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Original Article

Evaluation of Water Resources, Land Use and Land Cover for Sabarmati & Mahi River Basins with Rainfall Runoff Potential Based Modelling Using Computing Techniques & Novel TBBO (Shruti-A) Approach

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Abstract - *Designing and Innovation issues are extremely dubious and precarious in nature. Especially when questionable boundaries like precipitation, environment, and traffic are concerned, irregularity and ludicrousness are expanded to the top level. Here in the present study, an investigation of the Water assets, land cover and use of the watersheds is done. Sabarmati Bowl and Mahi Stream watershed are executed and performed. Rainfall and runoff anticipating have been performed for the review area, of which the daily precipitation data are arranged from SWDC and digital datasets. Many methodologies have been produced for the turn of events and improvement of precipitation gauge models inside the water designing space. Brain organization (as artificial intelligence or ML), delicate processing, and other powerful models, such as TLBO, further developed TLBO have been created in the past for creating and further developing models. In a water asset designing space, in the event that the model boundary is unsure and shaky, the issues should be created in black box estimating models. In the present review, a methodology is proposed that will surely and astoundingly improve model execution or boundary attributes. Utilizing contextual analyses, it has been shown that there is a major improvement in the model improvement area, which prompts better execution of the models by further developing boundaries. The methodology is named TBBO (Tuition teaching-based Optimization or SHRUTI-A Algorithm). This approach is an improvement towards the improvement of created models and others to foster another model. Examination and contextual analyses show that the model exhibition improvement is finished up to a few times, and the model qualities coefficient of Connection is worked on by 10 to 30 percent. For the monthly models (Best models work out results), the NLR model has an R2 of 0.79 and RMSE of 1.214. ANN model has an R^2 of 0.89 and an RMSE of 0.812. FL model has an R^2 of 0.845 and an RMSE of 0.772. TBBO model has an R^2 of 0.832 and an RMSE of 0.9221. For the yearly analysis performed, the NLR model has an R^2 of 0.735 and an RMSE of 1.6. ANN model has an R^2 of 0.87 and an RMSE of 0.712. FL model has an R^2 of 0.821 and an RMSE of 0.615. TBBO model has an R^2 of 0.81 and RMSE of 0.9324. These error analyses show that models developed perform well in which ANN is best suited for training the data sets. It is concluded that the constructed neural network model was capable of quite accurately predicting runoff for the catchments. This approach is great for specialists who are tackling design issues in water assets, as proposed in the event of the review.*

Keywords - *Watershed, Hydrology, LULC, Rainfall, TBBO, Modelling.*

1. Introduction

The watershed might be described by how much streamflow from precipitation got inside the ridgeline. The watershed might be small or huge, depending on the area. Different basins have sub-watersheds, and these sub-watersheds are added to get precipitation and streamflow from feeders of significant waterways. Land use Land cover investigation of the bowl plays a significant role in classifying the bowl into various heterogeneous regular and human improvement assets. Water assets inside the bowl give an inferred thought regarding the water collection. Water assets might be normal, for example, streams, streams, channels, and so on; these might be man-made, for example, Dams, reservoir conduits, trenches and so on. Watershed executives are worried about the accessibility of the water assets and distributing the expected water inside the watershed according to land use, land cover prerequisites and water system necessities. Precipitation occurs inside the watershed, which

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is a dubious boundary. It changes from one rainstorm to another. Streamflow is absolutely reliant upon the precipitation and misfortunes that happen inside the bowls. Misfortunes have been seen cautiously to amplify the assets. Presently a day it is being seen that the extraordinary precipitation, for example, precipitation occurring more in amount inside less time, is expanding unexpectedly. Streamflow must also be overseen inside the watershed. At times, there is the need to gauge the amount of precipitation and streamflow inside the bowls early. It very well may be alluded to as precipitation determining. Different numerical, streamlining and delicate registering approaches have been utilized in the part for something similar. Methods might be straight, non-direct programming and so on, ANN, Fuzzy Rationale, TLBO and so forth.

These two sections have been finished in the current work. The first is to analyse the land cover and use of water assets in the two watersheds. The second part is to process the rainfall-runoff anticipating. These structures the significant goals of the examinations recorded underneath.

(1) To evaluate water resources and land use-land cover aspects of both watersheds.

(2) Analysis of the rainfall and runoff potentials within watersheds.

(3) To model the rainfall-runoff using computing techniques and a novel TBBO Approach and compare it with state-of-art approaches.

The Research gaps have been identified to formulate the objectives of the work after a diversified and extensive literature review. It is found that the black box modelling approach can be used to address the nonlinear components and modelling. A novel TBBO approach has been proposed, which highlights the novelty of the research conducted. The results of the novel approach and analysis have been evaluated and compared with other approaches. Results show that the approach is useful in analysis.

2. Literature Review

Aitkenhead et al. (2009) studied the prediction of land cover using GIS and incorporated the algorithms in the work conducted [1]. Ahiablame L et al. (2017) studied the streamflow response to potential land use and climate changes within the study area [2]. Araya YH (2010) studied about the analysis and modelling of urban land cover change within the study area [3]. Behera MD (2012) modelled the watershed dynamics using Cellular Automata [4]. Cellular automata is a soft computing approach which has added features of black box modelling and can be incorporated into analysis and modelling. A. Butt (2015) mapped the land utilization using satellite data and GIS for the study area [5]. It was concluded in the analysis that the remote sensing data can be utilized with GIS to formulate the landuse land cover methods [5]. Beven K (2012) described the rainfall runoff modelling procedure [6]. Hydrologists use rainfall-runoff analysis and modeling to predict hydrologic data sets, which can be utilized for water resources management, flood control, and many hydrology aspects [6]. Bhagat N. K. (2017) find the rainfall-runoff correlation ship for the lower Mahi basin [7]. The general formulation of a runoff model involves bifurcating a watershed into sub-watersheds. Rainfall data with inputs are set into the model to find correlations within the basin [7]. Chang T. K. et al. (2018) used fuzzy inference to model rainfall and runoff [8]. A Fuzzy Inference System (FIS) is a key tool to address the prediction of the work. Clark et al. used deep learning methods in rainfall-runoff modelling [9]. Nowadays, various deep learning approaches are used in the rainfall-runoff analysis, and the same approaches for the analysis are provided. Chourushi S et al. (2019) performed a decadal analysis of LULC in the study area [10]. Decadal analysis of the land cover provides the change in land utilization over the years, which provides a better way for efficient watershed management.

C. Zhu and Y. Li (2014) studied the long-term hydrological impact within the study area [11]. Decadal analysis is the way to address the long-term impact within the area. J. Yadav (2019) studied the green energy generations for alternate energy harvesting [12]. Jana A. et al. (2022) predicted changes in land cover in river basins by adopting the CA-Markov model [13]. River basin analysis can be predicted using various approaches as well. M.I.Haque et. A. (2017) studied long-term changes for land cover change using GIS [14]. Spatio-temporal analysis and its study were duly conducted in the study area [14]. Gadrani L. et al. (2018) performed an F assessment of land use and land cover using remote sensing and GIS [15]. F-assessment is planned as the ongoing procedure. Formative assessment is a continuing, responsive procedure to manage the parameters in attaining various goals. Mallikarjuna P. et al. (2009) assessed the rainfall-runoff modelling work using the neural network models for the Monthly analyzed models [16]. Mohseni et. Al. (2023) performed rainfall-runoff analysis using the ANN [17]. Neural network analysis can be used in different combinations of inputs with various epochs and iterations to map the data sets. Namara et al. (2020) used HEC-HMS to model rainfall-runoff [18]. The system of the hydrologic model can be approached to model the precipitation stream flow analysis. Neil McIntyre et al. studied the arid catchment using regression-based analysis for the Sultanate of Oman [19].

Rajurkar M. P. et al. (2002) presented a daily runoff model with linear and non-linear regression within the study area [20]. Rao R. V. invented a novel TLBO algorithm, which is known as the Teaching Learning Based Optimization Algorithm [21]. Samantaray, S. (2020) studied runoff forecasts using various new algorithms in arid watersheds [22]. Senthil Kumar et al. (2005) present a comprehensive evaluation of the performance of Multiple-layer perceptron-based neural network analysis [23]. Technical Reports on Sabarmati Basin and Mahi Basin published in March 2014 by the National Remote Sensing Centre (NRSC), ISRO Department of Space, GoI and Central Water Commission (CWC) GoI. (http://www.india-wris.nrsc.gov.in/) described the detailed hydrological aspects of the river [24] [25]. Tayfur G. et al. (2015) applied fuzzy logic in the runoff modelling and analysis, and the results suggest that fuzzy logic can be used for rainfall modelling purposes [26]. A trial-and-error procedure has been adopted to train the neural network. [26]. Wang K. H. et al. (2012) compared a case study and developed a fuzzy logic model for the forecasting of total streamflow within the Cascina Scala basin, Italy [27]. Yeshewatesfa H et al. (2001) studied the use of fuzzy logic in the analysis [28]. It is analyzed that the evaluation of the decadal change in water resources with land use patterns will address the watershed potential-based utilization for the future. Research gaps are those where insufficiency or extension of work modules is present. It has been identified that the approach proposed can be incorporated with details to overcome the limitations of the black box modelling. Various approaches for the modelling work have been developed in the past, so a novel approach is addressed in this study. Research gaps heightened the fact that the new statistical approaches and the combination of using various soft computing may provide a good comparison of assessed results.

