (M-3, M-5, M-6, and M-7) performance in the validation period was subpar and showed a very low level of agreement with observed and simulated GWL. The results of the models also indicated that in the validation period, performance was lower than that of in the calibration period. This may be due to overfitting of models in short training and testing data sets (Singh *et al.*, 2018). All hybrid MLP-GA models resulted in higher RMSE during the validation period, and this might be due to the fact of smaller size (2011-2015) of data than the calibration period (2001-2010) (Mohanty *et al.*, 2013). In addition, it was found that incorporating all the inputs is essential for simulating groundwater behaviour accurately rather than a few variables for the study region. However, a combination of precipitation (PCP), groundwater recharge (GWR) and groundwater draft (GWD) inputs can be used for groundwater simulation that had considerable variability with the groundwater level of the study region, whereas the combination of GWR, GWD and crop evapotranspiration (ET_c) inputs did not show good performance in the model. Importantly, M-3 model results indicate that GWR and GWD had greater variability with groundwater hydrology in the region. Finally, ET_c exhibits a variability of less than 4%, while PCP shows nearly 20% variability with



6(a) **6(b)**

Fig. 6. A comparison of MLP-GA models performance during training and testing period

the groundwater system (Fig. 7). It may be due to an increase in heavy rainfall leading to higher runoff, resulting in a loss of effective rainfall available for crop plants. As a result, the remaining water demand of the crops is fulfilled by groundwater, leading to its decline. Hence, a combination of PCP and ET_c inputs is not better option for developing a groundwater model for selected region. Unsatisfactory results were reported by Javadinejad *et al.* (2020) while using two variables (rainfall and air temperature) as a combination of input parameters for groundwater level prediction.

However, in contradiction to this, some researchers found that a combination of input parameters like rainfall, air temperature, and reference evapotranspiration (ET_0) with the groundwater level resulted in acceptable simulation (Kisi *et al.*, 2017; Alizamir *et al.*, 2018). Results of the M-1 model also support the finding of past studies that incorporated numerous combinations of input parameters such as rainfall, temperature, evapotranspiration, groundwater level, river discharge, and groundwater pumping altogether to improve the accuracy of groundwater level prediction (Mirzavand & Ghazavi, 2015; Mirarabi *et al.*, 2019). Overall, it was

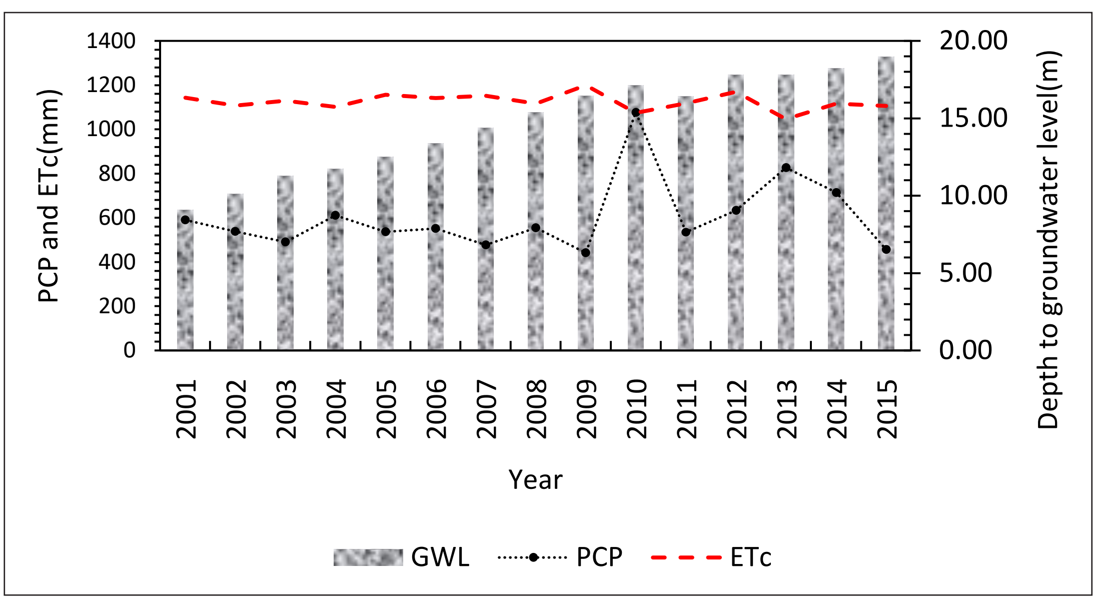


Fig. 7. Variability of groundwater level with precipitation (PCP) and crop evapotranspiration (ET_c)

found that based on statistical information of results of all models, the M-1 model can be used for groundwater level simulation.

