

**EARLY WARNING SYSTEM FOR FLOOD DISASTER PREDICTION IN WETLAND  
AREA IN GREATER YOLA USING ADAPTIVE NEURO FUZZY INFERENCE  
SYSTEM**

**ABSTRACT**

*Natural calamity disrupts our daily life activities; thereby bring many sufferings in our life. One of the natural disasters is the flood. Flood is one of the most catastrophic disasters. However, too much rainfall courses environmental hazard. These prompted to flood prediction in order to help communities and Government with the necessary tool to take precaution to safe human life and properties. This work was developed using an (ANFIS) Adaptive Neuro-Fuzzy Inference System to compare some weather parameter (temperature and relative humidity) with rainfall to forecast the amount of rainfall capable of coursing flood in the study area. From the above graph (Fig. 22) it can be seen that the actual and the forecasted rainfall followed the same pattern from 2008 to 2010 with slight decrease in 2011. A high amount of rainfall in 2012 was forecasted to be flooded during that year and tally with the forecasted rainfall on the above graph in 2012. Based on the results on the graph, it shows that from 2014 to 2017 gives a constant flow between the actual and forecasted rainfall. It is predicted that the maximum amount of rainfall forecasted was 124.0 mm which is far below the recommended flood level of 160.0 mm which reveals that, River Benue would not experience flood disaster in the year ahead. The model developed was validated using (MAPE) Mean Absolute Percentage Error as 4.0% with model efficiency of 96.0% which shows very high excellent prediction accuracy.*

## 26 **1.0 Introduction**

27 Natural calamity disrupts our daily life and brings many suffering in our life. Among the natural  
28 Disasters, flood is invariably, terribly the most catastrophic. Flood Prediction helps communities  
29 and government with the necessary tools to take precautions and save human lives. Several types  
30 of data parameter such as temperature, humidity and rainfall are used to predict flood water level  
31 in an area. Even in this twenty first century after so many technological innovations human are  
32 helpless in the hand of natural disaster. There are different natural disasters like floods, volcanic  
33 eruptions, earthquakes, and tsunamis. Flood is considered as the most catastrophic among the  
34 other natural disaster. Flood causes the highest number of fatalities and greater economic damage  
35 in comparison to other natural disasters. (Ahmad, Hussain, Riaz, Subhani, Haider, Alamgir, and  
36 Shinwari, 2013).

37  
38 Flood disaster prediction is a very expensive process in recent strategy, current methods add to  
39 the difficulty with the need for expensive equipment, centralized and computationally difficult  
40 flood prediction schemes. **There is a growing significance in obtaining wetland data due to the**  
41 **importance of the river to different features of human life activities.** Steering, fishing,  
42 environmental science and weather impact are some example of this import. However, even  
43 though casing more than 70% of the earth surface, the ocean is not well known due to their  
44 dimensions, complications of data acquisition and the high costs of maritime equipment and  
45 operations. Precise tidal estimate is an important problem for creation events in coastal area.  
46 Tidal data is vital for the construction of docks and direction finding. In revering areas, accurate  
47 data sample is helpful for successful and safe operation. The application of Wireless Sensor  
48 Network (WSN) contains a wide variety of scenarios. In most of them, the network is composed  
49 of significant number of nodes deployed in a targeted area in which all nodes are indirectly  
50 connected. Further the data exchange is carried by multi-hop communication system.  
51 Environmental calamities are essentially random and rise in very short periods of time. Hence  
52 technology has to be developed to capture suitable signals with tiniest observing interruption.  
53 Wireless sensor is one of the modem technology that can quickly act in response to rapid  
54 variations of data and send sensed data to a analysis center in areas where cabling is not possible.  
55 WSN technology has dexterity of quick capturing, processing and broadcast of critical data in  
56 real time with high resolve. However, it has its own constraint such as relatively low amount of

57 battery power and low memory availability compared to many existing technologies. It does,  
58 though, have the pro of deploying sensor in hostile atmosphere with a bare minimum of  
59 maintenance. This fulfills a crucial requisite for any real time monitoring, especially in unsafe or  
60 remote scenarios.

61  
62 According to Arabinda, Nanda, Omkarpattanaik, BiswajitaMohanty (2010) the usual practice for  
63 data acquisition and monitoring is based on many sensors congregated in one station operating  
64 on exterior power supply. This post is left in the water in the place of curiosity and hold onto  
65 recording data during some stipulated time, which may last for longer period of time. At the end  
66 the stipulated time the station is mend for data transfer, dispensation examination, and to perform  
67 predefined set of action. Victor Sea (2013) explained that to create an expert system, a user has  
68 an expert source of knowledge, an inference engine, an understanding on how to build a rule  
69 base, and knowledge of how to enter and retrieve IO (input and output) from the expert system.  
70 The hardest part is obtaining the knowledge to create the rule base. These knowledge sources can  
71 come from various places, such as domain expert, data mining, and other legacy devices. To  
72 currently create an expert system a programmer must take the knowledge source and translate it  
73 into rule form. While this may sound easy, it involves the programmer having a partial  
74 understanding about the knowledge that is being codified and the expert system language you are  
75 coding in. after the knowledge has been transferred to a rule base, the user must supply input into  
76 the expert system, in the form of a working memory. The input can come from a GUI, console,  
77 or script depending on the type of application. Once this is complete the user can run the expert  
78 system and translate the answer from the working memory.

79  
80 Predicting flood will help in the taking the necessary steps for human evacuation and other  
81 entities. Several types of data are used for predicting floods. These are the amount of rainfall,  
82 rainfall duration, the rate of change in river flow, river water level, the characteristics of a river's  
83 drainage basin and human activities. Some of these data are quantitative in nature and other are  
84 qualitative in nature. Hence, we need an integrated framework, which is able to process both  
85 qualitative and quantitative data in a single integrated framework.

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87 In this research, capability to process both qualitative and quantitative data in a single integrated  
88 framework to predict flooding in the study area. Sensor can be used to automatically collect  
89 different types of environmental data necessary for predicting flood and transmit these data to  
90 central system. Nowadays, due to the cost efficiency and protocol standardization, low-powered  
91 sensor is easily deployed in large scale for different systems. We can collect data for different  
92 environmental parameters like rainfall, water level, humidity and temperature by using different  
93 types of sensors. An efficient heterogeneous wireless sensor network (WSN) is needed for  
94 collecting and transmitting data as sensor are deployed in harsh environment (Anderson and  
95 Hossain, 2015).

## 96 **2.0 Conceptual Framework**

97 Floods are among the most devastating natural disasters in the world, claiming more lives and  
98 causing more property damage than anyone can image. In Nigeria, though not leading in terms of  
99 claiming lives, flood affects and displaces more people than any disaster; it also causes more  
100 damage to properties. According to NEMA at least 20% of the population is at risk from one  
101 form of flooding or another. Frequently, supreme states and Federal Government adopt  
102 immediate action, that is, a post-disaster reaction where relief materials are supplied to the  
103 affected victims. This research will emphasize on Early warning system for flood disaster and  
104 prevention in wetland area in greater Yola.

105 The approach in this study also attempts to describe the application of remote sensing and GIS in  
106 an environmental issue such as flooding in a developing Country. A data base will be created  
107 using both cartographic and attributes data collected from these and other sources. Spatial  
108 analyses will be carried using Arc GIS Desktop 10.1 and its Arc Hydro extension. In under  
109 developed like Nigeria, flood disaster has been perilous to people, communities and institutions.  
110 Between July and October 2012, flooding in Nigeria pushed rivers over their banks and  
111 submerge hundreds of thousands of acres of farmlands. In winter period, the flood had forced 1.3  
112 million people out of their homes and claimed 431 lives, according to Nigeria's National  
113 Emergency Management Agency (NEMA). Adamawa State was among the states that were  
114 affected by flood. The flood destroyed both the built-environment and the undeveloped areas.  
115 The most important feature about flood is that it does not discriminate, but marginalizes  
116 whosoever refuses to prepare for its occurrence. The results obtained in this study implicated that

117 dumpsites within the river channels as well as structure development within the floodplain and  
118 high amount of rainfall are the major causes of inundation in the city, especially, in the wet  
119 season. The study will conclude that the use of geo-information technology, if well implemented,  
120 would provide adequate decision support information to planners and decision makers.  
121 Recommendations are made towards flood disaster management agency NEMA in Yola  
122 metropolis.