3. Study Area and Methodology

3.1. Sabarmati and Mahi Basins

The Sabarmati and Mahi River basins in India represent two distinct facets of water resource management. While the Sabarmati basin is known for its extensive development projects, the Mahi basin is characterized by a more natural course. The Sabarmati basin, primarily in Gujarat, has witnessed extensive dam construction and water diversion projects to meet the region's growing water demands for agriculture and industrial use. In contrast, the Mahi basin, spanning across Gujarat and Madhya Pradesh, remains relatively untouched, showcasing the importance of preserving natural flow patterns and ecosystems. The details of the basins are shown below in Figure 1 and 2 [29, 30].

Sabarmati Stream Basin: The Sabarmati stream, originating in the Aravalli Range of Rajasthan, flows southwest through Gujarat, covering an area of approximately 21,674 KM^2. This basin has been a focal point for extensive development efforts, including dam construction and water diversion projects, aimed at meeting the increasing water demands of the region with the highest length and width, 300 km and 150 km. It comes between 70°58' to 73°51' E longitudes and 22°15' to 24°47' N latitudes. The stream basin is rough triangular shape-wise, with the Sabarmati stream as the foundation and the source of the Vatrak stream as the apex point. Sabarmati originates from the Aravalli region near Tepur Village in the Udaipur district of Rajasthan. The total length of the stream from start to outfall into the Arabian Sea is 371 km, and the tributaries joining are the Wakal, the Hathmati, Vatrak and Sei. The major part of the watershed is occupied with agriculture/ green areas, accounting for more than 70% of the total area. The mean annual precipitation of the Sabarmati catchment is 787.5 mm.

Mahi Stream Basin: Mahi Stream Basin, which extends to both Gujarat and Madhya Pradesh, occupies a vast region of about 34,842 KM^2. The Mahi basin shows the importance of managing the natural outflow patterns of a stream, as it plays a pivotal role in maintaining ecological ecosystem balance and biodiversity. The Mahi watershed extends over Madhya Pradesh, Rajasthan, and Gujarat states, with the highest length and width of 330 km and 250 km. It occupies between 72°21' to 75°19' E longitudes and 21°46' to 24°30' N latitudes, and its overall length is 583 km. It originates from the northern slopes of Vindhyas near village Bhopawar, Sardarpur tehsil, Dhar district, Madhya Pradesh.

Tributaries of west-flowing major rivers are Som, Anas, and Panam, which collectively outlet into the Arabian Sea at the Gulf of Khambhat. The majority part of the watershed is occupied with agricultural/ green land, accounting for 64% of the total area, and water assets cover 4% of the watershed. The mean annual precipitation of the Mahi stream basin is 698 mm. In comparing these two basins, the complex choices and challenges faced in managing water resources. The Sabarmati demonstrates the potential of human-engineered solutions to water resource challenges, while the Mahi emphasizes the need for sustainable and balanced approaches that protect the natural environment. Both basins hold valuable lessons for regions around the world grappling with the delicate balance between human needs and ecological preservation in their pursuit of water resource management.

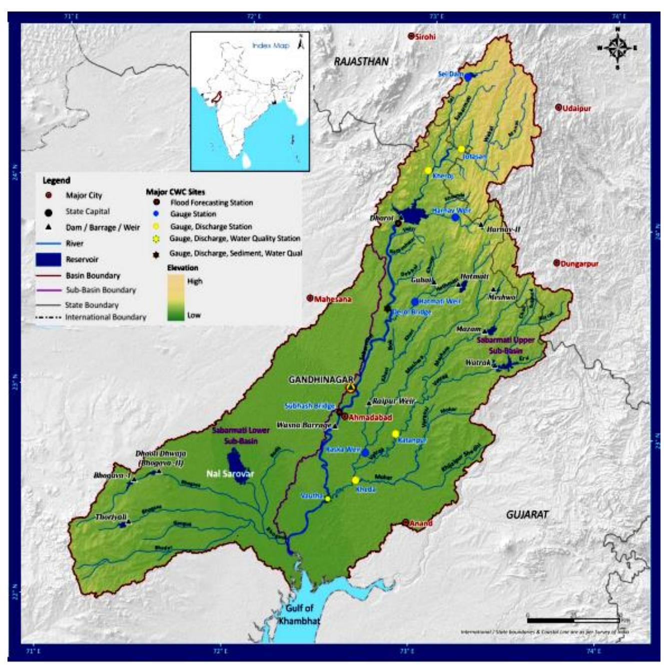


Fig. 1 Sabarmati basin map

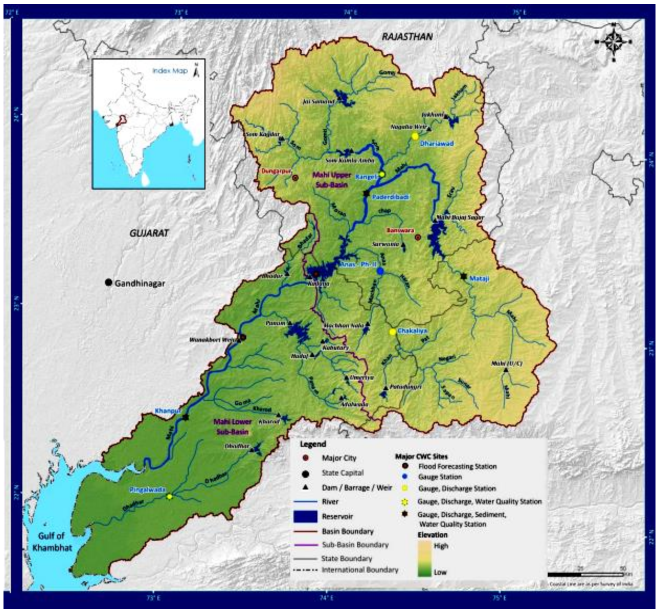


Fig. 2 Mahi basin map

3.2. Data Collection

The Precipitation information from 1991 to 2020 has been gathered and acquired from the State water server farm, Gandhinagar division, Central Water Commission division, Gandhinagar and various information is gathered likewise from the https://power.larc.nasa.gov information site. The precipitation and streamflow information was gathered from the State Water Server farm, SWDC Gandhinagar.

Additionally, the Trills Day to day precipitation worldwide information has been likewise gathered for the review. Code. Earthengine.google.com is utilized to foster the coding for the advancement of different LULC maps. The toposheets-based Digital Elevation Model is ready based on the information gathered from Cartosat WGS 84 goal 30 m. Information on precipitation has been gathered from the Trill's day-to-day precipitation for 30 years. The 30 years of data and information are utilized for the alignment, and later, long-term information is utilized for approval and expectation.

3.3. Methodology

The flowchart beneath portrays the definite system of the review. Fundamentally, work is separated into two sections. In the initial segment, the segment examination for LULC has been finished for the two bowls, and in the second part, the hydrological.

Soft computing procedures are a gathering of strategies that are utilized to take care of complicated issues that are challenging to settle utilizing conventional figuring methods. Soft computing is a field of study that is concerned with the improvement of computational methods that are motivated by normal, natural frameworks, like the human cerebrum, sensory system, and safe framework.

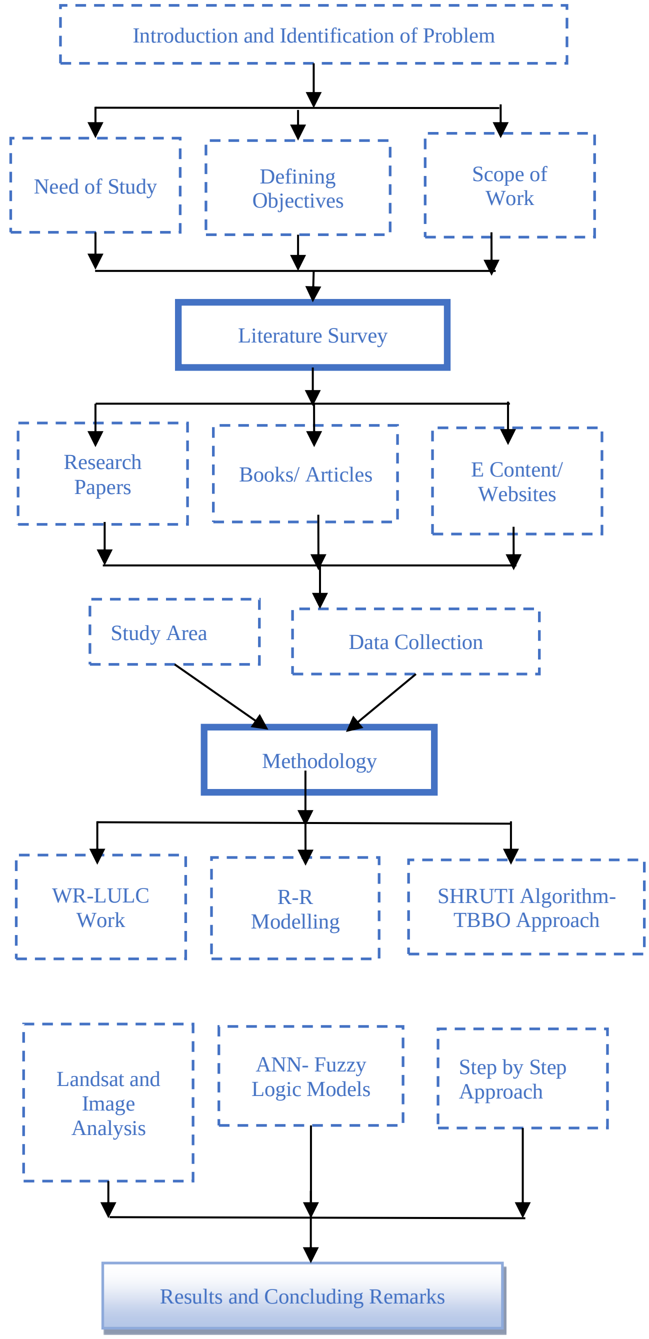


Fig. 3 Methodology of the research

There are a few distinct sorts of delicate figuring procedures, each with its own exceptional qualities and applications. Here are probably the most widely recognized kinds of delicate registering methods and their purposes: Brain Organizations: Brain networks are a sort of man-made reasoning that are intended to gain from information. They are utilized in many applications, including picture and discourse acknowledgement, regular language handling, and example acknowledgement.

