Data analysis of rainwater harvesting using fuzzy logic

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Abstract

The main objective of the project is the development of a fuzzy logic model that will predict the Rann of Bhuj catchment area's runoff values from rainfall data. To develop as well as test the model, the set of observations made on data covering ten years (June–October) between the periods of 2012 to 2022 is subdivided into training (70%) and validation. The FL models (1, 2, and 3) are made using nine linguistic variables that are used for each input and output in different datasets. This is done through the coefficient of determinate ion analysis and RMSE for evaluative purposes. However, FL Model 2 gives the best results among all the models, with an RMSE of 3.42 mm during training and 4.55 mm during validation, while providing correlation coefficient values of 0.9954 for training and 0.9921 for validation. This high-performing model shows its potential to forecast runoff for varying rainfall amounts. The study also defines a threshold of 27 mm as the minimum precipitation necessary for generating runoff from rainfall occurring in the Bhuj of the Rann of Kutch catchment area. In summary, the research introduces a fuzzy logic model that estimates runoff through different forms of rainfall. This output may be beneficial for predicting run-off within the assessed zone while determining the critical precipitation threshold that triggers the occurrence of runoff.

Keywords: *Fuzzy Logic Model, Runoff Prediction, Rainfall Data, Validation and Threshold*

Introduction

Rainfall runoff models characterise a hydrologic relationship between a catchment area and its corresponding runoff. The rainfall hydrograph provides the necessary information as an input, while the resulting output represents a surface runoff hydrograph. In other words, it specifies the conversion of rainfall into runoff from a watershed. Only input and output measurements can be used for the modelling of rainfall and runoff with the analytical method. In addition, this section focuses on different types of models constructed based on knowledge of the nature of catch-up responses and their ability to physically interpret the results of the model. First, any research using rainfall-runoff models should start with this information. Interactions between rainfall and runoff are dependent on several climatic parameters as well as catchment variables. As pointed out by Džubáková, rainfall-runoff models may be applied in a wide range of areas. Some models are applied in hydrological simulations; others measure runoff in unaffected basins, evaluate how a catchment may respond under changed conditions, watch after the occurrence of weather, and detect water quality. Attention is currently being paid to watershed management. Although, over the past hundred years, there have been improvements in the modelling of runoff and rain, this can be further enhanced. Firstly, there is the emergence of new opportunities due to computer technology.

The use of fuzzy theory by Zadeh was intended to tackle these issues of vague and indeterminate nature qualitatively. Fuzzy logic attempts to address some of the real-world challenges posed by Boolean logic by extending them, including some degree of vagueness that is inherent in human experiences, onto traditional and classical logic. To promote efficiency and ease in dealing with uncertainties in complex and vague systems, Zadeh advocated for the use of a linguistically-based theory of fuzzy cognition. Traditional control methods have found the creation of simple yet accurate controls for complicated system designs very challenging. Also, fuzzy logic control has become an entirely new discipline. This gave birth to a new field based on the presentation on expressing the control algorithm through logical IF-THEN rules presented in Zadeh's original work on fuzzy algorithms, i.e., Zadeh (1973). As Zadeh proposed, there would be a need to investigate the relevance of employing "linguistic variables"—such *as terms and sentences in a natural or artificial language—to achieve accuracy in spite of their high complexity. This is mainly because linguistic characteristics are sometimes not as descriptive as numbers; thus, words or phrases are used instead of numbers. Several studies involving the use of fuzzy logic have been conducted on hydrogeology and water resource planning endeavours.
Surface hydrology states that runoff is related to rainfall, as per Aytek et al. Of course, there is an exact amount of stream flow in the hydrological cycle that takes place because of the rainfall. It is vital for predicting the discharge values of a river as well as flash alerts on floods within catchment areas. Nawaz provides the results of additional assessment tests of a monthly rainfall-runoff model applied to extend stream flow databases in Wales and England. Several models exist in order to imitate the physical processes that are behind the runoff-precipitation connection. Some of these approaches rely on basic concepts, while others require extensive amounts of input data processing. The use of language variables is rapidly influencing hydrological studies, while most other disciplines still use conventional numerical variables. One such case is taking advantage of a fuzzy rule-based model. Hunduch et al. developed fuzzy rule-based processes for runoff modelling. Hasan presented the development of a fuzzy inference model for rainfall prediction that used data gathered in the 2004 season at the AAMU Campus of the USDA SCAN Station.