123 There is no doubt that the people in the study area (flood prone zone) are under serious threat  
124 from the environment: from China to Mexico, Indonesia, United States of America, The British  
125 Kingdom and Nigeria, researchers argued that the environment was only responding to the  
126 abuses heaped on it by man's activities (Christopherson, 1997). The disquiet is that the world  
127 may be getting close to extinction through natural disasters unless immediate actions are put in  
128 place to checkmate the incident of flood; and the signs are just too apparent to be ignored  
129 (Christopherson, 1997; Oyegbile, 2008). Around 21th May 2008, floods triggered by heavily rain  
130 which killed dozens of people across the Region of China, while thousands of others were  
131 victims of landslides caused by the downpours. China is not alone.

132 It stated that over 14 million Indians that were victims to the flood of August 2007 in SathyaSai-  
133 Baba, a major human settlement, of that region. The Federal Government could not organize any  
134 emergency relief material immediately, instead they spent over \$1.6 billion on Hawk Jets.  
135 Hunger and diseases stalked the Indian children and the poor in the region. Report shows that  
136 the devastating flood of Lahore, Pakistan in July 2011 where transportation systems were halted  
137 and businesses were closed down for days. Constructions increase along rivers and decrease rate  
138 of population around submergible areas, the flood-induced damages are increasing. Flood  
139 prediction with the installation of great flood control structures like flood dams are not justified  
140 due to its high cost. It is not, socially, economically and environmentally an optimum idea either.  
141 Due to these facts, the flood forecasting system can have a tremendously role in flood  
142 management through logical utilization of weir-gates and dam reservoirs. In this direction,  
143 different systems have been innovated for different countries around the world (Williams, 1994;  
144 Xiaoliu, 2000).

145 Predicting or forecasting flood is important to prevent probable loss of life and to reduce  
146 damages of properties, to sites of high economic importance. The floods occur when there is

147 blockage on river ways or channels; runoffs cannot be contained in stream channels, natural  
148 ponds and constructed reservoirs, and the land surface becomes submerged, sweeping away all  
149 its content. Terminal floods are resulting during heavy rainfall occur naturally on many rivers,  
150 making the area known as the flood plain. The precipitation often cause the rivers to overflow  
151 their banks, sometimes with a velocity and enormously destructive surge. Study has also  
152 recorded that flood disaster is not recent, and its destruction are sometimes enormous. For  
153 instance, the Johnston flood of May 31, 1889 in Johnston, Pennsylvania, USA left about two  
154 third of Johnstown submerged under water, its rail and telegraph lines washed out.

155 Frequent of floods in the cities and towns of Nigeria in recent times have been a great concern  
156 and challenge to the people, Governments and researchers, (Akintola, 1982;Aderogba, 2012 and  
157 Aderogba et al., 2012). However, there are journalistic and non-quantitative reports of flood for  
158 several parts of Nigeria. Most a times they are thorough and lack directions for professionals and  
159 policy makers (Aderogba, 2011). The works of Adeaga (2008), Oyegbile (2008) and Oyebande  
160 (1990 and 2005) are paraphrasing, disjointed or sectional. Occurrences of flood in most southern  
161 cities in Nigeria are so prominent that some inhabitants in many of these settlements have often  
162 described it as ‘an act of God’. However, flood disaster in many river way in some communities  
163 in Nigeria, are mostly due to poor perception of the residents on environmental information,  
164 inadequate or sometimes absolute lack of spatial information of flood prostrate areas, waste  
165 dump and construction of buildings (commercial and residential, etc) on river channels or ways  
166 without adequate measure for water flow. Similarly, floods are natural persistent hydrological  
167 phenomena that affect human lives. The danger of flood are chiefly in urban regions, are vital  
168 from both human settlement and economical perspectives in recent times, the estimation of flood  
169 dangerous impacts and the development of GIS-based flood deluge maps have been considered a  
170 crucial demand. (Khalid et al., 2012).

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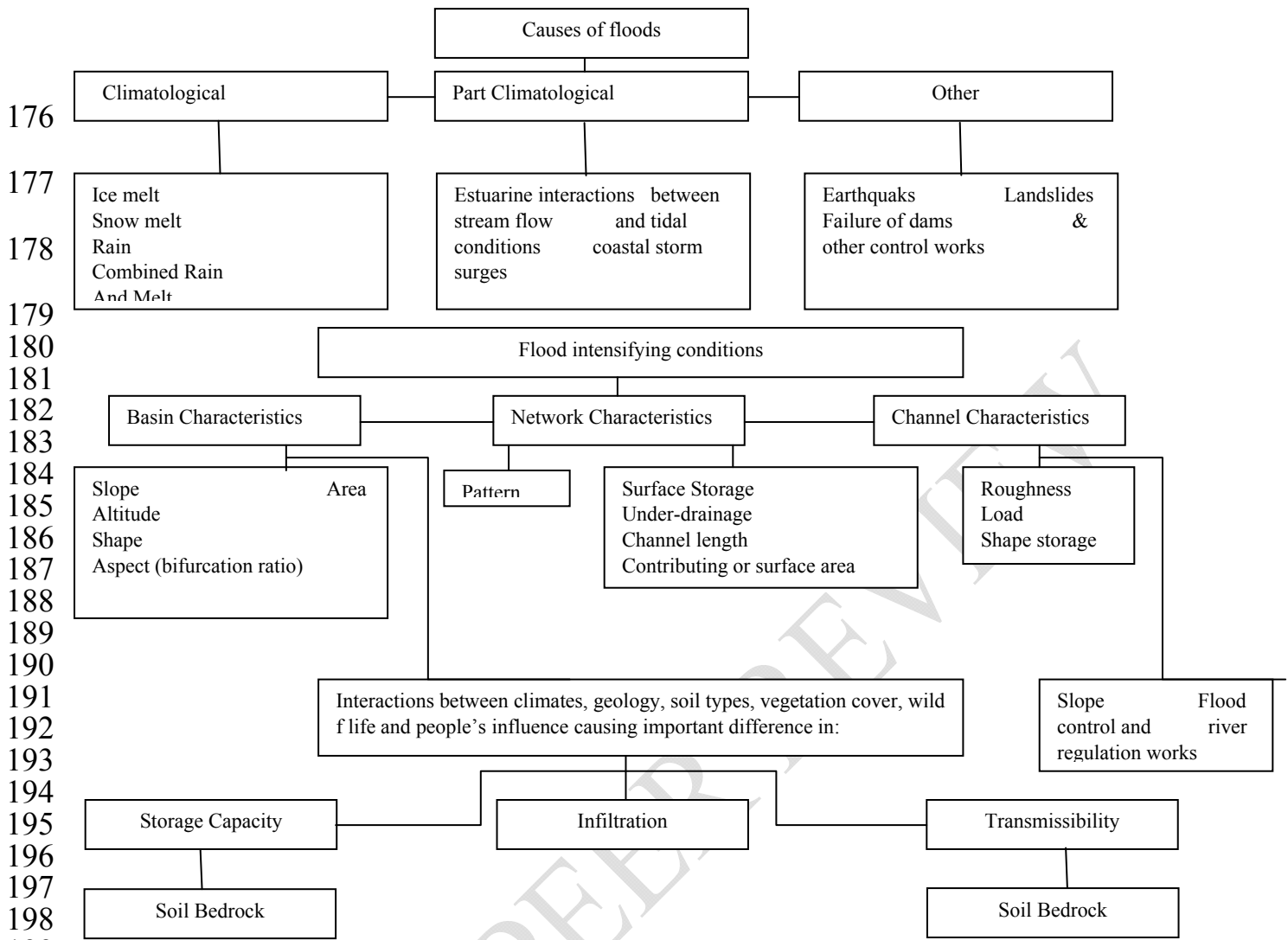


Fig. 1. The chart showing the causes of floods and flood intensifying conditions (NEMA, 2012)

Year	Location	Cause	Estimated damages	Source
2001	Abia, Adamawa, Akwa-Ibom States	Rainfall	5000 people affected	Famous Ebebi 2012
2001	Zamfara State	Rainfall	12,300 persons displaced	
2005	Taraba State	Rainfall	50,000 people displaced	
2008	Imo State (Awo-idemili)	Rainfall	12,250 people displaced	Vanguard newspaper 24/9/08
2008	Edo State (Benin City)	Rainfall	20 houses collapsed and four dead	Vanguard newspaper 23/9/08

2008	Benue State	Rain Storm	Destroyed 350 houses	Vanguard newspaper 27/9/08
2012	Plateau State	Rainfall leading to overflow of Lamingo dam	39 people died, 200 homes submerged and 3000 people displaced	Wikipedia downloaded on 19/10/2014

Table 1. The showing a review of some flood disaster cases in Nigeria (NEMA, 2012).