3.3.1. Fuzzy Logic

It is a numerical structure that considers vulnerability and imprecision in information. It is utilized in various applications, such as control frameworks, direction, and master frameworks.

3.3.2. ANN-Transformative Calculations

Developmental calculations are a sort of improvement calculation that utilization standards of normal choice to track down ideal answers for complex issues. They are utilized in different applications, like designing plans, monetary displays, and game hypotheses.

3.3.3. GA-Hereditary Calculations

Hereditary calculations are a sort of transformative calculation that utilization standards of hereditary qualities and normal determination to track down ideal answers for complex issues. They are utilized in various applications, like improvement, booking, and planning.

3.3.4. Swarm Knowledge

Multitude insight is a sort of aggregate insight that is propelled by the way in which social bugs behave, like insects and honey bees. It is utilized in different applications, like enhancement, mechanical technology, and transportation.

3.3.5. Artificial Immune Framework System

Counterfeit insusceptible frameworks are a sort of computational model that is motivated by way of behaving of the human safe framework. They are utilized in different applications, such as irregularity identification, information mining, and example acknowledgement.

Generally, Soft computing procedures are utilized to take care of intricate issues that are hard to tackle utilizing customary processing strategies. They are utilized in a large number of uses, like designing plans, monetary displaying, picture and discourse acknowledgement, and transportation

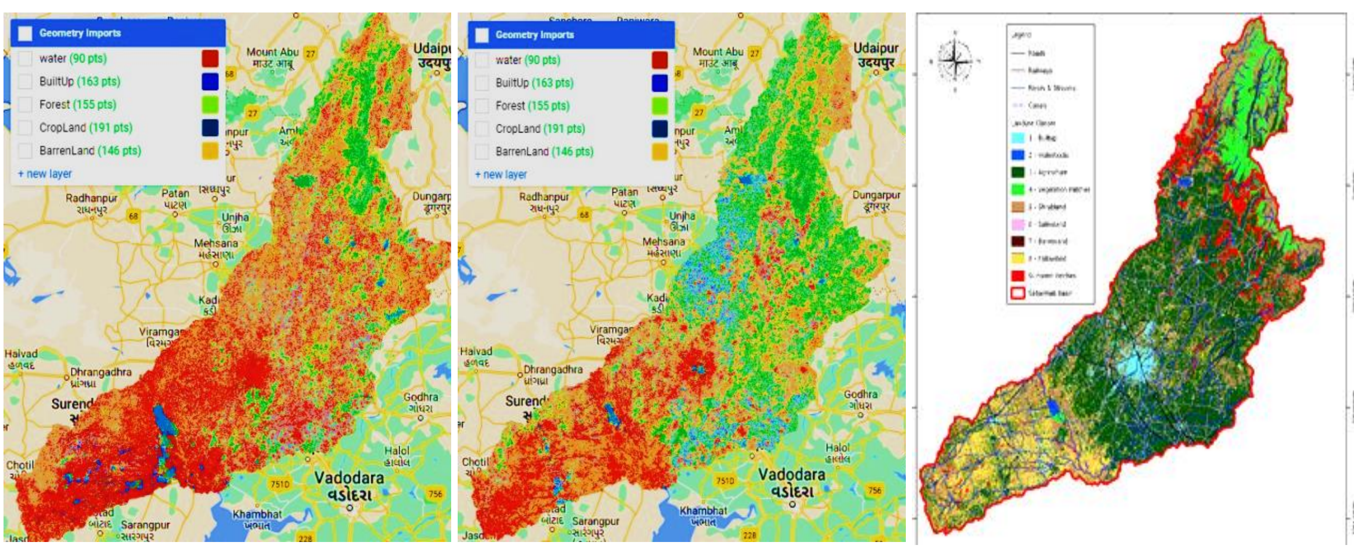
3.4. LULC Data Analysis and Work Performed

Different LULCs have been created for both watersheds. Landsat 8 and Landsat 9 have been utilized to develop the LULC utilizing the code.earthengine.google.com system. Similar time series-based LULC has been produced for the time span of 2013, 2018 and 2022. The relative examination of the LULC and water assets has been finished and introduced in Figures 4 and 5.

The figure portrays the change over the years inside the watershed, and the table depicts a similar investigation of the bowl LULC for the two bowls. Figure 4 shows the correlation of LULC for quite a long time from 2013 to 2023, out of which the information examination of LULC has been finished in earth motor coding involving Landsat 8 for years 2013 and 2018. However, Landsat 9 is utilized for the year 2022. Toposheets-based DEM is prepared from the information gathered Cartosat WGS 84 goal 30 m resolution. Information for precipitation has been gathered from the CHIRPS daily precipitation for 30 years.

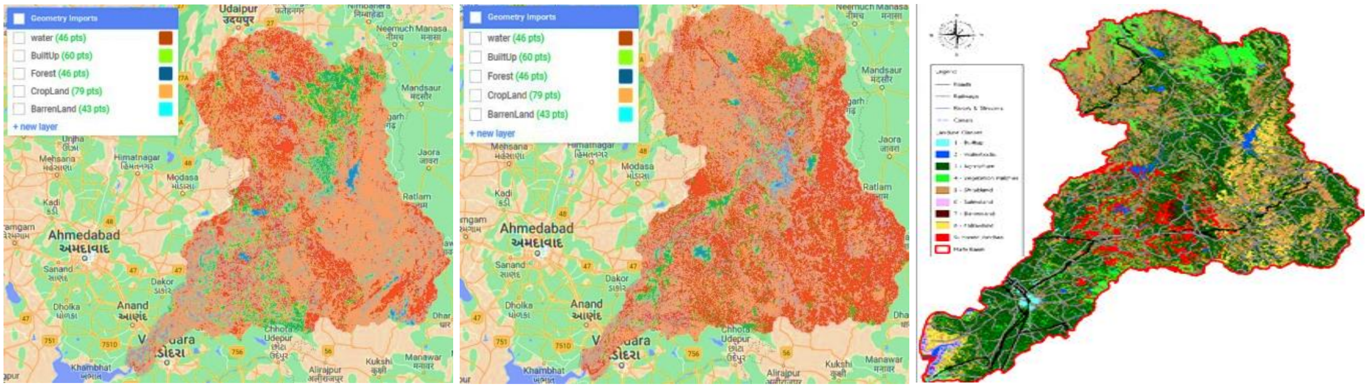
Precipitation, and climate information are gathered from SWDC, Gandhinagar, from 1991 to 2020. The information from 1991 to 2008 is utilized to foster the model and framework, and the data from 2009 to 2020 is utilized to approve the outcomes.

Landsat-9 (30m Spatial Resolution) (Winter), Basin Boundary derived from Government Source of India, QGIS Software 3.10 with Plugin was used for LULC classification for 2022.



Sabarmati-2013 **Sabarmati-2018** **Sabarmati-2022-23**

Fig. 4 Water resources, land use land cover analysis for sabarmati region



Mahi-2013 **Mahi-2018** **Mahi-2022-23**

Fig. 5 Water resources, land use land cover analysis for mahi basin

Table 1. Comparative hydrological details of Sabarmati and Mahi River basins

River Name	Sabarmati River/ Basin	Mahi River/ Basin
Basin Extent (Longitude and Latitude)	70° 58’ to 73° 51’ E 22° 15’ to 24° 47’ N	72° 21’ to 75° 19’ E 21° 46’ to 24° 30’ N
Length of Sabarmati River (Km)	371	583
Catchment Area (Sq.km.)	21674	34842
Annual Average Rainfall (mm)	787.5	698
Built-up area (in Hectare)	4.77	1.42
Waterbodies (in Hectare)	0.94	2.12
Agriculture and Vegetation Patches (in Hectare)	53.65	55.31
Shrubland (in Hectare)	19.63	27.6
Saline land and Barren land (in Hectare)	0.88	1.78
Fallow land and Forest Patches (in Hectare)	20.13	11.78
Mean Water Resource based Potential (MCM)	3810	11020
Usable Surface Water based Resource (MCM)	1900	3100
Live Storage Potential of Completed Projects (MCM)	1567.0	5015.0
Live Storage Capacity of Projects Under Construction (MCM)	110.0	160.0
Total Live Storage Capacity of Projects (MCM)	1677.0	5175.0
No. of Hydrological Observation Stations (CWC) and No. of Flood Forecasting Stations (CWC)	15	14

Figure 5 shows a comparative LULC analysis for the years 2013 to 2023, out of which the data analysis of LULC for the Mahi River basin was done using earth engine coding using Landsat 8 for the years 2013 and 2018. In contrast, Landsat 9 is used for the year 2023.