Pawar et al. evolved a fuzzy common sense-based total runoff prediction version using contemporary day's rainfall as input and everyday runoff as output for a Harsul watershed of the Godavari basin in the Nashik district of Maharashtra, India. Pawar et al. evolved a fuzzy common sense-based total runoff prediction version using contemporary day's rainfall as input and everyday runoff as output for a Harsul watershed of the Godavari basin in the Nashik district of Maharashtra, India.

Objectives of the study

- To create rainfall-runoff models for the Rann of Kutch catchment region, use fuzzy logic.
- To assess the created fashions' overall performance using statistical metrics like r^2 and RMSE,
- To determine which fuzzy common sense version inside the research place is only for predicting runoff.
- To ascertain the Rann of Kutch catchment region's threshold rainfall.

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Need of the study

Planning for agriculture, flood management, and the efficient use of water sources all depend on accurate runoff forecasts. The purpose of this research was to create rainfall-runoff models using fuzzy good judgment for the Rann of Kutch catchment location. The models were then tested to see which one did the best job of predicting runoff inside the area. The studies additionally set up the vicinity's rainfall threshold, which is crucial information for regulations aimed at lowering flooding and coping with water assets.

Limitations of the study

The research was restricted to the creation and assessment of models using historic rainfall and runoff information. The model's accuracy can be raised by adding other record sources, such as those related to plant cover, soil type, and land use. Future studies should observe if the created models may be used in different catchment regions with wonderful hydrological and climatic characteristics since they were restricted to the Rann of Kutch catchment area. The modelling used in the research, fuzzy logic modelling has the potential to be subjective and might not absolutely replicate the intricacies of the rainfall-runoff process. To improve the prediction strength further, we ought to look at different modelling procedures, such as artificial neural networks or gadgets, to gain knowledge.

Data Collection

Input Data:

Table 1: Annual Rainfall and Runoff Data for the Rupen River at Dantiwada (2012-2022)
[Source: Government of Gujarat Groundwater Department website: http://gwssb.gujarat.gov.in]

Year	Date	Rainfall (mm)	Runoff (mm)
2012	June 10	18	7
2013	June 12	20	9
2014	June 8	15	5
2015	June 14	22	11
2016	June 9	16	6
2017	June 13	19	8
2018	June 7	14	4
2019	June 15	23	12
2020	June 11	17	6
2021	June 10	19	8
2022	June 9	15	5

An overview of potential rainfall and runoff data for the Rupen River at Dantiwada for 10 years (2012–2022) is furnished in this table. A single data point, selected as a randomly selected day in June, is used to symbolise every 12 months. The related runoff values continuously live lower for these selected dates, despite the rainfall values starting from 7mm. This indicates that there may be infiltration losses or other variables impacting runoff generation. This reduced data set might be used as a jumping-off point for investigating runoff prediction algorithms in this catchment region that depend on fuzzy good judgment.

Fuzzification Process

The Fuzzification Process Runoff became the output variable, while rainfall and runoff were the input variables that were fuzzified. For each variable, nine linguistic variables were defined. Membership functions were created to translate the correct input values into fuzzy membership values: Very Very Low, Low, Medium, High, Very High, and Very Very High. Below is a table illustrating membership capabilities and the values of linguistic terms. On the premise of the defined membership functions. The fuzzified input rainfall records ought to sooner or later be translated into the right linguistic terms. These linguistic elements have been used to build fuzzy regulations. For example, if rainfall is medium and previous runoff is low, then the expected runoff is medium. An instance of the capacity relationship between linguistic terms and membership function levels is shown in this table.