202  
203 In some develop society is one which progresses in its development while equitably meeting its  
204 present needs and not compromising the ability of future generation to develop and meet their  
205 own needs (UNGA 1987). The challenges posed by disasters, technological changes and other  
206 challenges can result in negative impacts for development. Disasters can be complexly  
207 exacerbated by global poverty and can have very detrimental impacts on development and on  
208 efforts to eradicate poverty. Effective and comprehensive knowledge on disaster risks can enable  
209 greater resilience to such stresses and enable development opportunities (Mc Bean, 2014). There  
210 is need to focus on the “essential relationship between disaster decrease, enable development and  
211 poverty eradication” (UNISDR, 2005). This is the grant challenge of incorporated research on  
212 disaster risk. Since the 1980s the impacts of disasters have risen rapidly, affecting developed and  
213 developing countries and almost all sectors of economy at local, national and regional levels.  
214 Several hundred million people are affected annually, and losses reached over USD 400 Billion  
215 in 2011 (Munich Rein, 2014). Federal Government attending the World Conference on Disaster  
216 Reduction in 2005 in Kobe, Japan, agreed on a series of priorities for action (HFA), including  
217 action related to the understanding of disaster risk and the enhancement of early warning systems  
218 and the roles of knowledge innovation and education for the building of a culture of safety and  
219 resilience. The High Functioning Autism (HFA) was the first framework to enlighten, express  
220 and factor the work that is required from all different sectors and actors to reduce disaster  
221 victims. There is a developmental arrangement and agreement with the many partners needed to  
222 reduce disaster challenges for Government, International Agencies, disaster experts and many  
223 others by bringing them into a common system of coordination. The HFA bring out five  
224 priorities for action and offered guiding principles and practical means for achieving disaster  
225 hardiness. Their goal was, and is, to substantially reduce disaster losses by the year 2015, by



226 building the resilience of nations and communities to disasters. This means reducing defeat of  
227 lives and social, economic and environmental assets when hazards wallop.

### 228 **3.0 Methodology**

229 This chapter deals with the methodology used in designing the ANFIS model for flood prediction  
230 in the study area that is greater Yola.

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232

### 233 **3.1 Study Area**

234 Yola is located in North-East Geopolitical Zone of Nigeria. The town lies around latitude  
235  $9.2035^{\circ}$  N and longitude  $12.4954^{\circ}$  E of the equator and has many rivers around the city, but my  
236 interest is raised to study the flood prediction of wet land in greater Yola, because of the number  
237 of lifes and properties that are situated along the river bank. This prompted me to conduct this  
238 project research.

### 239 **3.2 Method of Data Collection:**

240 The method used in collecting data is secondary method of data obtained from Nigeria  
241 Meteorological Agency Yola Airport for the past 10 years from 2008 – 2017 comprising of three  
242 (3) parameters which include Temperature, Humidity and Rainfall.

243

### 244 **3.3 Data Analysis**

245 There are many factors that contribute to flooding in every environment and most of this risk  
246 factors includes meteorological (precipitation, rainfall, temperature, wind speed), hydrological  
247 (land use, vegetation, terrain, soil textures), human activities (Dam creation, agriculture, social,  
248 blockage of water channels, building infrastructure, etc). But for this study, the researcher intent  
249 to used monthly water level reading, rainfall, temperature for both minimum and maximum and  
250 humidity to predict flood in the study area.

251

### 252 **3.4 Procedure for ANFIS Design**

253 ANFIS based modeling combines the transparent linguistic representation of fuzzy systems with  
254 the learning ability of neural network so that they can betrained to perform an input/output

255 mapping. The ANFIS is essentially a hybrid learning system which can be seen as fuzzy  
256 inference system that uses neural network theory to derive its parameters through learning  
257 algorithm.

### 258 3.6 ANFIS Architecture

259 ANFIS is a simple data parameter that uses Fuzzy Logic to Change a given inputs into a desired  
260 output through highly interconnected Neural Network processing elements and information  
261 connections, which are weighted to map the numerical inputs into an output. It incorporate two  
262 technique for machine learning (Fuzzy Logic and Neural Network) into a single technique. An  
263 ANFIS works by applying Neural Network learning methods to tune the parameters of a Fuzzy  
264 Inference System (FIS). There are many functions that make ANFIS to achieve it success.

- 265 1. It refines fuzzy IF-THEN rules to describe the behavior of a complex system.
- 266 2. It does not require prior human expertise.
- 267 3. It is easy to implement.
- 268 4. It enables fast and accurate learning.
- 269 5. It offers desired data set; greater choice of membership functions to use; strong  
270 generalization abilities; excellent explanation facilities through fuzzy rules.
- 271 6. It is more easier to combine together linguistic and numeric knowledge for problem  
272 solving.

273 Diverse system cannot share the same output membership function. The number of membership  
274 functions must be equal to the number of rules. ANFIS architecture can be presented in two  
275 ways: IF-THEN rules based on a first order Sugeno model are considered:

276 Rule (1): IF  $x$  is  $A_1$  AND  $y$  is  $B_1$ , THEN

277 
$$f_1 = p_1 x + q_1 y + r_1.$$

278 Rule (2): IF  $x$  is  $A_2$  AND  $y$  is  $B_2$ , THEN

279 
$$f_2 = p_2 x + q_2 y + r_2.$$

280 It is possible to identify two (2) parts in the network structure which consist of premise and  
281 consequence part. The architecture is composed by five (5) layers. The first layer takes the input  
282 values and determines the membership functions belonging to them which is called

283 “fuzzification layer”. The membership degrees of each function are computed by using the  
284 premise parameter set called dataset (a,b,c). the second layer is responsible of generating the  
285 firing strength for the rule, due to its function, the second layer is called or denoted as “rule  
286 layer”. The function of the third layer is to normalize the computed firing strength by plunging  
287 each value for the total firing strength. The fourth layer take as input the normalized value and  
288 the consequence parameter dataset. The fifth layer returned the value by defuzzificated ones and  
289 those value are passed to returnthe final output.

### 290 **3.7 Assigning of Membership Function**

291 Membership function is a graph that defined how input and output are mapped between 0 and 1.  
292 Membership function may be classified into mainly two sub-classes: continuous (Triangular,  
293 gbell, trapezoidal, Gaussian and piecewise) and discrete (generic singleton and singleton). In this  
294 work Gaussian membership function will be adopted. It is chosen because of its flexibility in  
295 accepting all kinds of data.

### 296 **3.8 BLOCK DIAGRAM OF ANFIS STRUCTURE**

297 ANFIS Structure is basically a graphic network representation of Sugeno-type fuzzy system  
298 endowed with the neural learning capabilities and the network is comprised of nodes with  
299 specific functions collected in layers. It normally has 5 layers of neurons of which neurons in the  
300 same layer are of the same function family. ANFIS Structure can construct a network realization  
301 of IF/THEN Statement or Rules. To achieve the desire result require the ANFIS structure below  
302 will be used.

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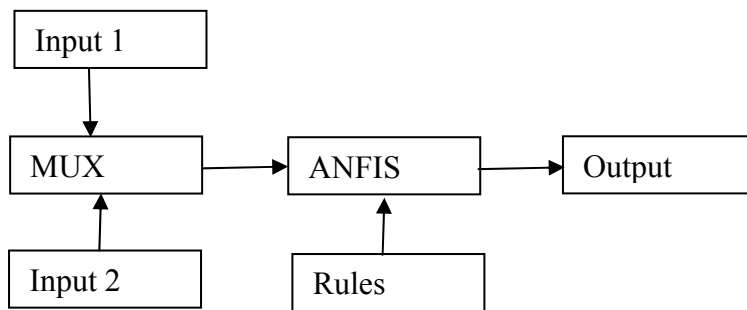


Fig. 2: Block Diagram of ANFIS Structure

### 3.9 ANFIS FRAMEWORK

ANFIS framework is class of adaptive networks that incorporate both neural networks and fuzzy logic principles. Neural networks are supervised learning algorithms which utilize a historical dataset for the prediction of future values. ANFIS is an attractive, powerful modeling techniques, combining well established learning laws of ANNs (Artificial Neural Network) and the linguistic transparency of fuzzy logic theory within the framework of adaptive networks and FIS (Fuzzy Inference System) are one of the well known application of fuzzy logic.