A comparison of the basin explains that the Mahi stream basin is found to be more acquainted with the land cover than the Sabarmati Basin, and the number of streams within the basin is also higher.

Analysis shows that the requirements of watershed management practices may enhance the basin's water utilisation. Streamflow can also be increased within that. Sabarmati Basin receives comparatively more rainfall than the Mahi Basin, as the annual average rainfall is 787.5mm for the former.

3.5. Steps and Methodology in brief followed for Fuzzy Logic and Neural Network

Using fuzzy logic in MATLAB typically involves several steps:

Step 1: Defining Input and Output Variables: Identify the input and output variables for your fuzzy system and specify their ranges (universe of discourse).

Step 2: Fuzzification: Create membership functions for each input and output variable. These functions represent the degree to which a value belongs to different fuzzy sets (e.g., "low," "medium," "high").

Step 3: Rule Base: A rules set is defined, which describes the relationship between input parameters and output variables. These rules are in the form of "IF-THEN" statements.

Step 4: Inference-Based Engine: Apply the if-then (Fuzzy) else rules to the input values to determine the degree to which each rule is satisfied. Various methods, like Mamdani or Sugeno, can be used for this.

Step 5: Aggregation: Combine the outputs from each rule to obtain a comprehensive result fuzzy set.

Step 6: Defuzzification: Convert the fuzzy result obtained as output into a rigid/ crisp value, typically by calculating a weighted average or using a method like centroid, mean of maxima, or a custom function.

Step 7: Implementation: Finally, implement your fuzzy logic system in MATLAB using built-in functions or custom code. These steps help you create a fuzzy logic system in MATLAB to model and solve problems with imprecise or uncertain data.

The following steps are the procedure to Develop an ANN Model with the nntool toolbox of MATLAB.

Step 1: Formulate a framework and decide on input and output with ranges.

Step 2: Data Collection: The requisite data (hydrology and meteorological data) from the gauge site is collected.

Step 3: Import Data: The added collected datasets are introduced into the toolbox as input data and target data.

Step 4: Developing Network: The network is developed by deciding a suitable type of network that may be fed forward or back propagated by selecting nodes, epochs, and hidden layers.

Step 5: Count of Neurons: For any network, the count of neurons is selected as 10 or 15 or, 30 or 50.

Step 6: Training of Network: The created network is trained on the basis of activation function performance.

Step 7: Result: After network-based training, the outputs are analysed by regression plot to obtain output.

Step 8: Further-Training: Re-initialization of weights has to be conducted if results are not promising by neuron count change and may be an activation function if needed.

Step 9: Model Evaluation: Evaluate the model based on available statistical parameters.

The following are the steps to be performed to Create a neural network with nnstart.

Step 1: Formulate a framework and decide on input and output with ranges.

Step 2: Neural Fitting App to be opened: The Fitting neural network app will assist in adding data developed to create and train the network to analyse and perform using error analysis statistical parameters.

Step 3: Selection of the Data: Input and output data have to be framed, and the input variable data are in a suitable 6×36 matrix. Also, the output data must be in a 1×36 matrix.

Step 4: Test Validation: Training, Analysis, testing and validation percentages within the data can be changed, but the normally adopted ratio is 70% (for training), 15% (for validation), and 15% (for testing).

Architecture Network: For any network, the count of neurons is selected as 10 or 15 or 30 or 50.

Step 5: Select Algorithm: Any suitable algorithm for ANN may be used.

Step 6: Network's Training: To fit input variables and precedent dataset, train the network.

Step 7: Further-Training: Re-initialization of weights has to be conducted if results are not promising by neuron count change and may be an activation function if needed.

Step 8: Final Result: The predicted objective is obtained only by fixing the regression plot and error analysis.

3.6. SHRUTI-A Algorithm (TBBO Algorithm Approach)

An advanced algorithm has been formulated that has similarities to TLBO or an altered version of TLBO (Teaching Learning (T-L) Based Optimization Algorithm) Rao et al. (2011) [21]. This algorithm adds to the advancement of the tuition process apart from teaching the students other than regular teaching-learning activities. The name given to this algorithm is Tuition Batch-based Optimization Algorithm (TBBO) or Shruti-A Algorithm. The Concept behind the development is the set of students (models in our case or parameters) who are weaker or critical, and even after a regular Teaching Learning Approach, they are not able to perform to provide promising results or output; special tuition or personal assistance is required for them to improve the learning.

This approach is very promising, realistic, and practical as it improves the model over the parameter study. There are three basic stages in this Algorithm. First is Teaching Learning phase. The second part of the first step is the Teaching phase, in which the teacher will teach students. The second sub-part is the learning phase, in which students will teach students to learn. The second and most important phase is learning through the tuition batch for parameters and model, respectively. The third part is the Development of the final TBBO model with Comparison using the other (at least one) optimization model or statistical method. Smart Heuristic Regression-based Ultimate Testing Intel Algorithm (SHRUTI-A) is the technical name given to this algorithm.

Steps in TBBO (Shruti Algorithm):

Step 1: It is a Teaching Learning segment in which work similar to TLBO will be performed by the developed Algorithm.

Sub Part 1: Teaching phase: The teacher will teach all the students and select bright students and others as well.

Sub Part 2: Good Students or brighter students will teach and assist other remaining students.

Sub Part 3: The teacher will take a quick follow-up for the part done by the student to assess improvement and learning and decide on the weaker/ critical students.

Step 2: Performing with TBBO: The weaker students/ learners, including the model or parameters within the model. A tuition batch will be made to improve learning and enhance the performance of the model or parameter.

Step 3: Comparison of the TBBO Model (Shruti-A Algorithm) using at least one any other statistical model or optimization model is required to be performed.

Step 4: Uncertainty and sensitivity analysis of the models for validation of the developed model.

It can be assessed and separately discussed as a variable parametric study or development of an approach in which an integrated approach can be solved. The problem definition and explanation need to be very clear. Many approaches have been developed in the past for the modelling sector to ease the problems in engineering and technology perspectives. Many statistical approaches (white box models) and black box models, such as soft computing Techniques, have been developed in the past. Optimization algorithms have also been developed to solve the problems.

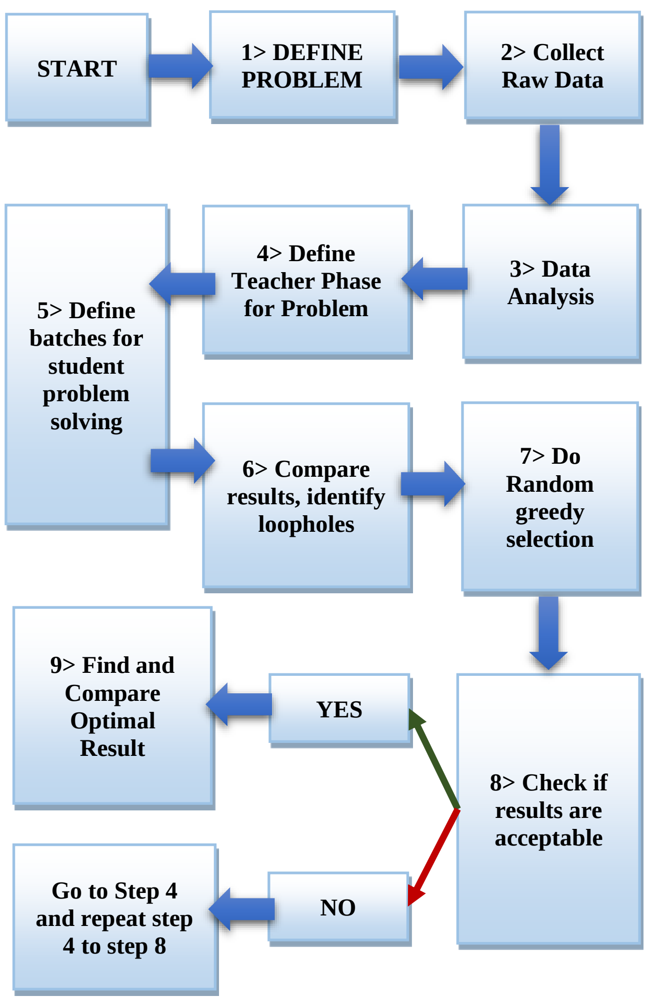


Fig. 6 Methodology of the SHRUTI Algorithm [TBBO Technique]

All the problems or model development have been done through scientific procedures and technical background. Here, one algorithm and approach is proposed, known as the Tuition batch-based optimization TBBO Algorithm or Shruti algorithm. In this, a step-wise flowchart-based hierarchy will be used not only to model but also to improve the performance of the developed model. Figure 6 shows the flowchart-based methodology.