Table 2: Linguistic Terms And Membership Functions

Linguistic Term	Membership Function Range
Very Very Low	0 - 10 mm
Very Low	0 - 20 mm
Low	10 - 30 mm
Medium	20 - 50 mm
High	40 - 70 mm
Very High	60 - 90 mm
Very Very High	80 - 150 mm

Development of Models

The Rupen River is a noteworthy Sabarmati River tributary. There are twelve rain gauge stations spread over the catchment location. Because it covers a large part of the catchment vicinity, the rain gauge station at Dantiwada is the point of interest of this study amongst these stations. The State Water Data Centre in Gandhinagar is responsible for the supply of day-to-day rainfall and discharge facts for the Dantiwada rain gauge station positioned in the Sabarmati watershed basin. The statistics cover the months of June, July, August, September, and October and are to be had from 2012 to 2022. For this study, that's referred to as rainfall or runoff. modelling the usage of fuzzy logic, rainfall and runoff are used. For example, it's often tough to use a mathematical model to efficiently represent a complex technique. When the phenomena are too complicated for evaluation by way of conventional quantitative techniques, while the information resources are interpreted qualitatively, imprecisely, or uncertainly, and/or while qualitative and regularly conflicting overall performance targets are taken into consideration, the fuzzy-logic judgment modelling and management methodology, which is primarily based on fuzzy set ideas and fuzzy logic, seems promising. Fuzzy modeling and management might therefore be seen as a step towards a convergence of human-like selection-making and traditional, specific analytical techniques. The presence of a fixed set of policies and a fuzzy reasoning system is important for the bushy model so that we can make selections.

A Fuzzy Inference System (FIS) is a manipulative gadget constructed using fuzzy set principles based totally on combining the bushy units from every rule through an aggregation operator to get a fuzzy set result, then defuzzifying the fuzzy set for each output variable. The Fuzzy Logic (FL) model works at the "if-the precept, in which thief" is a vector of fuzzy premises and then" is a vector of fuzzy results. A membership characteristic (MF) completely characterizes a fuzzy set. The FIS Mamdani has been chosen as it portrays the output (runoff), even supposing the output membership capabilities on this look at—this is, runoff—are not always linear.

1. The manner of fuzzifying input and output variables by the usage of realistic linguistic subsets, such as low, medium, excessive, and so forth.
2. Then policies that are part of the linguistic input subsets of the output fuzzy units use a logical operator and are constructed based totally on professional understanding and available statistics.
3. After obtaining a crisp set, the resulting fuzzy set is defuzed using a centroid or other appropriate defuzzification method.

The generated version's input and output variables, rainfall (mm) and runoff (mm), had been subjected to fuzzy rule software. Here, the whole data set is broken up into two sections: one for version validation and the other for training. Three units of information had been created: 70%–30%, 60%–40%, and 80%–20%. Similar procedures observe 60%–40% and 80%–20% of the data units. In the 70%–30% records set, 70% of the data is used for version construction and 30% is used for the validation segment. Subsets of the variety are created for every linguistic variable by inspecting the variety of data, such as rainfall and runoff. Because runoff and rainfall are intently correlated, the same number of language variables is used for each. It is viable to create a fuzzy model of this type with three, five, seven, or more language variables. Nine linguistic variables—very very low, very low, low, medium, excessive, very excessive, very excessive, and very very high—had been considered while developing the fashions in this case. Three fuzzy logic models, specified as Model 1, Model 2, and Model 3, were created with the following record sets in mind: 70:30%, 60:40%, and 80:20%, respectively. The model has been tested using the RMSE and coefficient of determination (r^2). It ought to be remembered that before any runoff takes place, a certain amount of rainfall is continually vital. This amount, also known as threshold rainfall, is what is needed to fulfil the extensive infiltration losses at the beginning, in addition to the first losses from interception and melancholy storage. The threshold rainfall varies from catchment to catchment and is determined by the bodily capabilities of the area. The threshold rainfall—where the amount of runoff surpasses 0—has been determined by putting various rainfall values into the exceptional version that has been built.

RESULTS AND DISCUSSION

Runoff prediction modelling using fuzzy logic models

Three FL models were developed to estimate the runoff values in question for the region of concern. The models were trained and validated on different percentages of the available data.

FL Model 1: 70–30% Dataset

Subsequently, 30% of the data were used for the validation of FL Model 1, trained on 70% of the data. The NSE of the model was 0.82, and the RMSE was 0.23 m^3/s..