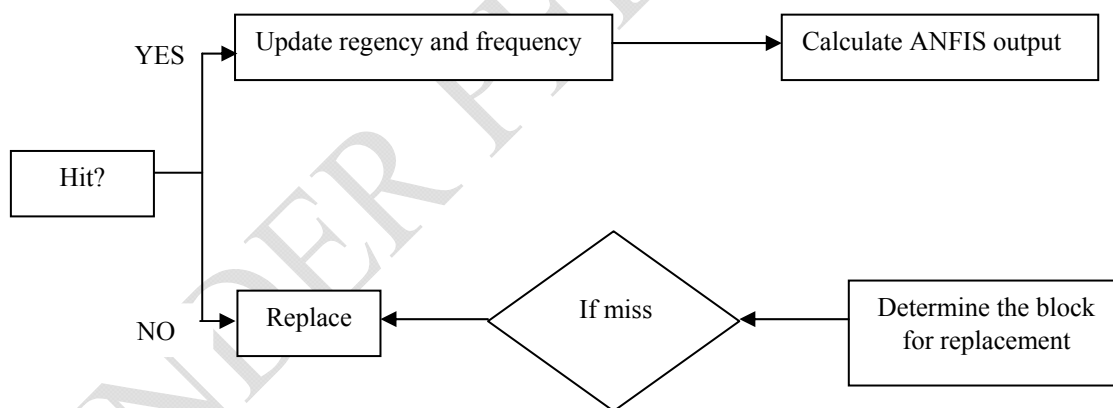


Fig. 3: Diagram of ANFIS framework

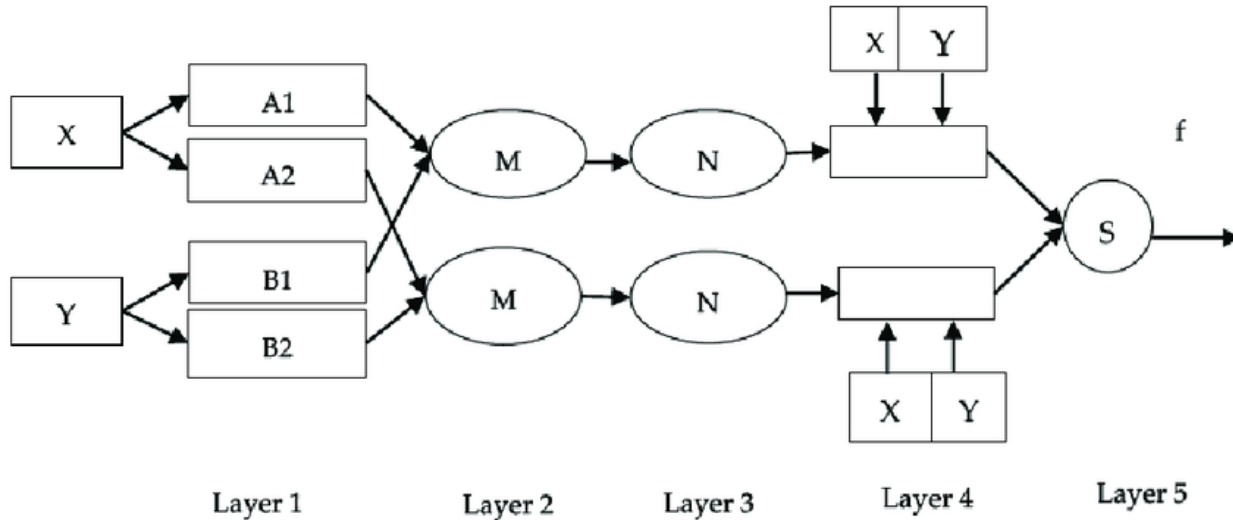


Fig. 4: General framework of ANFIS

**i) Required Data sets size**

The required dataset used is 10 years from 2008 – 2017 will be used as training sample which comprises of monthly temperature, humidity and rainfall.

**ii) Data Preparation**

Data preparation is one of the major key step in every Neural Network Application. In order to train the Neural Network, the data set would have to be normalized. Normalization shows that all from values the data set should take values within the range of 0 to 1. Therefore, the dataset to be used in this research work would be done using the formula below:

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} * (-1) + 1 \dots \dots \dots (1)$$

Where,

- $x_n$  = Normalized value
- $x$  = Value that should be normalized
- $x_{min}$  = Minimum value of  $x$
- $x_{max}$  = Maximum value of  $x$

i. Data requirement: the required data used in this research work is 10 years from 2008-2017 is used as sample data which comprises of temperature, relative humidity and monthly rainfall. Required data are prerequisite to measure data quality and also serve as a bench mark that evaluate or describe how to express data requirement.

353 ii. Data preparation: is an important step in modeling for every Neural Network and the procedure  
354 for the preparation of data effects many important parameter and it also reduce the modeling  
355 errors, speeds up the process of training the neural network and leads to simplification of the  
356 system as a whole, the data set should take values within the range.

357 **3.10 Modeling Design Process for ANFIS**

358 Adaptive Neuro Fuzzy Inference System is an intellectual Neuro-Fuzzy technique that is used for  
359 the modeling and control of ill-defined uncertain system based on the input/output data sets or  
360 pairs of the system under consideration of learning context. The learner profile contains a  
361 learner's preferences, knowledge, goals, plans, place and possibly other relevant aspects that are  
362 used to provide personalized learning content. The ANFIS is a class of adaptive networks that  
363 combine the processing of neural networks and fuzzy logic principles. ANFIS, as an adaptive  
364 multilayer feed-forward network. It is an effective technique for modeling/mapping the input and  
365 output relationship in complex and nonlinear systems.

366 **3.6 Error Analysis**

367 The measure of the prediction accuracy is considered using Absolute Percentage Error (APE) and  
368 Mean Absolute Percentage Error (MAPE) as given in a equation (2) and (3)

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$$APE = \left| \frac{actual - forecast}{actual} \right| \times 100\% \dots\dots\dots(2)$$

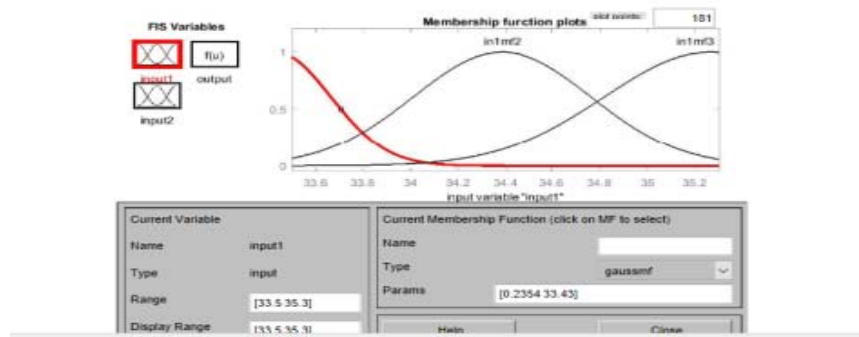
370 
$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{actual - forecast}{actual} \right| \times 100\% \dots\dots\dots(3)$$

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379 **4.0 Result**

380 This chapter presents the results obtained from the ANFIS developed. A Membership function is  
381 the graph that defines how input and output are mapped between 0 and 1. However the diagrams  
382 below shows the Membership Function developed for temperature, Humidity and Rainfall.

383 **4.1 Membership Functions**

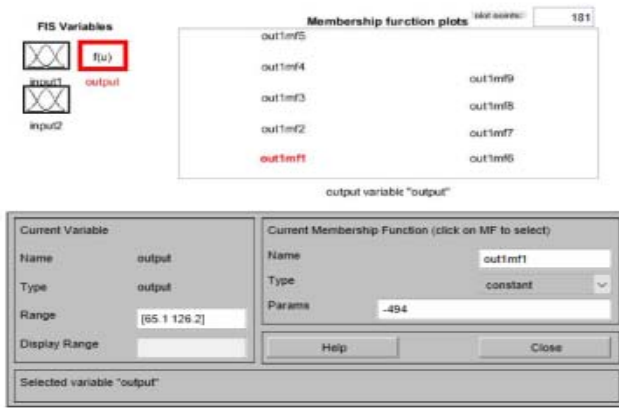


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385 Fig. 5: Membership Function for Temperature