3.7. TBBO Lucid Example

The input parameters are formulated into tuition batches with atleast three-step development, i.e. division-wise 3-step classification. Similarly, output or target parameters are also formulated as division-wise three-step classifications. The input segments have three parameters, and the output segment has one parameter.

Suppose the optimization method or any other soft computing method has to be applied; then the whole parameter ranges are taken into account except the target feeding approach. In optimization using the TBBO Algorithm, the target will be initially specified in one section (the best possible optimized portion) of the output. It will help to avoid the worst answer within the calibration, testing and validation of the modelling. It is based on the conventional TLBO Algorithm developed by Prof. Rao et al. (2011). However, it is inspired by the traditional tuition batch phenomenon for the weaker students in a class in which weaker students are made brighter by tuition teaching. Weaker students, critical, average students and stronger students will target their weakest portion to score well; hence, they will be divided into tuition batches. A class may have many batches, a maximum of up to 20. Even the batch size may vary from a few students to up to 33 percent of the whole class. The input will have more than 3 divisions up to 20 in number (3 to 20). An example in Table 2 shows a three-input division and one output as a targeted class. Batches in each division may also have 5 to 20 batches. In the first parameter, 6 batches have been characterized also for the other two inputs and target set as well. The same thing may occur within the batches. For example, batches may have sub-batches inside as well. Now, there are 6 batches in Input 1 and 30 sub-batches in Input 1, and each sub-batch has 5 batches. Batch-wise learning and teaching within the batches will be good for the model development and learning of students. A combination of input batches will target a batch from the output parameter. However, the sub-batch may be concerned by the model for accuracy. For example, if a student is weak in one subject but strong in all others, it may be possible that the student may be weak only in a few portions of the subject, but it may also happen that certain topics are harming him to get good grades. In this example, the subject is the input parameter, the portions or units are batches, topics are sub-batches, and the grades are output. If the student wants to get good grades in the weak subjects, then this tuition batch-based approach will enrich the teaching and learning outcomes of the student.

Table 2. Tuition batch based optimization (TBBO) input output correlation for steps 2-3

Input Target			Output
First Input Parameter	Second Input Parameter	Third Input Parameter	Target Output Parameter
I1-Batch 1	I2-Batch 1	I3-Batch 1	O1-Batch 1
I1-Batch 2	I2-Batch 2	I3-Batch 2	O1-Batch 2
I1-Batch 3	I2-Batch 3	I3-Batch 3	O1-Batch 3
I1-Batch 4	I2-Batch 4	I3-Batch 4	O1-Batch 4
I1-Batch 5	I2-Batch 5	I3-Batch 5	O1-Batch 5
I1-Batch 6	I2-Batch 6	I3-Batch 6	O1-Batch 6

3.7.1. Brotherhood at Batches in TBBO

For the one combination of the input batches, the target output batch will randomly take a minimum of seven values within the range of batch and perform an error analysis. The error analysis is done using error analysis between the targeted value and the observed/optimized value. The least value among the minimum seven values will be selected as a result of the present effort, and this process of randomly greedy selection is termed as Brotherhood at batches in TBBO.

Error Analysis Formulae: $e = SQRT\ of\ [(A_o - A_T)^2 / A_T]$

where Ao is the random value, and A_T is the targeted value. In the present study, a case study of the rainfall-runoff model is presented as the justification for the proposed algorithm. The results have been compared with Linear optimization, Non-Linear Optimization, TLBO algorithm, and Soft computing approaches such as evolutionary algorithms, GA, neural networking and fuzzy logic.

Results show various positive attributes of the TBBO techniques over the other techniques. The best part is that the TBBO Algorithm targets the optimized portion of the best results in batches. However, there are very few limitations that can be overcome to develop the technique as a recommendation.

In the present case study, rainfall, infiltration, and runoff are characterized as two inputs and one output for the model. Rainfall is characterized in five batches, whereas seven batches characterize infiltration. The output is characterized as seven batches. For inputs, 35 combinations target the seven batches of output. The results below show the productivity of the outcomes developed through the analysis of the batch.

Brotherhood at TBBO (SHRUTI-A) Algorithm will be performed as the greedy selection of randomly selected more than 7 values. In this step, which is the most important part of the TBBO batch selection analysis, seven or more than seven values are selected randomly, the average of error analysis with observed and targeted values will be calculated, and the minimum error analysed will be identified as the output value. As in the present case in the figure 7 mentioned below, the Seven values identified are 43, 57, 89, 108, 141, 172, and 182.

These values are randomly identified by the system or model and error analysis as compared with the observed value 85 and targeted value 85. The average error analysis for 89 shows the least error. Similarly, for the fourth combination, the random values within the target batch are identified as 624, 726, 764, 792, 639, 663, and 736.

INPUT 1 (RANGE 0 TO 100)				
BATCH 1	BATCH 2	BATCH 3	BATCH 4	BATCH 5
0 to 20	20.01 to 40	40.01 to 60	60.01 to 80	80.01 to 100
INPUT 2 (RANGE 0 TO 100)				
BATCH 1	BATCH 2	BATCH 3	BATCH 4	BATCH 5
0 to 20	20.01 to 40	40.01 to 60	60.01 to 80	80.01 to 100
INPUT 3 (RANGE 0 TO 100)				
BATCH 1	BATCH 2	BATCH 3	BATCH 4	BATCH 5
0 to 20	20.01 to 40	40.01 to 60	60.01 to 80	80.01 to 100
OUTPUT 1 (RANGE 0 TO 1000)				
BATCH 1	BATCH 2	BATCH 3	BATCH 4	BATCH 5
0 to 200	200.01 to 400	400.01 to 600	600.01 to 800	800.01 to 1000

			RANGE	BROTHERHOOD IN BATCHES- 7 RANDOM VALUES							OBSERVED	TARGETED
FOR 1st Combination	OUTPUT	BATCH 1	0 TO 200	43	57	89	108	141	172	182	85	85
FOR 2nd Combination	OUTPUT	BATCH 2	200.01 to 400	310	395	211	318	243	314	339	250	250
FOR 3rd Combination	OUTPUT	BATCH 3	400.01 to 600	460	448	544	423	583	466	434	455	450
FOR 4th Combination	OUTPUT	BATCH 4	600.01 to 800	624	726	764	792	639	663	736	772	775
FOR 5th Combination	OUTPUT	BATCH 5	800.01 to 1000	875	887	805	855	861	810	859	880	875

See Sample Calculation for First Combination Below

Random Values	OBSERVED VALUE	TARGETED VALUE	E.A. With Observed Values	E.A. With Targete	Average of RMSE Error
43	85	85	4.55553961	4.5555	4.55
57	85	85	3.03702641	3.037	3.03
89	85	85	0.43386092	0.4339	0.433
108	85	85	2.49470026	2.4947	2.49
141	85	85	6.07405282	6.0741	6.07
172	85	85	9.43647492	9.4365	9.43
182	85	85	10.5211272	10.521	10.52

See Sample Calculation for Fourth Combination Below

Random Values	OBSERVED VALUE	TARGETED VALUE	E.A. With Observe	E.A. With Targete	Average of RMSE Error
624	772	775	5.3266	5.4241	5.3754
726	772	775	1.6556	1.7601	1.7079
764	772	775	0.2879	0.3951	0.3415
792	772	775	0.7198	0.6107	0.6652
639	772	775	4.7868	4.8853	4.836
663	772	775	3.923	4.0232	3.9731
736	772	775	1.2957	1.4009	1.3483

Total 125 Combinations will be created as shown below some sample collections

BATCH 1	INPUT 2	BATCH 1	INPUT 3	BATCH 1
BATCH 1	INPUT 2	BATCH 1	INPUT 3	BATCH 2
BATCH 1	INPUT 2	BATCH 1	INPUT 3	BATCH 3
BATCH 1	INPUT 2	BATCH 1	INPUT 3	BATCH 4

Fig. 7 Calculations of Brotherhood at Batches in TBBO (Random Greedy Selection) and responses

While comparing the observed value of 780 and the targeted value of 775, the error analysis shows that 772 is the optimal answer. Iterations may vary from one to maximum. Batch selection may be carefully chosen; biased batch selection and forced batch selection should be avoided. They should be selected based on the optimal requirements of the students for performing better.

3.7.2. Target for Tuition Batch-Class Wise CASE A.

Students can be divided into batches. A minimum of 4 batches is required, but 5 to 20 are preferable. For example, the maximum population is 50, and the maximum scoring is 100. Burdon is defined as the weight of target achievement depending upon the student/ batch population count. Suppose the population is larger for a batch compared to others, and then target achievement is more focused on that batch. Burdon is inversely proportional to batch count. Maximum Burdon should be given priority for the achievement.

Targeted Fractional Target = Percentage of (Percentage of Batch count X Target /100).

Formulae for Burdon = Percentage of (Percentage of Batch count X 100/ Target).

Both fractional targets and Burdon are important to initiate the iteration process. Also, which batch is critical can be identified for improvement. The targeted fraction depends directly on the batch count, whereas Burdon increases as the target decreases.