3.2 Comparison of Numerical and Hybrid AI-based Models

A comparison was done to evaluate the simulation performance of the numerical (MODFLOW) and one best-chosen hybrid MLP-GA model (M-1). The effectiveness of both models was evaluated for the training/calibration and testing/validation periods using different statistical indicators. The statistical indicators for the numerical model were PBIAS (0.07 and -0.02), RMSE (2.36 m and 1.85 m), r (0.98 and 0.96), CE (-0.96 and 0.94), PI (0.032 and 0.045), WI (0.99) and LMI (0.30 and 0.40) during calibration and validation period, respectively (Table 2). These statistical indicators revealed that the numerical model accurately simulated the groundwater behaviour, with good agreement between the simulated and actual groundwater levels. While comparing the results of the numerical and MLP-GA model M-1, the M-1 model's results weren't better than those of the numerical model (Table 2). It may be because the MLP-GA model predicts the output based on the input and output relation, whereas the numerical model allows users to develop a prototype real physical aquifer system (conceptual model) that represents area-specific physics of groundwater system correctly by assigning numerous kinds of boundary condition and hydraulic parameters. However, in previous studies, researchers reported that the AI-based model was superior to the numerical model (Malekzadeh *et al.*, 2019; Chen *et al.*, 2020). Importantly, all of these studies were based on monthly groundwater simulation, whereas in this study, pre-monsoon season (annual) groundwater level simulation was done.

Thus, AI models showed better performance in short-time horizon (large data size) groundwater simulation than in long-time horizon (small data size). It was also found that the numerical model simulates groundwater level reasonably well both for short- and long-term time horizons, however, it needs a good hydrological expert as well as considerable time to calibrate and validate the groundwater flow behaviour of any region. Whereas AI models do not need additional data/parameters like lithology, hydraulic properties of sub-strata, or assigning of numerous boundary conditions that are essential for the representation of the groundwater system. Notably, numerical models are best suited for creating a variety of scenarios to assess aquifer yield, which can be crucial for resolving water management concerns and creating a sustainable water management plan. Overall, our study suggests need for more systematic research to ascertain which model is more accurate for long-time horizon groundwater simulation because groundwater behaviour varies from place to place, climatic conditions, and human intervention.

3.3 Impact of climate change on groundwater level

Figure 8 depicts the spatial-temporal variations in groundwater levels under the RCP4.5 climate change projections, considering the prevailing agricultural system, with specific reference to the year 2015. The simulation results using MODFLOW numerical model showed that the rates of groundwater decline in Zones 1 and 5 ranged from 0.07 to 0.12 meters per year and 0.62 to 0.68 meters per year, respectively, depending on the future time period under RCP4.5. The relatively lower decline in groundwater levels in Zone 1 could be attributed to the limited utilization of marginal quality groundwater for crop production, as there is adequate canal water supply in the area. Conversely, intensive rice-wheat farming relying on groundwater in Zone 5 is likely the main cause for the highest groundwater depletion observed there. Based on the simulation results, it is expected that the average groundwater levels will decline by approximately 7.7 meters by the end of the early period (2039) compared to the reference year of 2015.

The MLP-GA model (M-1) was used for future predictions under the existing system suggesting that the groundwater level in all zones would decline by 5 meters by the end of the early century compared to the reference year of 2015. It is worth noting that the MLP-GA model predicted a lower decline in groundwater levels compared to the numerical model (Fig. 8c and 9). Interestingly, the numerical model consistently projected a decline in groundwater levels throughout the simulation period from 2016 to 2039, while the hybrid MLP-GA model showed significant fluctuations, including both rises and falls in groundwater levels. However, the overall trend in both models was similar. The hybrid MLP-GA model provided comparatively reasonable forecasts for groundwater levels until the year 2031. Beyond that period (2032-2040), there was a sudden change in the rise and fall of groundwater levels, which is not realistic in a real-world system. Therefore, the numerical model is better suited for assessing the long-term impacts of future climate on groundwater behavior, as it captures the physics of the entire system.