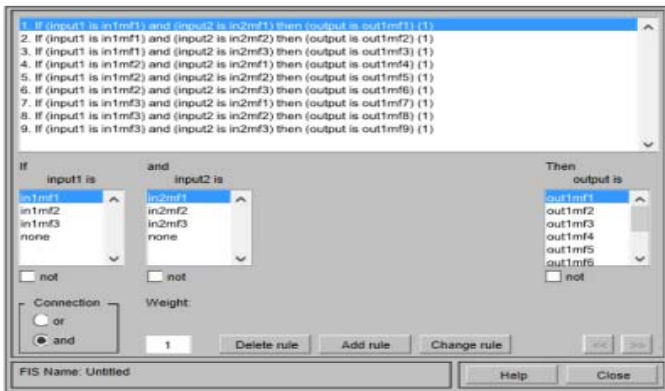
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388 Fig. 6: Membership Function for Humidity



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 390 Fig. 7: Membership Function for Rainfall  
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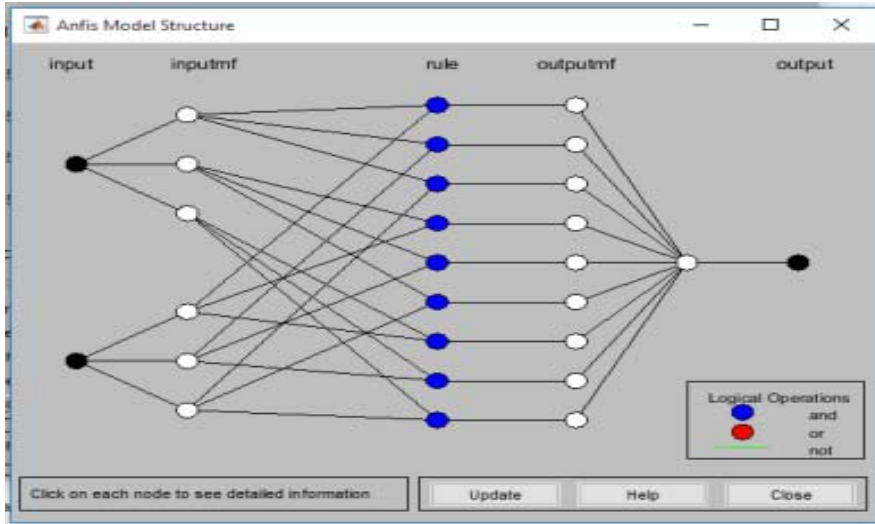


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 393 Fig. 8: Rules Generated by the ANFIS System Model  
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395 **4.3 ANFIS MODEL STRUCTURE**

396 Based on the membership function developed the ANFIS simulated network model of two inputs  
 397 is shown below.





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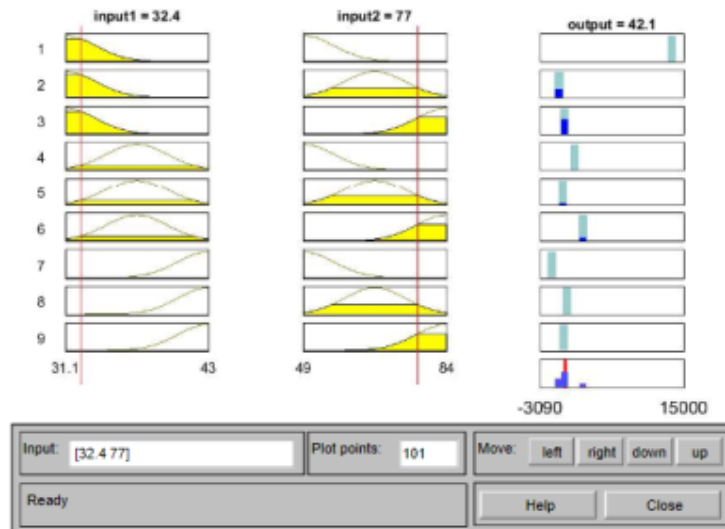
399 Fig. 9: Simulated ANFIS Model Structure

400 It can be seen that the ANFIS model structure shows the equivalent of two inputs and three  
 401 inputs membership function, nine rules generated by the model, nine outputs membership  
 402 function also generated by the model with one output.

403

#### 404 4.4 RULE VIEWER

405 The Rule viewer depicts the defuzzified out of the ANFIS model. The diagram below present the  
 406 result of a sample dataset taken in the year 2008 for the month of July, where the temperature is  
 407  $32.4^{\circ}$ , humidity 77.0mm and forecasted rainfall as 42.1mm.



408

409 Fig. 10: Defuzzified predicted out of one sample data for the month of July 2008

410

411 **4.5 RESULTS**

412 SAMPLE DATASET FOR FORECASTED RAINFALL FOR 10 YEARS FROM 2008-2017

413 The below tables show a samples dataset for forecasted rainfall from the year 2008-2017, which  
414 later on combine to have a mean average forecasted for 10 year. Below are yearly prediction.

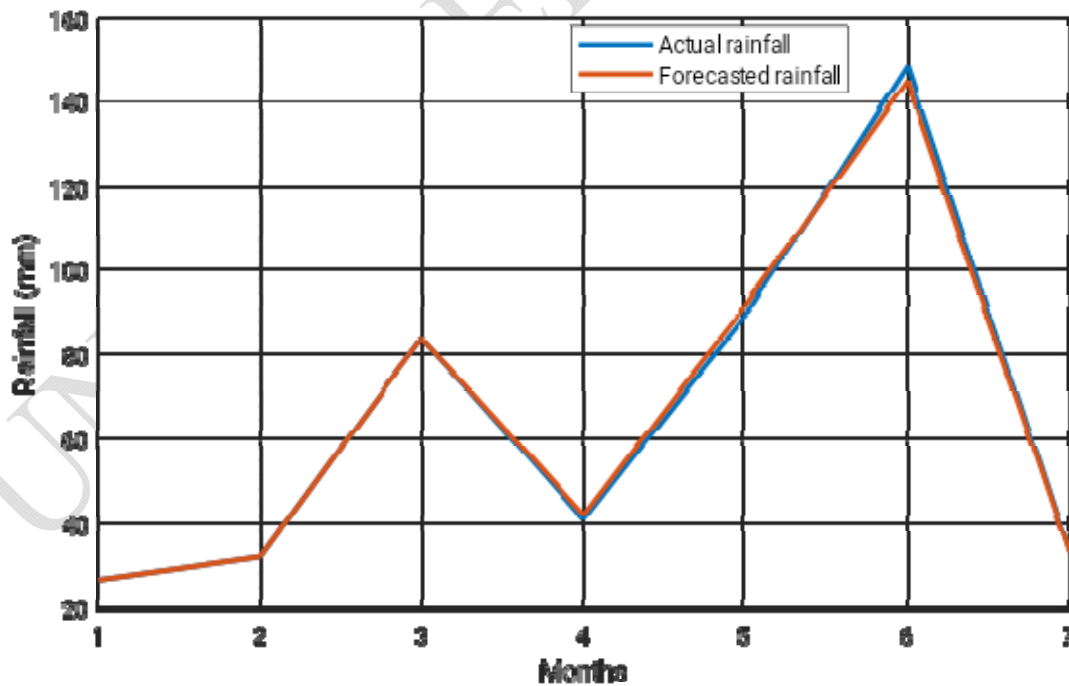
415 Table 2: 2008 Dataset

2008				
MONTH	TEMPERATURE (°)	HUMIDITY (%)	RAINFALL (mm)	FORECASTED RAINFALL (mm)
APRIL	39.8	49	26.8	26.8
MAY	36.8	65	32.3	32.3
JUNE	34.0	77	84.0	84.0
JULY	32.4	77	41.1	42.1
AUGUST	31.1	84	89.2	91.6
SEPTEMBER	31.5	84	148.5	145.0
OCTOBER	33.2	67	33.7	33.4

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Fig. 11: Forecasted results for 2008 flood prediction graph

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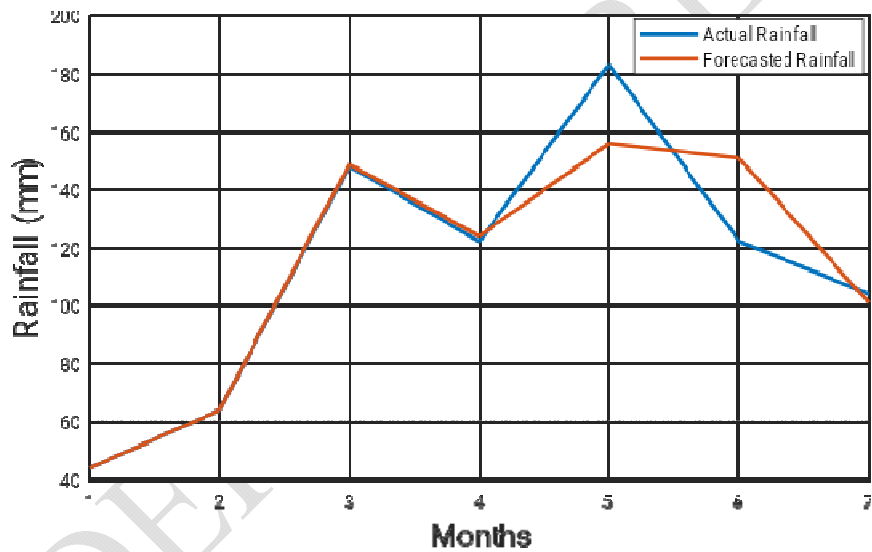
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423