Batch status is defined as the quality of students and numbers for the same. If the quality of students is higher and the count is lower, then the status is not good. It can be referred to as Good and Bad. It is good if more students are there in higher batches, and if the student count is higher in lower batches, then it is also bad. It is also recommended sometimes to keep higher students out of analysis and prepare a table of students scoring 80 percent only. Here, we have considered all populations and all classes. The iteration process will be continued to a minimum of calculation and 4 iterations, i.e. 5 calculations. Maximum iterations are infinite. The iteration is continued until the cumulative fraction is more than 40 percent in the top 30 percent of batches and less than 20 percent in the least two batches.

Criteria for Good and Bad batch status (<7 Batches): (It is just a status cover for the batch)

Batch numbers are allotted in reverse chronological order, which means batch 2 will be just below batch 1. Also, after the improvement, batch 2 students may go to batch 1, and batch 3 may go directly to batch 1. It is also preferable that the student/batch population do not degrade and retains at least the nominal status for the higher 2 batches. The remaining steps and iterations are depicted in Appendix 1 for the tuition batch-based optimization method.

Table 3. Criteria for Good and Bad batch status (<7 Batches): (It is just a status cover for the batch)

Batch status	Batch count (Compared to total)	Status	Otherwise
Higher batch (top 60 percent)	> 20 percent	GOOD	BAD
Batch 40 to Batch 60 percent	> 20 percent	GOOD	BAD
Batch less than 40 percent	<20 percent	GOOD	BAD

Table 4. Criteria for Good and Bad batch status (> =7 Batches): (It is just a status cover for the batch)

Batch status	Batch count (Compared to total)	Status	Otherwise
Higher batch (top 60 percent)	> 20 percent	GOOD	BAD
Batch 40 to Batch 60 percent	> 15 percent	GOOD	BAD
Batch less than 40 percent	<15 percent	GOOD	BAD

Table 5. The calculations for Tuition Batch

Batch no.	Criteria	Batch count	Percentage of batch count	Batch status	Target for batch	Targeted Fractional	Burdon	Remarks
Batch 1	Students scoring more than 85 percent marks	3	6	Good	95	7.960894	4.37	Least batch count
Batch 2	80 to 84.99	6	12	Good	90	15.0838	9.22	-
Batch 3	70 to 79.99	7	14	Bad	85	16.62011	11.38	-
Batch 4	60 to 69.99	9	18	Bad	75	18.85475	16.59	Highest Batch count
Batch 5	55 to 59.55	7	14	Good	65	12.7095	14.89	-
Batch 6	45 to 54.99	8	16	Bad	60	13.40782	18.43	-
Batch 7	Less than 45	10	20	Bad	55	15.36313	25.13	-
	Total	**50**	100					

4. Model Evaluation and Experimentations

4.1. WR-LULC Model in GIS

Land utilization and land covering analysis with water resources has been performed and analysed using the QGIS software and https://code.earthengine.google.com/. The model has been prepared for the decadal analysis of 2013 to 2022 using three Land sat images. It is also explained in detail in the above section.

The overall accuracy assessment has been obtained to be 87 to 92 percent. The land for agriculture has been found to be dominant, as per the model analysis. Also, the green belt is found to be good for both basins. The water resources present are found to be less in the Sabarmati river basin; however, they are sufficient in the Mahi basin.

4.2. NLR Model and Evaluation

Nonlinear regression-based models have been prepared for the various combinations of inputs for the yearly and monthly analysis to compare the other modelling techniques with observed actual values. Analysis of the prepared NLR Model reveals that the model is good. With a coefficient of determination mean of 0.79 for the station models.

4.3. ANN Model and Analysis

Neural networks are proven to be best in model fitting. In this analysis, various model combinations for the yearly and monthly analyses have been approached for modelling, as depicted below.

A. Inputs used are the Precipitation (Pr_n), Temperature (T_n), Humidity (Hr_n) and Wind speed (Ws_n), whereas output is the runoff (R_n) within the sub-watershed. A similar analysis is done for the basin wise.

B. Inputs used are Precipitation (Pr_n), Last Year's Runoff (R_{n-1}), Temperature (T_n) and Wind speed (Ws_n), whereas Output is the runoff (R_n) to be measured for the subbasin.

C. Inputs used are Precipitation (Pr_n) and last Year's Runoff (R_{n-1}), whereas Output is the runoff (R_n) to be measured for the subbasin.

D. Inputs used are Precipitation (Pr_n), whereas Output is the runoff (R_n) to be measured for the sub-basin.

Model number 3 (C) with input combination of precipitation, last year's runoff proved to be the best nn model. At the same time, the first model proves to be just satisfactory.

4.4. Fuzzy Logic Analysis and Model

Fuzzy logic techniques have been incorporated in many solutions of water resources to model the problems. In our case, the work is done for yearly and monthly analyses. In the monthly analysis, the results are quite better than those of the yearly model.

In fuzzy logic, the input combinations used are the Precipitation (Pr_n), Last Year's Runoff (R_{n-1}), Temperature (T_n), Humidity (Hr_n) and Wind speed (Ws_n). In contrast, output is the runoff (R_n) within the sub-watershed. A similar analysis is done for the basin wise. The model proved to be good when analysed using the FIS editor in MATLAB.

4.5. TBBO Model Analysis

The model is prepared using the novel TBBO technique and procedure, as shown in section 3.7. The input parameters used are 4, whereas the output parameter is one, i.e. runoff.

The TBBO is compared in results with the other analysed techniques, and it is observed that it provides a good result in the analysis and can be used as a quasi-statistical approach in the analysis and modelling of parameter combinations.

4.6. Error Analysis of Models

The models analysed and analysed are shown below in Tables 6 and 7 for all the developed models. The coefficient of determination and Root mean square error analysis are done and compared for the models.

The monthly and yearly model analysis shows that the ANN, FL and TBBO models perform well. Also, the ANN-based model is the best among all developed models, followed by the FL model and the TBBO Model.

Table 6. Monthly model error analysis

Sr. No.	Model Name	R^2 (Coefficient of Determination)	RMSE
1	NLR Based Model	0.79	1.214
2	ANN Model (Best Model)	0.89	0.812
3	FL Model	0.845	0.772
4	TBBO Model Analysis	0.832	0.9221

Table 7. Yearly model error analysis

Sr. No.	Model Name	R^2 (Coefficient of Determination)	RMSE
1	NLR Based Model	0.735	1.6
2	ANN Model (Best Model)	0.87	0.712
3	FL Model	0.821	0.615
4	TBBO Model Analysis	0.81	0.9324

5. Results and Discussion

5.1. LULC Analysis for Sabarmati Basin and Mahi Basin with Comparison

Figures 3 and 4 show the relative investigation of LULC and water assets in the Sabarmati and Mahi stream bowls. The figure portrays the change over the years inside the watershed, and the table depicts the relative investigation of the bowl LULC for the two bowls. Figures 3 and 4 show the correlation of LULC for a really long time, 2013 to 2023, out of which the information examination of LULC has been finished in earth motor coding involving Landsat 8 for years 2013 and 2018, though Landsat 9 is utilized for the year 2022. Examination shows that the utilization of water assets expanded from 2013 to 2023, and the region created was additionally expanded. Endeavours for the recovery of infertile terrains and land changes ought to be finished for the ideal utilization of water assets inside the watershed. In fact, the total accuracy of Water resources enabled by LULC 2013 (Landsat 8 O.L.I.) is 88.4% and for W.R.-LULC 2018 (the Landsat 8) is 87.5 and 92.1% for WR-LULC 2013 (Landsat 9). Results found for the Kappa coefficient vary from 0.87 to 0.93, which shows that the assessment performed meets the analysis. During the supervised classification of the images under analysis, it was not easy to differentiate among barren land in the catchment with the empty urban areas and village areas in the basin or agricultural landform from the existing grassland. However, the results and the producers' accuracy reveal that the maps of land use are acceptable and may be utilized for basin analysis.

5.2. Results of Precipitation forecasting using ANN based Approach, Fuzzy Logic approach, Non-Linear regression approach and TBBO Algorithms

Below mentioned Figures 8 to 11 shows the comparison of different adopted techniques in which all the model results are compared with the Observed actual runoff. Error analysis has also performed for the same and results are showing promising outputs using the techniques.