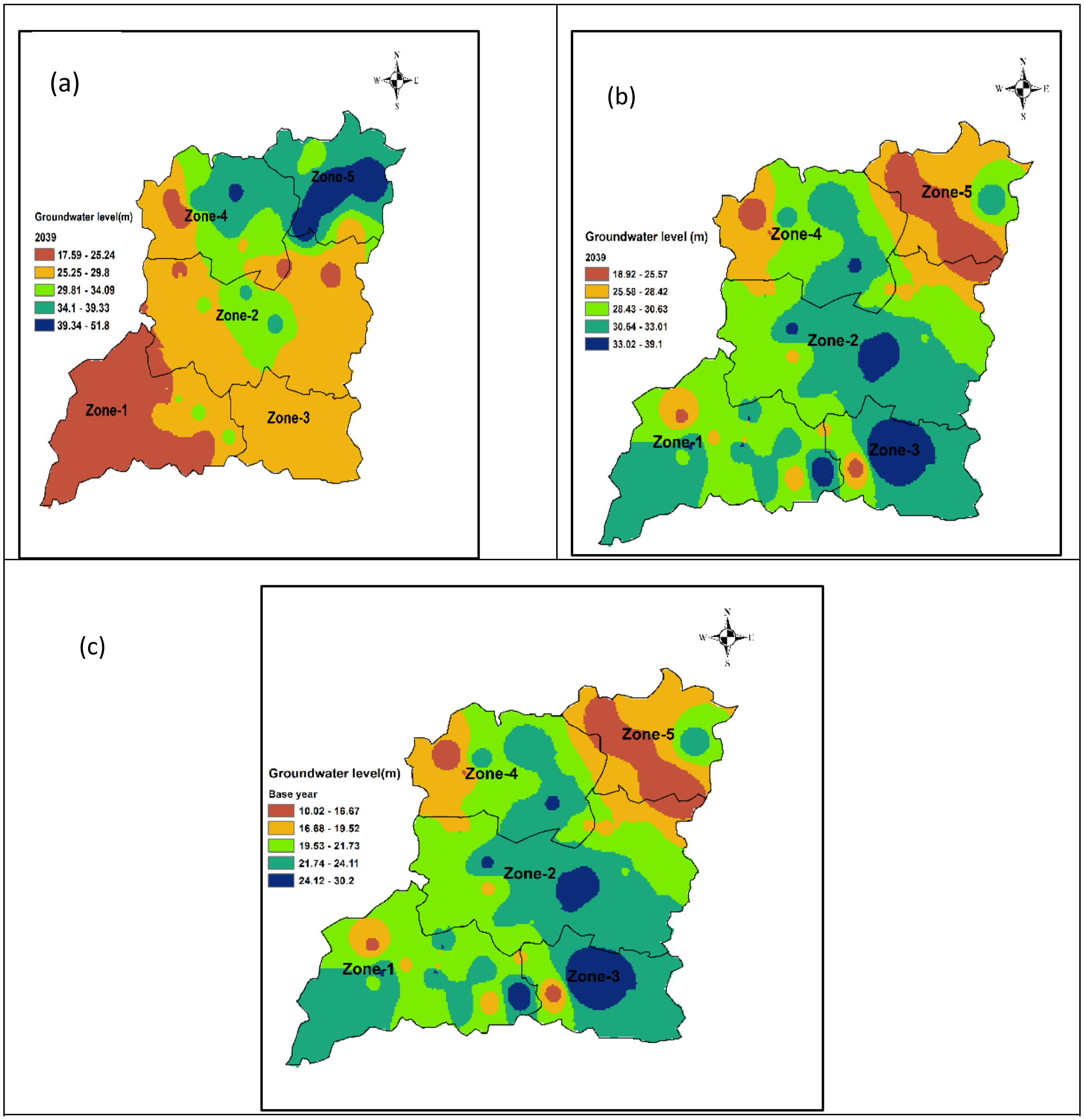


Fig. 8. A comparison of simulated spatial groundwater level (m) between MODFLOW (a) and MLP-GA hybrid model(b) under RCP 4.5 climate projections with reference to the base year (c)

On the other hand, MLP-GA-based models may be more suitable for short-time predictions as they rely on the relationship between past input and output data.