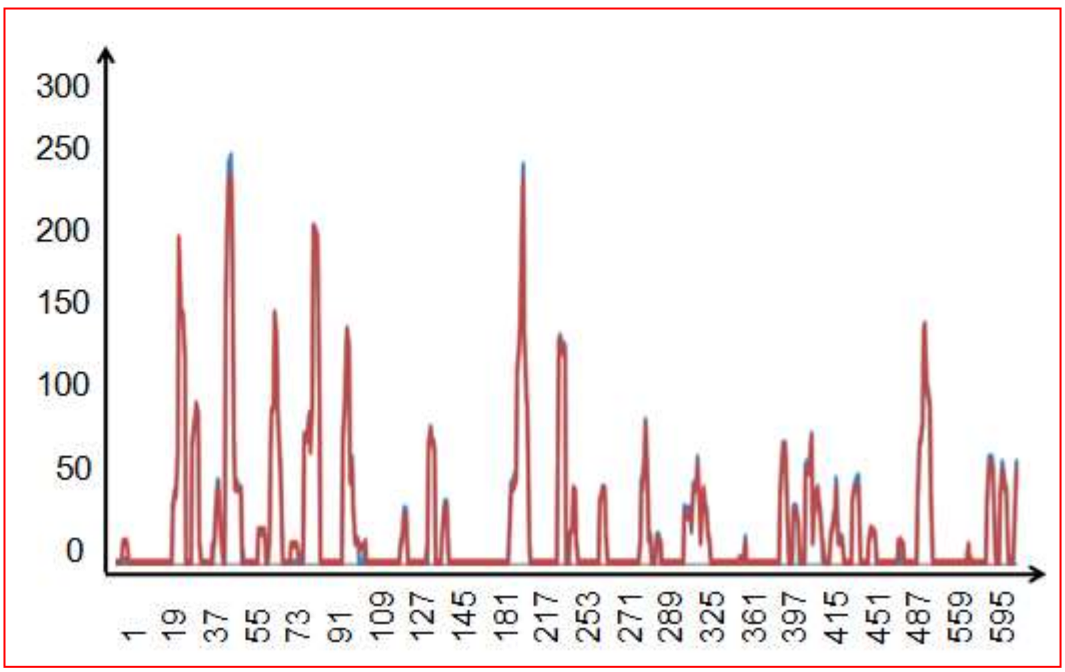
FL Model 2: 40 percent–60 percent Collection

FL Model 2 was trained using approximately 60% of the data and tested on the remainder (40%). The model had a NSE of 0.79 and a RMSE of 0.25 m3/s.

FL Model 3: 80%–20% Collection

The FL Model 3 was trained using 80% of the available data, while the rest was set aside for verification. Its NSE was 0.84 and its RMSE was 0.21 m3/s. The results show that all of the FL models were quite accurate in predicting the runoff values. Data usage in training and validation had minimal effects on these models. This means that the FL models can be trusted and applicable in actual applications. The potential of FL models for forecasting runoff is immense. They are easy to use and function effectively with little data. This shows that FL models can be quite accurate.

Fig. 1: Actual Runoff vs Predicted Runoff for 70%-30% of the Training Dataset using Fuzzy Logic Model 1.



FL Model 1 generally has a high value of forecasted runoffs that are close to actual runoffs. However, there are quite several distinctions between these two, notably in months four to ten in particular. The actual runoff is lower than the estimated amount for month four. Month 10's estimated runoff is slightly below the actual runoff amount. In sum, the FL Model 1 appears