424 Table 3: 2009 Dataset

2009				
MONTH	TEMPERATURE ( <sup>o</sup> )	HUMIDITY (%)	RAINFALL (mm)	FORECASTED RAINFALL (mm)
APRIL	38.5	56	43.9	43.9
MAY	35.7	68	63.9	63.9
JUNE	33.6	79	148.3	149.0
JULY	32.6	80	122.2	124.0
AUGUST	31.5	84	183.3	156.0
SEPTEMBER	31.7	84	122.3	151.0
OCTOBER	33.0	81	104.0	101.0

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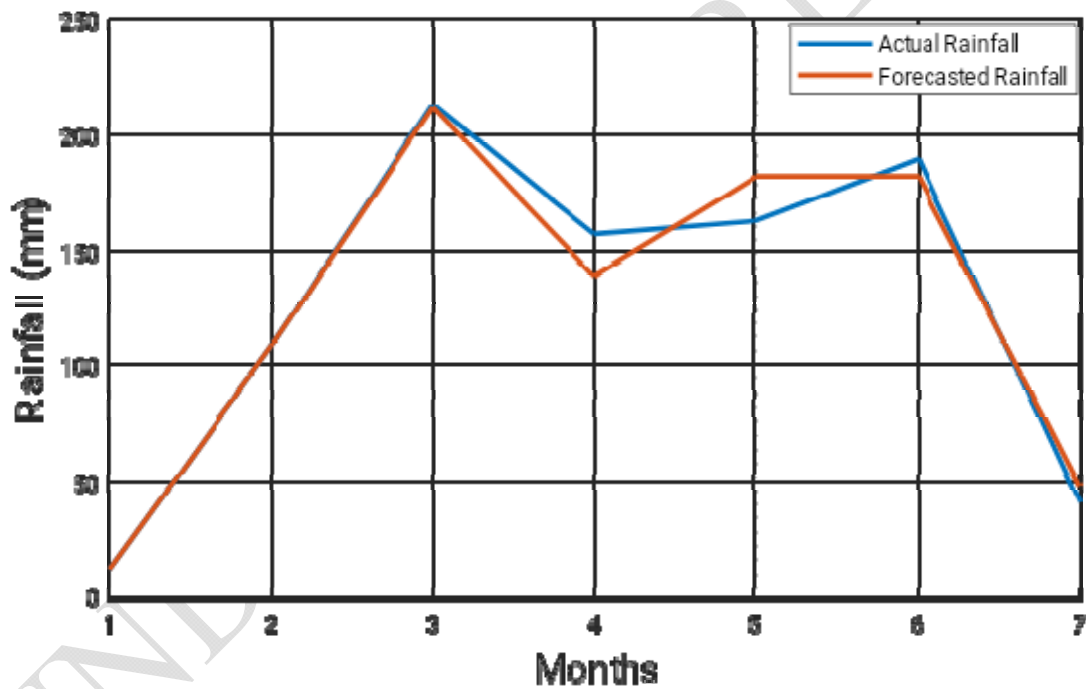
Fig. 12: Forecasted results for 2009 flood prediction graph

429 Table 4: 2010 Dataset

2010				
MONTH	TEMPERATURE (°)	HUMIDITY (%)	RAINFALL (mm)	FORECASTED RAINFALL (mm)
APRIL	42.3	42	34.9	34.9
MAY	37.3	67	50.7	50.6
JUNE	33.5	71	193.7	194.0
JULY	31.4	82	176.0	174.0
AUGUST	30.9	85	135.6	154.0
SEPTEMBER	31.1	85	162.4	144.0
OCTOBER	32.6	81	55.9	57.5

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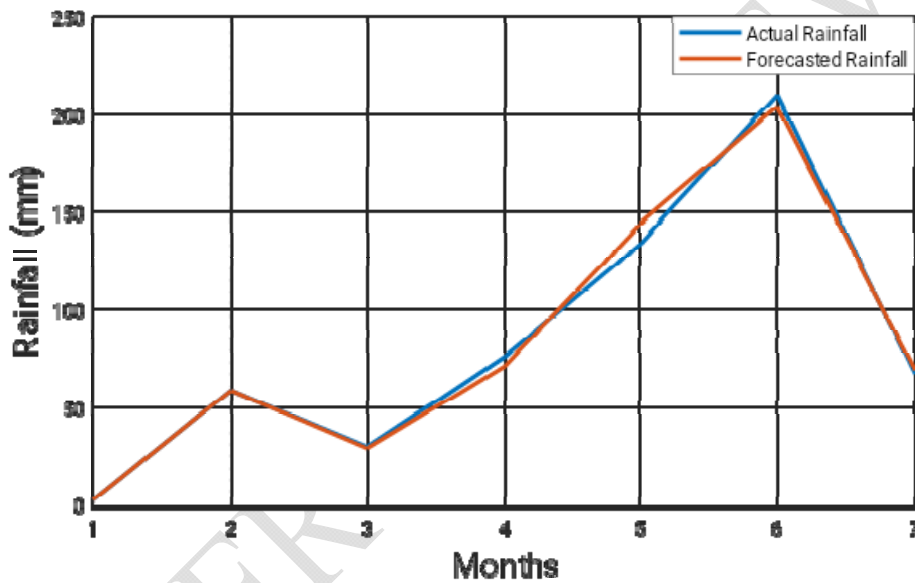
433 Fig. 13: Forecasted results for 2010 flood prediction graph

434

435 Table 5: 2011 Dataset

2011				
MONTH	TEMPERATURE (°)	HUMIDITY (%)	RAINFALL (mm)	FORECASTED RAINFALL (mm)
APRIL	40.9	42	2.5	2.5
MAY	36.9	65	58.8	58.8
JUNE	34.8	79	29.9	29.1
JULY	32.4	78	75.7	71.1
AUGUST	31.4	82	134.1	144.0
SEPTEMBER	30.6	85	210.0	204.0
OCTOBER	33.5	77	67.2	69.2

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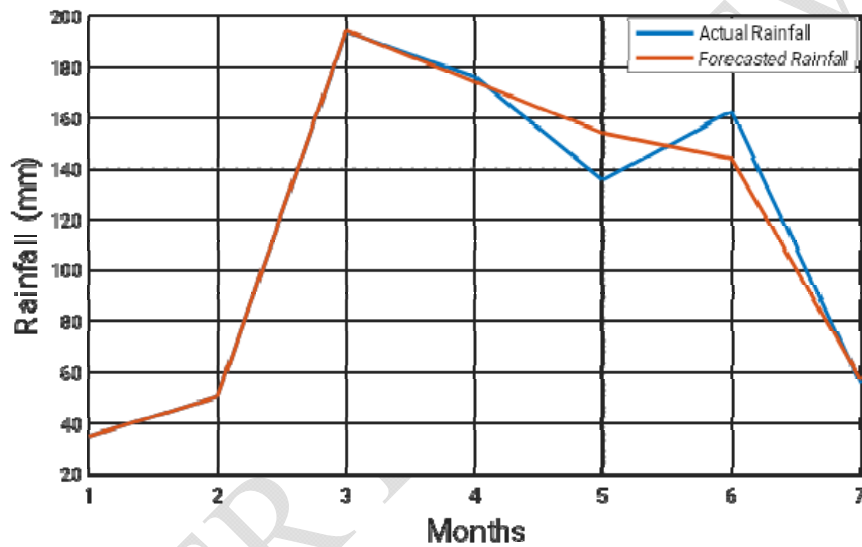
Fig. 14: Forecasted results for 2011 flood prediction graph

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440 Table 6: 2012 Dataset

2012				
MONTH	TEMPERATURE (°)	HUMIDITY (%)	RAINFALL (mm)	FORECASTED RAINFALL (mm)
APRIL	40.9	48	12.0	12.0
MAY	36.9	67	108.0	108.0
JUNE	34.8	70	213.4	212.0
JULY	32.4	84	157.1	139.0
AUGUST	31.4	85	162.8	182.0
SEPTEMBER	30.6	84	189.5	182.0
OCTOBER	33.5	80	40.9	48.0