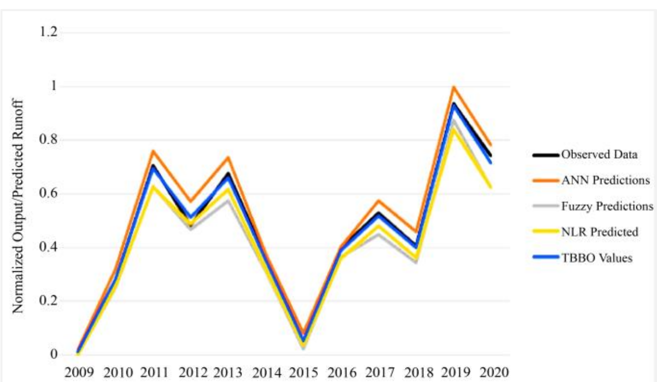


Fig. 8 P-R prediction comparison for Bhilpur RG Station, Mahi River basin

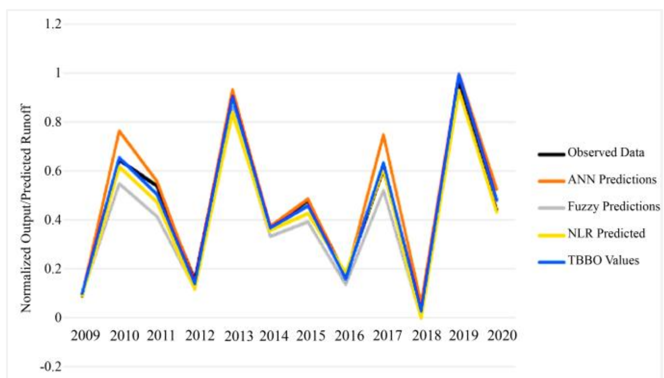


Fig. 10 P-R prediction comparison for Sabarmati Raingauge Station, Sabarmati Basin

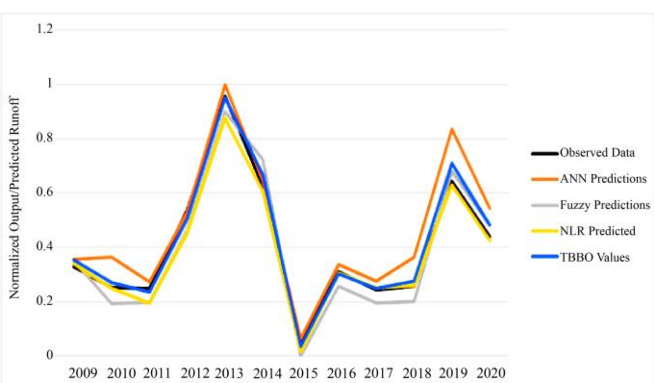


Fig. 9 P-R prediction comparison for Devhat RG Station, Mahi River basin

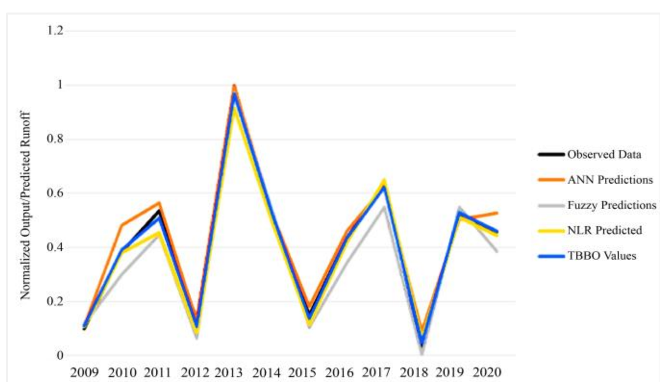


Fig. 11 Precipitation prediction comparison for Dhandhuka Raingauge Station, Sabarmati Basin

Table 8. LULC Area class-wise

Land use Classes	Area (Ha)	%
Built-up	142634.00	4.77
Waterbodies	28033.57	0.94
Agriculture	1415190.45	47.30
Vegetation Patches	190002.35	6.35
Shrubland	587420.31	19.63
Saline land + Barren land+ Fallow land	475035.86	15.88
Forest Patches	153423.30	5.13
Total	**2991739.82**	**100.00**

Table 9. Accuracy Assessment of LULC for Sabarmati Basin

Sr. No	Class Name	Producers Accuracy
1	Built-up	100.00
2	Waterbodies	100.00
3	Agriculture	100.00
4	Vegetation Patches	88.26
5	Shrubland	88.99
6	Saline land + Barren land + Fallow land	100.00
7	Forest Patches	100.00

5.3. Results of Precipitation forecasting Using TBBO Algorithm, SHRUTI Algorithm (Smart Heuristic Regressional Ultimate Testing Intel Algorithm) Based Approachs

Precipitation Streamflow expectation has been surveyed and performed utilizing different methods, and results are displayed beneath with examination and a clever strategy; for example, Shruti Calculation (TBBO Calculation Approach) is proposed, too. TBBO is alluded to as educational cost Showing Streamlining and is presented to be a sort of Smart Heuristic Regression-based Ultimate Testing Intel Algorithm (SHRUTI-A). The method might be utilized in any space of life and is not restricted to science, design, and innovation. Tables 8 and 9 depict the land distribution classes and their distribution over the geographical tract of the Sabarmati basin, along with accuracy assessment. Overall accuracy in the developed GIS model is 93 %.

5.4. Discussion on the Presentation of Results

Water resource identification using the GIS technique was done using land cover analysis of the basins. It is revealed that the agricultural portion and activities are high. The analysis reveals a low runoff potential zone as well as a good green cover as per LULC assessment. Vegetation patches and shrubland, which cover almost 26 % of the area, can be improved for better effective watershed planning. Its producer's accuracy is reported to be 89 %. Also, the water bodies identified can be effectively increased with more storage space. Also, water bodies can be planned, and potential sites can be identified for sustainable development. Accuracies and kappa coefficients are obtained within the range of 885 to 92.1 5 and 0.87 to 0.93, respectively, which shows an acceptable analysis. Producers and overall accuracy reveal that the LULC assessment can be utilized for basin analysis. Analysis of the various approaches for the rainfall-runoff modelling has been performed using the neural network approach, fuzzy logic, nonlinear approach and novel TBBO approach. Neural network analysis has been identified as a deep learning tool to model the data sets provided with a coefficient of determination of site up to 0.88, which is performed using the nnstart tool in MATLAB software. Fuzzy logic provides the results with a coefficient of determination in the range of 0.83, along with the TBBO approach as well. TBBO evolved to be a novel and efficient approach in the analysis of the modelling work for input-output correlation works. Non-linear fitting regression analysis provides the results of a 0.79 coefficient of determination as a mean of stations. A combination of hybrid approaches can be made to perform the modelling.

6. Conclusion

The following points may be summarized as an outcome of the present study.

A. The land use land cover and water assets examination reflects hydrological reliance satisfaction towards the elements of the study region. Land use and land cover show the presence of more green cover inside the Mahi stream catchment, and the improvement of infrastructure water structures is moderately high in the Sabarmati basin.

B. Precipitation is the key tool for effective and sustainable watershed development when the runoff and water resources are concerned. The study is carried out for the rainfall-runoff analysis as well. This work explains how the NLR, ANN, FL and TBBO models may be implemented to get and estimate monthly and yearly runoff for catchment areas. Runoff estimation for the input parameters was performed using fis editor, nntool, nnstart, and XLSTAT for

NLR work. Various combinations were adopted to train the neural network work. Yearly and monthly models have been prepared. For the monthly models (Best models work out results), the NLR model has an R^2 of 0.79 and RMSE of 1.214. ANN model has an R^2 of 0.89 and an RMSE of 0.812. FL model has an R^2 of 0.845 and an RMSE of 0.772. TBBO model has an R^2 of 0.832 and an RMSE of 0.9221. For the yearly analysis performed, the NLR model has an R^2 of 0.735 and an RMSE of 1.6. ANN model has an R^2 of 0.87 and an RMSE of 0.712. FL model has an R^2 of 0.821 and an RMSE of 0.615. TBBO model has an R^2 of 0.81 and RMSE of 0.9324. This error analysis shows that the models developed perform well in which ANN is best suited for training the data sets.

C. TBBO-based approach is utilized for the work and gives good execution. Results show that the development of any evolved model exhibition is expanded a few times, and the coefficient of assurance is expanded by 10 to 30 percent from past outcomes. The issues can be dissected and evaluated utilizing this method. This is a basic calculation that gives imperativeness to critical thinking applications. It is like the TLBO Calculation Approach, yet the idea is unique. It very well may be utilized to further develop models having vulnerability and greater awareness.

Results have shown promising advancement in the examination of this methodology, and it can be utilized to take care of numerous issues. For the TBBO model, the optimized model has MSE values of 0.7993, RMSE values of 0.9324, and R values of 0.9345 for a value. In a comparison of TBBO models with soft computing models, it is observed that the TBBO performed in line with the capacities of the soft computing models. The created framework is supportive in dealing with the tasks and models.

Strategy and framework have consolidated the arbitrariness and vulnerability of the hydrological boundaries; every one of the boundaries has been examined and investigated. The developed algorithm is very much accountable for optimization management and multiple parameter analysis. Methodology and the developed system have been incorporated with the random behavior and accounting uncertainty hydrological parameters, and variables have been studied and analyzed.

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Appendix 1

Appendix 1: Remaining Steps of the Tuition Batch-based Optimization Methods

Criteria for Good and Bad batch status (<7 Batches): (It is just a status cover for the batch)

Table 3. Criteria for Good and Bad batch status (<7 Batches): (It is just a status cover for the batch)

Batch status	Batch count (Compared to total)	Status	Otherwise
Higher batch (top 60 percent)	> 20 percent	GOOD	BAD
Batch 40 to Batch 60 percent	> 20 percent	GOOD	BAD
Batch less than 40 percent	<20 percent	GOOD	BAD

Table 4. Criteria for Good and Bad batch status (> =7 Batches): (It is just a status cover for the batch)

Batch status	Batch count (Compared to total)	Status	Otherwise
Higher batch (top 60 percent)	> 20 percent	GOOD	BAD
Batch 40 to Batch 60 percent	> 15 percent	GOOD	BAD
Batch less than 40 percent	<15 percent	GOOD	BAD

Table 5. Table showing the calculations for Tuition Batch.