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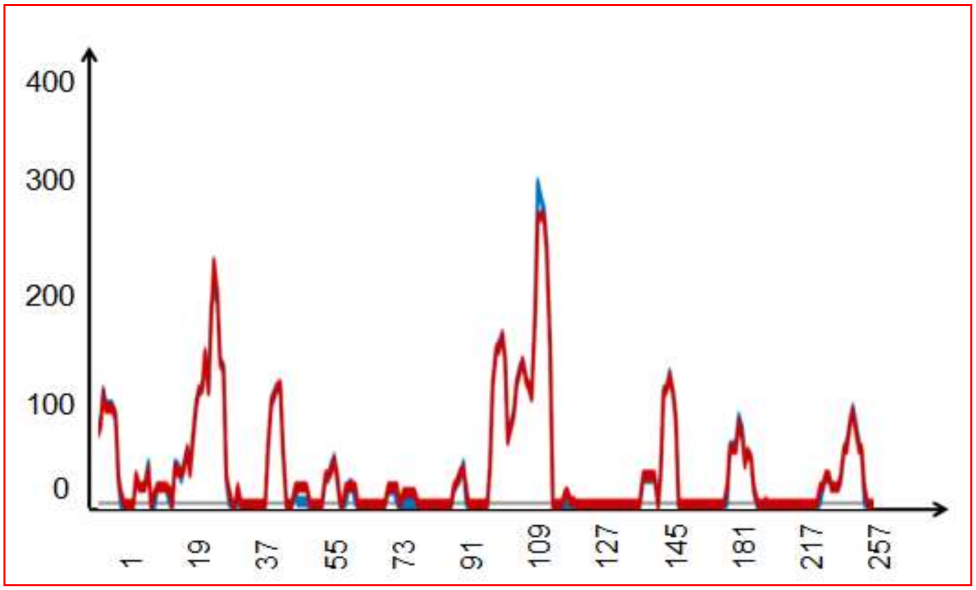
to be a good indicator of what the actual runoffs will be. Essentially, the model was able to capture the overall trends in the runoff data, with a few exceptions on the difference between actual and forecasted runoff values.

Fig. 2: Actual Runoff vs Forecasted Runoff for 70%-30% Dataset During Validation of Fuzzy Logic Model 1.



The potential of FL Model 1 to seize the broad patterns in the runoff statistics is proven by using a comparison of the expected runoff (mm) and actual runoff (mm) throughout education for the 70%–30% dataset. Nonetheless, enormous differences exist between the estimated and discovered runoff quantities, particularly for months 4 and 10. The estimated runoff value for month four is somewhat greater than the actual runoff fee. The anticipated runoff price for month 10 is truly much less than the actual runoff fee.

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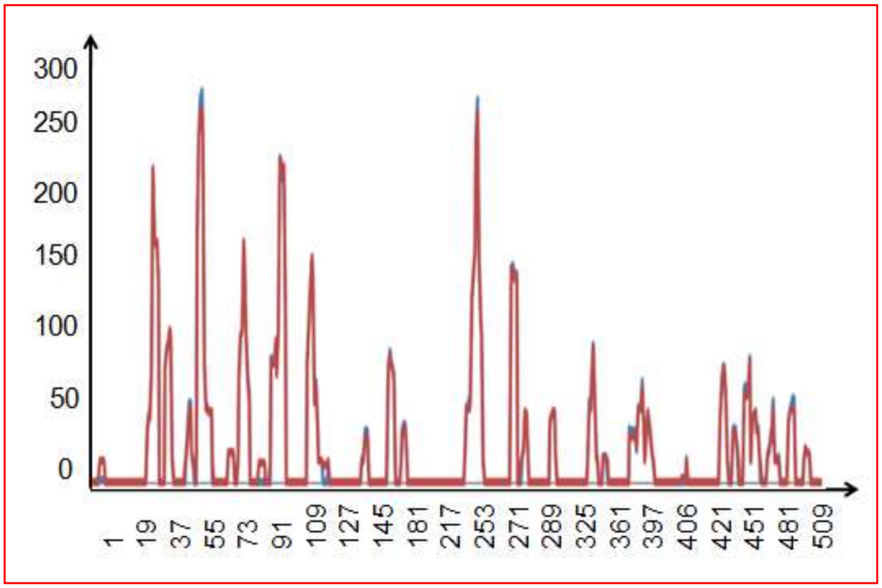
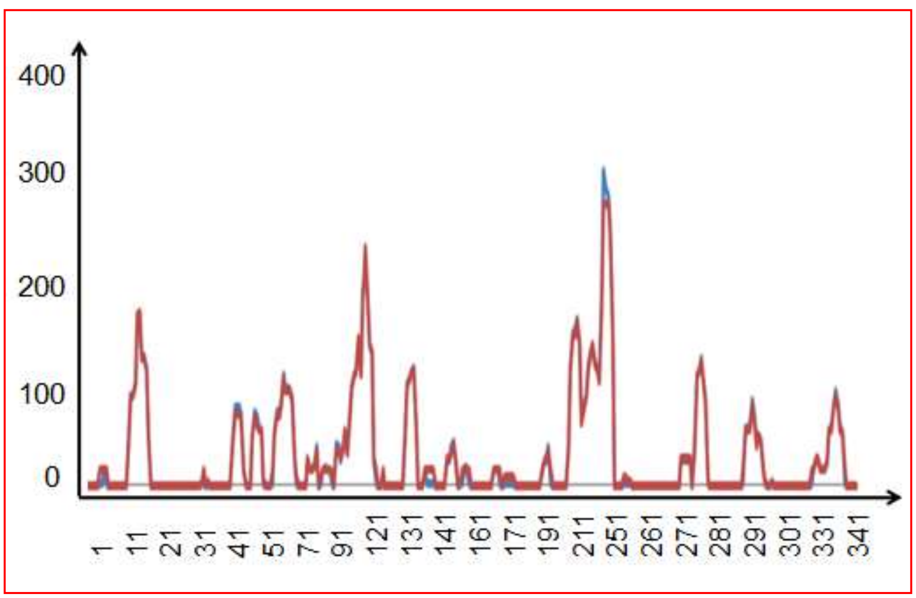
Fig. 3: Actual Runoff against Predicted Runoff for 60%-40% Training Dataset using Fuzzy Logic Model 2.