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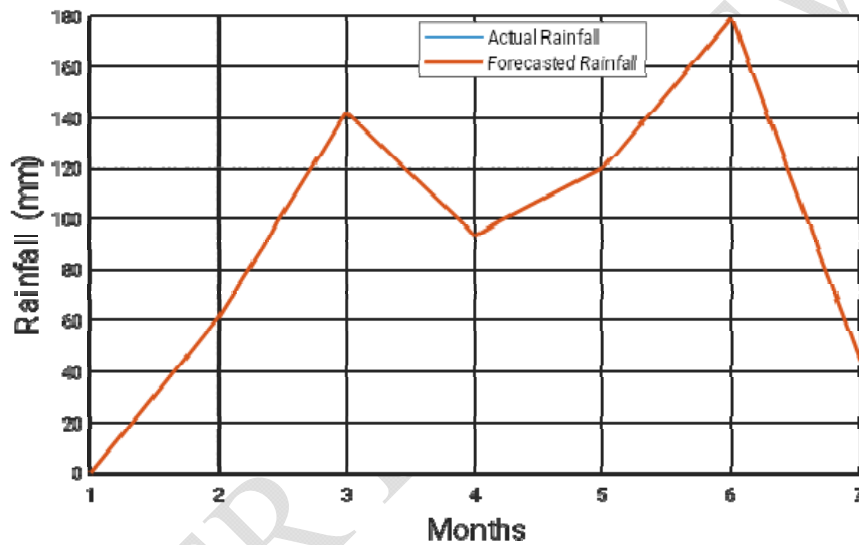
Fig. 15: Forecasted results for 2012 flood prediction graph

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445 Table 7: 2013 Dataset

2013				
MONTH	TEMPERATURE (°)	HUMIDITY (%)	RAINFALL (mm)	FORECASTED RAINFALL (mm)
APRIL	40.2	48	00.0	00.0
MAY	37.9	60	61.0	61.0
JUNE	34.7	77	142.4	142.0
JULY	31.5	80	93.8	93.7
AUGUST	30.8	81	120.0	120.0
SEPTEMBER	31.5	83	178.7	179.0
OCTOBER	34.1	75	44.7	44.7

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Fig. 16: Forecasted results for 2013 flood prediction graph

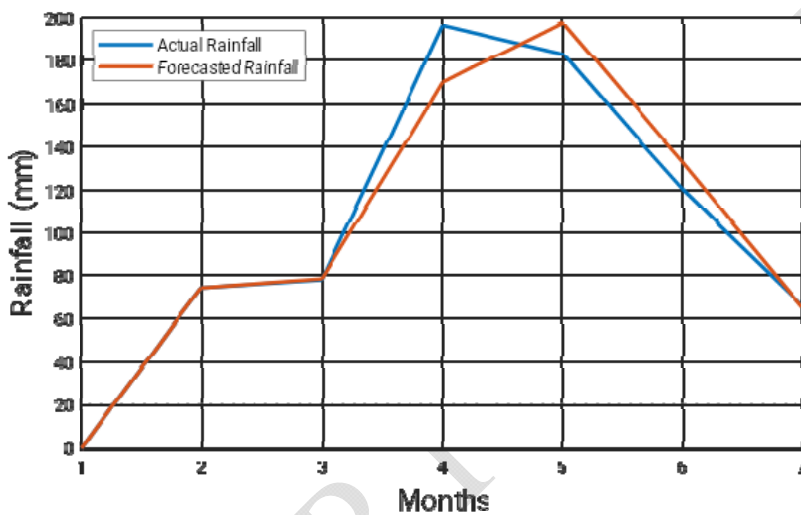
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451 Table 8: 2014 Dataset

2014				
MONTH	TEMPERATURE (°)	HUMIDITY (%)	RAINFALL (mm)	FORECASTED RAINFALL (mm)
APRIL	38.9	50	00.0	00.0
MAY	34.6	73	74.1	74.1
JUNE	34.2	71	77.8	78.3
JULY	31.6	80	196.8	170.0
AUGUST	31.6	81	183.3	198.0
SEPTEMBER	31.7	79	120.5	133.0
OCTOBER	33.7	73	65.7	64.9

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Fig. 17: Forecasted results for 2014 flood prediction graph

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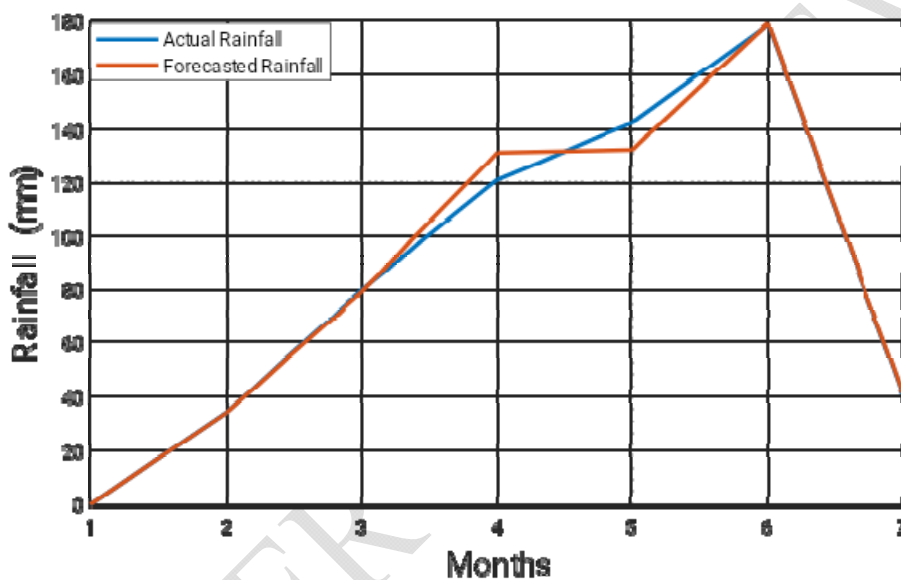
456



457 Table 9: 2015 Dataset

2015				
MONTH	TEMPERATURE (°)	HUMIDITY (%)	RAINFALL (mm)	FORECASTED RAINFALL (mm)
APRIL	38.7	46	00.0	00.0
MAY	36.3	62	34.1	34.0
JUNE	33.5	73	79.8	79.1
JULY	30.2	83	120.9	131.0
AUGUST	30.0	83	142.2	132.0
SEPTEMBER	31.1	72	178.5	179.0
OCTOBER	34.6	69	40.9	41.4

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Fig. 18: Forecasted results for 2015 flood prediction graph

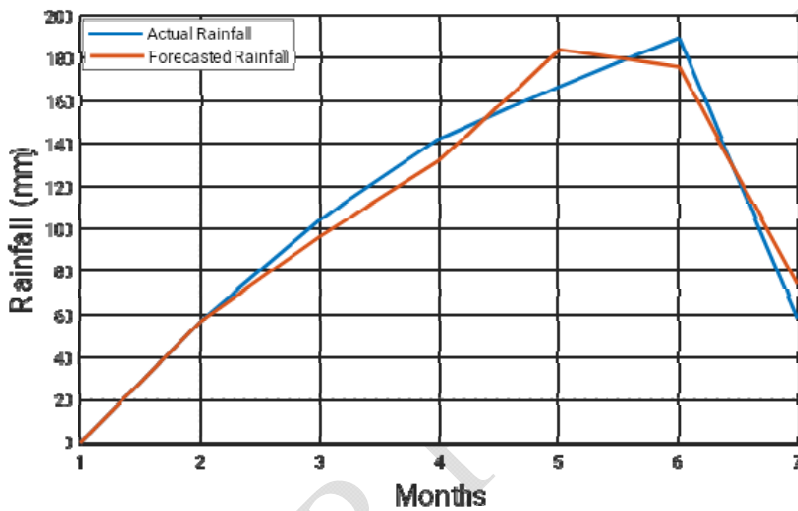
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463 Table 10: 2016 Dataset

2016				
MONTH	TEMPERATURE (°)	HUMIDITY (%)	RAINFALL (mm)	FORECASTED RAINFALL (mm)
APRIL	41.4	49	00.0	00.0
MAY	40.5	60	56.4	56.4
JUNE	35.0	73	104.0	96.1
JULY	33.5	83	142.4	132.0
AUGUST	31.5	83	167.0	184.0
SEPTEMBER	31.3	81	189.5	176.0
OCTOBER	34.5	76	58.1	73.8