4. CONCLUSIONS

Groundwater is a crucial freshwater resource that caters needs of various sectors. With the growing human population and climate variability, the demand for groundwater has increased, necessitating the need to protect this valuable resource for future generations. Groundwater models have emerged as decision-making tools to address this objective. While numerical groundwater models provide realistic representations of groundwater behavior, they require extensive data and expertise. In this study, a comparison was made between a numerical model (MODFLOW) and seven hybrid Genetic Algorithm-based Multilayer Perceptron (MLP-GA) models for predicting groundwater levels in both the present and future periods. It was found that by incorporating all relevant hydrological input components, a reliable hybrid MLP-GA groundwater model can be developed for accurate predictions. Among the seven hybrid AI-based models, the M-1 hybrid model with four input nodes, 29 neurons in the hidden layer, and one output node demonstrated superior prediction accuracy. However, the numerical

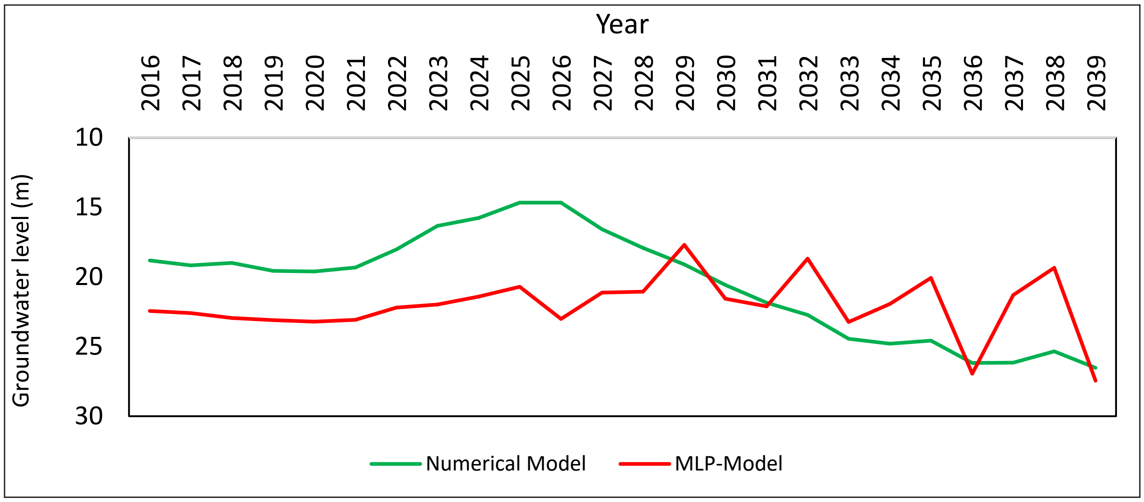


Fig. 9. Predicted groundwater level by numerical model (MODFLOW) and best Genetic Algorithm-based Multilayer Perceptron (MLP-GA) model under changing climate scenario

model outperformed the M-1 hybrid model in predicting groundwater levels. The numerical model projected an average decrease of 7.7 meters in groundwater levels by the end of the early century (2039) under RCP4.5 projected climate change scenario compared to the reference year 2015 in the entire study region. On the other hand, the hybrid MLP-GA model (M-1) predicted a decline of 5 meter in groundwater levels by the end of the early century under RCP4.5. Though the hybrid MLP-GA model M-1 provided comparatively reasonable simulation for groundwater levels in the near future (until 2031), but it failed to simulate groundwater levels reasonably well with the rise and fall of groundwater levels, which is not realistic in a real-world system, beyond the year 2031 (2032-2040). Based on the findings of this study, the numerical model was considered a more reliable tool for long-time (seasonal /annual) groundwater level predictions than the hybrid MLP-GA model (M-1). However, further research is needed to determine the best model for annual groundwater level simulations in different climate regions. Additionally, other AI-based models should be explored and compared with the numerical model to validate their performance.

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AUTHOR CONTRIBUTIONS

V. Nand: Conceptualization, Methodology, Investigation, Formal Analysis, Writing – original draft, Writing – review & editing; **B. Narjary:** Supervision, Writing – review & editing; **V. K. Singh:** Methodology, Investigation, Writing – review & editing; **N. Kumar:** Methodology, Validation, Writing – review & editing; **A. Islam:** Methodology, Data Curation, Formal Analysis, Writing – Review & Editing; **S. Kumar:** Conceptualization, Supervision, Funding acquisition, Writing – review & editing.

CONFLICT OF INTEREST

The authors affirm that there is no conflict of interest in any form that could have influenced the research work reported in this paper.

DATA AVAILABILITY STATEMENT

The data will be made available by the corresponding author on receiving a reasonable request

FUNDING

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