Batch no.	Criteria	Batch count	Percentage of batch count	Batch status	Target for batch	Targeted Fractional	Burdon	Remarks
Batch 1	Students scoring more than 85 percent marks	3	6	Good	95	7.960894	4.37	Least batch count
Batch 2	80 to 84.99	6	12	Good	90	15.0838	9.22	-
Batch 3	70 to 79.99	7	14	Bad	85	16.62011	11.38	-
Batch 4	60 to 69.99	9	18	Bad	75	18.85475	16.59	Highest Batch count
Batch 5	55 to 59.55	7	14	Good	65	12.7095	14.89	-
Batch 6	45 to 54.99	8	16	Bad	60	13.40782	18.43	-
Batch 7	Less than 45	10	20	Bad	55	15.36313	25.13	-
	Total	**50**	100					

Batch numbers are allotted in reverse chronological order, which means batch 2 will be just below batch 1. Also, after the improvement, batch 2 students may go to batch 1, and batch 3 may go directly to batch 1. It is also preferable that the student/batch population do not degrade and retains at least the nominal status at least for the higher 2 batches.

Table 6. Iteration 1 of the Batch

Batch no.	Criteria	Batch count	Cumulative batch count	Previous CBC	Status up	Percentage of batch count	Batch status	Target for batch	Targeted Fractional	Burdon	Remarks
Batch 1	Students scoring more than 85 percent marks	5	5	4	Improved	10	Good	95	9.5	10.5263158	Least batch count
Batch 2	80 to 84.99	9	14	12	Improved	18	Good	90	16.2	20	-
Batch 3	70 to 79.99	10	24	21	Improved	20	Bad	85	17	23.5294118	-
Batch 4	60 to 69.99	9	33	32	Improved	18	Bad	75	13.5	24	Highest Batch count
Batch 5	55 to 59.55	5	38	38	Improved	10	Good	65	6.5	15.3846154	-
Batch 6	45 to 54.99	6	44	44	Improved	12	Good	60	7.2	20	-
Batch 7	Less than 45	6	50	50	Improved	12	Good	55	6.6	21.8181818	-
	Total	**50**				**100**					

Iterations 2 and 3 have been performed the same way and below mentioned is the Iteration 4 of the Batch.

Table 7. Iteration 4

Batch no.	Criteria	Batch count	Cumulative batch count	Previous CBC	Status up	Percentage of batch count	Batch status	Target for batch	Targeted Fractional	Burdon	Remarks
Batch 1	Students scoring more than 85 percent marks	5	5	5	Improved	10	Good	95	9.5	10.5263158	-

Batch 2	80 to 84.99	12	17	17	Improved	24	Good	90	21.6	26.6666667	Highest Batch count
Batch 3	70 to 79.99	12	29	28	Improved	24	Bad	85	20.4	28.2352941	-
Batch 4	60 to 69.99	12	41	40	Improved	24	Bad	75	18	32	-
Batch 5	55 to 59.55	4	45	45	Improved	8	Good	65	5.2	12.3076923	-
Batch 6	45 to 54.99	4	49	49	Improved	8	Good	60	4.8	13.3333333	-
Batch 7	Less than 45	1	50	50	Improved	2	Good	55	1.1	3.63636364	Least batch count
	Total	**50**				**100**					

Table 8. Comparison of improvement using tuition batched based optimization

Batch Count	CBC5	CBC4	CBC3	CBC2	CBC1	Addition
Batch 1	5	5	5	5	4	24
Batch 2	17	17	16	14	12	76
Batch 3	29	28	26	24	21	128
Batch 4	41	40	37	33	32	183
Batch 5	45	45	41	38	38	207
Batch 6	49	49	46	44	44	232
Batch 7	50	50	50	50	50	250

As per the above table, the improvement in the tuition batch can be seen from CBC1 to CBC5.

The target for Tuition Batch-Observed data as targeted target-wise CASE B. Observed records can be divided into batches Minimum of 4 batches maximum as per requirement, but 5 to 15 are preferable. For example, the maximum population size of data collected is 500. The maximum scoring is 100 in percentage. Burdon is defined as the weight of target achievement depending upon the student/ batch population count. If the population is more for a batch compared to others, then target achievement is more focused on that batch. Burdon is inversely proportional to batch count. Maximum Burdon should be given priority for the achievement.

Targeted Fractional Target = Percentage of (Percentage of Batch count X Target /100).
Formulae for Burdon = Percentage of (Percentage of Batch count X 100/ Target).

Both fractional targets and Burdon are important to initiate the iteration process. Also, which batch is critical can be identified for improvement. The targeted fraction depends directly on the batch count, whereas Burdon increases as the target decreases. Batch status is defined as the quality of students and numbers for the same corresponding to the targets identified as observed records or standard records. The iteration process will be continued to a minimum of calculation and 4 iterations, i.e. 5 calculations. The standard deviation should preferably reduced to 20 percent as of the initial iteration after the last iteration. Maximum iterations are infinite. The iteration is continued until the average is stagnant near the standard deviation within 1 to 5 or less. Criteria for Good and Bad: Good is considered if the batch size retains within or equals 80 to 120 percent of the target for the selected batch class. For example, if the batch class is 100, then the values from 80 to 120 are referred to as “Good” and other than this is “Bad”.

Table 9. The calculations for Tuition Batch for rainfall estimates within a basin.

Batch no.	Criteria	Batch count	Cumulative batch count	Previous CBC	Status up	Percentage of batch count	Batch status	Target for batch	Targeted Fractional	Burdon	Remarks
Batch 1	Monthly	10	10	-	-	2	Bad	20	0.4	10	Least

	Rainfall > 200mm										batch count
Batch 2	Monthly Rainfall 151 to 200mm	30	40	-	-	6	Bad	50	3	12	-
Batch 3	101 to 150mm	75	115	-	-	15	Bad	100	15	15	-
Batch 4	Monthly Rainfall 76 to 100mm	85	200	-	-	17	Good	100	17	17	-
Batch 5	50 to 75	60	260	-	-	12	Bad	80	9.6	15	-
Batch 6	26 to 50	100	360	-	-	20	Bad	80	16	25	-
Batch 7	Less than 25mm	140	500	-	-	28	Bad	70	19.6	40	Highest Batch count
	Total	**500**				**100**		**500**		**19.14285714**	
									S.D.	10.35098339	

Batch numbers are allotted in reverse chronological order, which means batch 2 will be just below batch 1. Also, after the improvement, batch 2 students may go to batch 1, and batch 3 may go directly to batch 1. It is also preferable that the student/batch population do not degrade and retains at least the nominal status at least for the higher 2 batches.

Table 10. Iteration 1 of the Batch

Batch no.	Criteria	Batch count	Cumulative batch count	Previous CBC	Status up	Percentage of batch count	Batch status	Target for batch	Targeted Fractional	Burdon	Remarks
Batch 1	Monthly Rainfall > 200mm	14	14	10	Improved	2.8	Bad	20	0.56	14	Least batch count
Batch 2	Monthly Rainfall 151 to 200mm	40	54	40	Improved	8	Good	50	4	16	-
Batch 3	101 to 150mm	80	134	115	Improved	16	Good	100	16	16	-
Batch 4	Monthly Rainfall 76 to 100mm	90	224	200	Improved	18	Good	100	18	18	-
Batch 5	50 to 75	70	294	260	Improved	14	Good	80	11.2	17.5	-
Batch 6	26 to 50	116	410	360	Improved	23.2	Bad	80	18.56	29	Highest Batch count
Batch 7	Less than 25mm	90	500	500	Improved	18	Bad	70	12.6	25.71428571	-
	Total	**500**				**100**		**500**			
										5.625176814	

Similarly, iterations 2 and 3 have been performed, and iteration 4 shows that the burdon has been successfully increased and optimized from 5.60 to 7.78.

Table 11. Iteration 4 of the Batch

Batch no.	Criteria	Batch count	Cumulative batch count	Previous CBC	Status up	Percentage of batch count	Batch status	Target for batch	Targeted Fractional	Burdon	Remarks

Batch 1	Monthly Rainfall > 200mm	19	19	18	Improved	3.8	Good	20	0.76	19	-
Batch 2	Monthly Rainfall 151 to 200mm	49	68	66	Improved	9.8	Good	50	4.9	19.6	-
Batch 3	Monthly Rainfall 101 to 150mm	98	166	158	Improved	19.6	Good	100	19.6	19.6	-
Batch 4	Monthly Rainfall 76 to 100mm	103	269	248	Improved	20.6	Good	100	20.6	20.6	-
Batch 5	50 to 75	85	354	333	Improved	17	Good	80	13.6	21.25	-
Batch 6	26 to 50	78	432	418	Improved	15.6	Good	80	12.48	19.5	-
Batch 7	Less than 25mm	68	500	500	Improved	13.6	Good	70	9.52	19.42857143	-
	Total	**500**				**100**		**500**		**19.85408163**	
										0.782089661	

As per the above tables, the improvement in the tuition batch can be seen from CBC1 to CBC5. The standard deviation after the optimization and iterative process is reduced to 0.78 rather than 10 in the initiate stage.