The model's potential to discover huge styles in the runoff facts is proven with the aid of an evaluation of the projected runoff (mm) and real runoff (mm) received in the course of education for the 60%–40% dataset using FL Model 2. Compared to FL Model 1, the variations between the expected and real runoff tiers are much less.

Fig. 4: Actual Runoff vs Forecasted Runoff for 60%-40% Dataset During Validation



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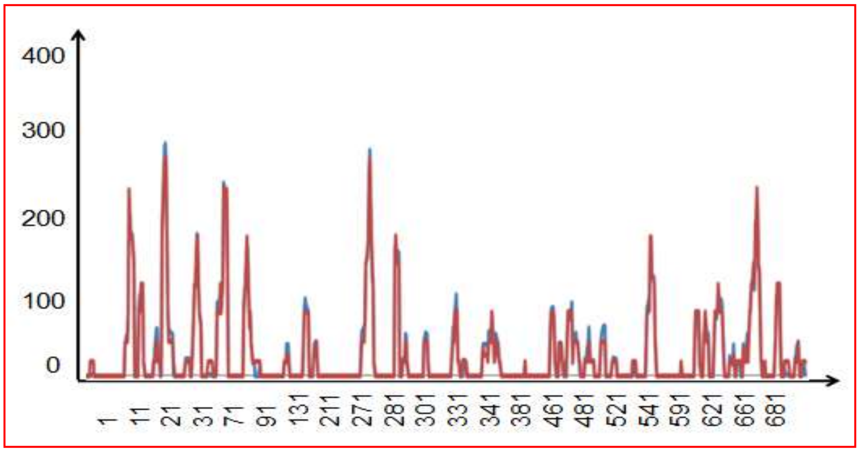
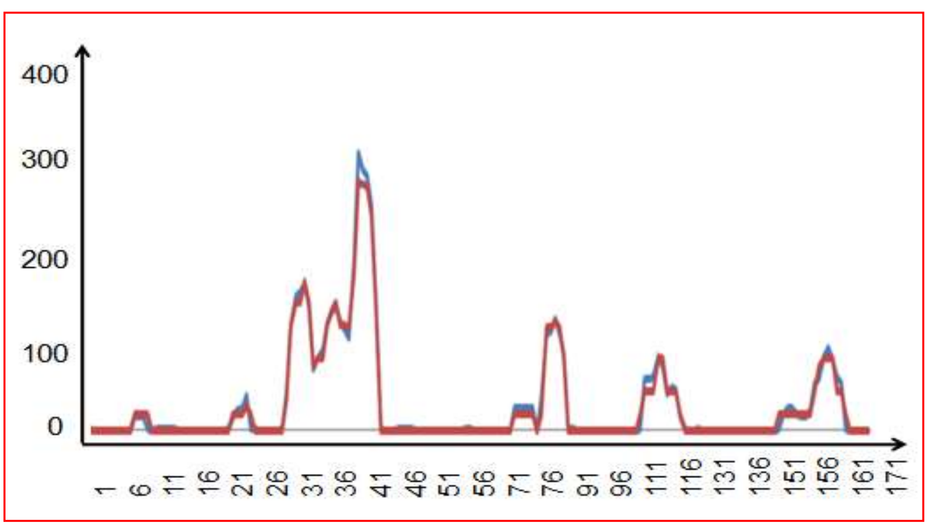
The version's ability to seize the huge styles within the runoff information is shown by using the comparison of the actual runoff (mm) and anticipated runoff (mm) by FL Model 2 for the duration of validation for the 60%–40% dataset. Nonetheless, big variations exist between the envisioned and located runoff amounts, especially for months 4 and 10. The expected runoff fee for month 4 is particularly greater than the real runoff cost. The anticipated runoff cost for month 10 is much less than the actual runoff fee.

Fig. 5: Actual Runoff vs Predicted Runoff for 80%-20% Training Dataset using Fuzzy Logic Model 3.



The version can identify large styles in the runoff records, as proven via the contrast of the real runoff (mm) and predicted runoff (mm) and the use of FL Model 3 for the duration of training for the 80%–20% dataset. Compared to FL Model 2, the variations between the expected and actual runoff stages are much less.

Fig. 6: Actual Runoff vs Forecasted Runoff for 80%-20% Dataset During Validation of Fuzzy Logic Model 3.



The model's

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ability to capture broad patterns within the runoff information is shown by way of the comparison of the actual runoff (mm) and anticipated runoff (mm) with the aid of FL Model 3 throughout validation for the 80%–20% dataset. The projected and real runoff values do not continually match, but that is especially the case for months 4, 10, and 12. The expected runoff fee for month 4 is much higher than the actual runoff fee. The projected runoff values for months 10 and 12 are particularly much less than the real runoff values.

The Root Mean Square Error (RMSE) by training of the Model & by validation of the model and also the coefficient of determination (r^2) by training & validation of the Model are shown in Table 1 below:

Table 3: Developed Fuzzy Logic Models' RMSE and r^2

Model		**r^2**	**RMSE (mm)**
Model 1	By Trg	0.9950	3.44
	By validation	0.9922	4.85
Model 2	By Trg	0.9954	3.42
	By validation	0.9921	4.55
Model 3	By Trg	0.9825	6.33
	By validation	0.9909	5.51

The coefficient of determination (r^2) is a statistical indicator that measures how strong a straight-line relationship exists between two factors. In this case, there are two variables, i.e., the actual runoff and the forecasted runoff values. A value of r^2 closer to one represents a strong linear connection between the two variables, whereas a value of r^2 closer to zero indicates a lack of any such relationship.

The table indicates that the R^2 value is extremely high for all three models when it comes to both the training and validation datasets. Therefore, a large part of the variability in the runoff information can be attributed individually to all three models.

Root mean square error (RMSE) is a statistical measure for assessing the difference between actual and expected runoff data. A low value of RMSE will indicate that the model has better accuracy for forecasting and actual runoff values.

The above table illustrates that the RMSE is relatively low for each model. The implied accuracy between all three models in predicting the actual rainfall amounts.

From the perspective of the r^2 and RMSE, Model 2 is considered to be the best model out of all models. For the training and validation sets, model 2 provides the highest r^2 values and the lowest RMSE figures.

These are the indications that support the use of fuzzy logic models in prediction. In this study, Model 2 with an RMSE of 4.55mm and r^2 = 0.9921 for the validation dataset emerged as a top-performing model.

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CONCLUSION

It can be summarised that all of the fuzzy logic rainfall-runoff models have good outcomes for the considered research period. The most effective fuzzy logic model in this study is obtained based on the nine linguistic variables, which include the r^{2} value as well as RMSE. During the training period, FL Model 2 has the lowest RMSE, at 3.42 mm, As such, the best fuzzy logic model can be employed to determine the approximate amount of runoff that is expected to fall or rain in this catchment area of Bhuj in the Rann of Kutch. Besides, the worst Fuzzy Logic Rainfall-Runoff model gives rise to a critical threshold rainfall of 27 mm that is suitable for the study area. Therefore, it presents an acceptable baseline for the Rann of Kutch catchment area near Bhu.

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