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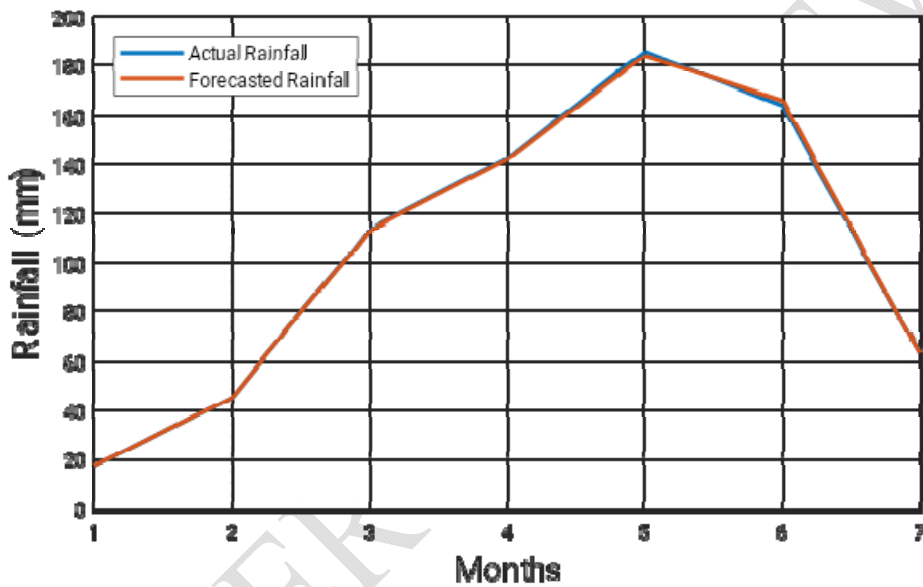
Fig. 19: Forecasted results for 2016 flood prediction graph

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2017				
MONTH	TEMPERATURE (°)	HUMIDITY (%)	RAINFALL (mm)	FORECASTED RAINFALL (mm)
APRIL	40.2	25	17.1	17.1
MAY	37.9	45	45.1	45.1
JUNE	34.7	69	113.3	113.0
JULY	31.5	75	142.4	142.0
AUGUST	30.8	83	185.6	187.0
SEPTEMBER	31.5	81	164.0	166.0
OCTOBER	34.1	76	63.1	62.9

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Fig. 20: Forecasted results for 2017 flood prediction graph

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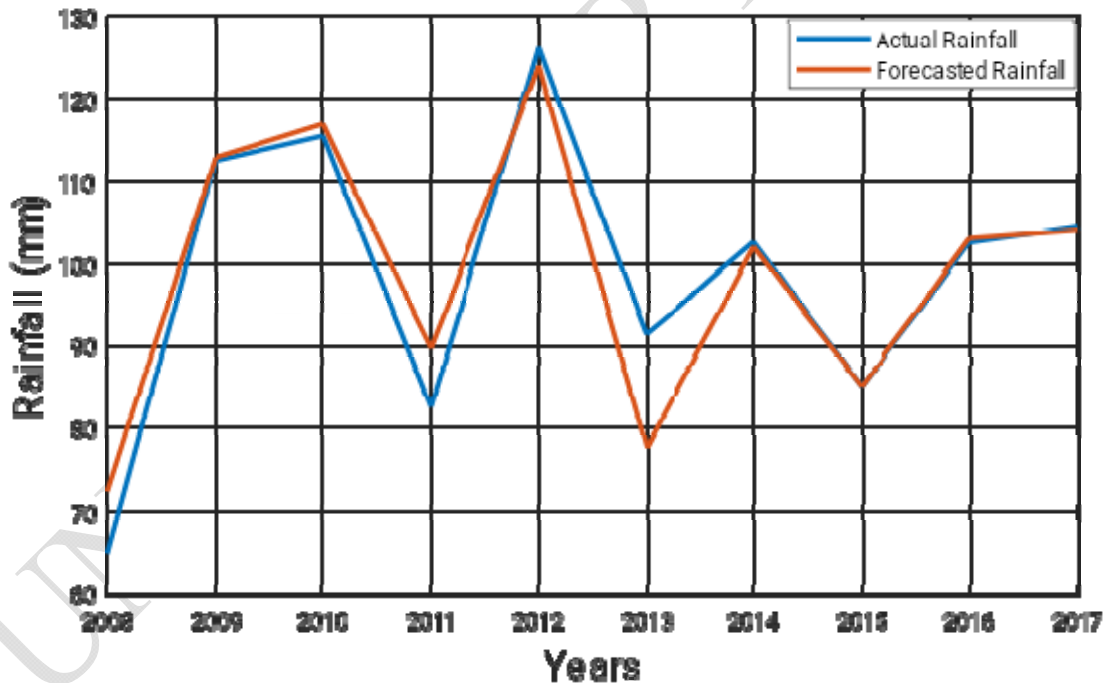
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481 Table 12: Mean Average Dataset for 10 Years

MEAN AVERAGE FOR 10 YEARS					
YEARS	TEMPERATURE (°)	HUMIDITY (%)	RAINFALL (mm)	FORECASTED RAINFALL (mm)	APE (%)
2008	34.1	71.9	65.1	72.5	11.37
2009	33.8	76.0	112.6	113.0	0.36
2010	34.2	73.3	115.6	117.0	1.21
2011	34.4	72.6	82.6	89.8	8.72
2012	34.4	74.0	126.2	124.0	1.74
2013	34.4	72.0	91.5	77.7	15.08
2014	33.8	72.4	102.6	102.0	0.59
2015	33.5	69.7	85.2	85.2	0.00
2016	35.3	72.1	102.5	103.0	0.49
2017	34.4	64.9	104.4	104.0	0.38
					MAPE = $\sum APE\%$ = 4.0%

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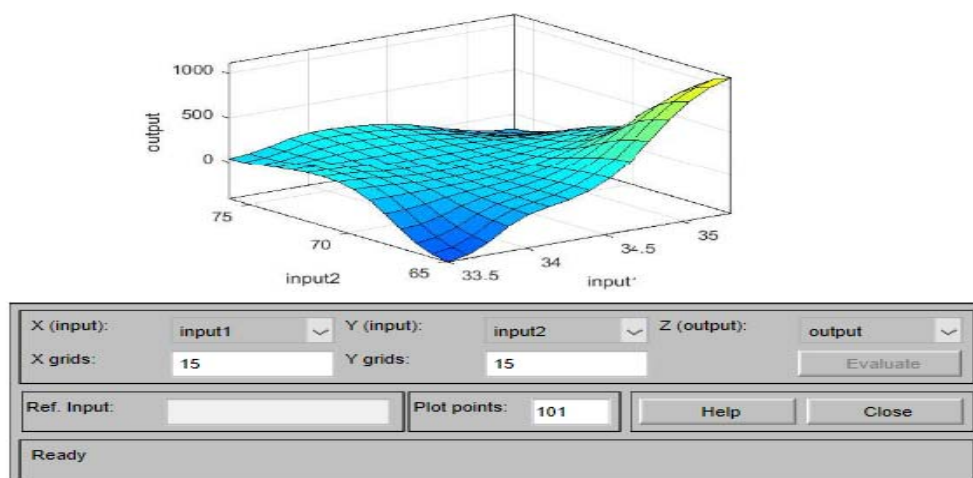
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484 **Fig. 21: Mean Average Forecasted results for 10 years (2008-2017) flood prediction**  
 485 **graph**

486 From the above graph (Fig. 21) it can be seen that the actual and the forecasted rainfall  
 487 followed the same pattern from 2008 to 2010 with slightly decrease in 2011. A high

488 amount of rainfall in 2012 was forecasted to be flooded during that year and tally with the  
489 forecasted rainfall on the above graph in 2012. From 2014 to 2017 gives a constant flow  
490 between the actual and forecasted rainfall. However, the prediction accuracy using Mean  
491 Absolute Percentage Error (MAPE) was determined as 4.0% using equation (3) and the  
492 model efficiency of the prediction accuracy was validated as 96.0% which shows a very  
493 high excellent prediction accuracy.

#### 494 4.7 3 DIMENSIONAL SURFACE VIEWER



495  
496 Fig. 22: 3 Dimensional curves for Temperature, Humidity and Rainfall.

497 The Rule viewer shows one calculation at a time and in great details. In this sense, it presents a  
498 sort of micro view of the ANFIS. The mapping of the surface viewer is done in one plot showing  
499 two input and one output case of the entire output surface of the system through the surface  
500 viewer. It shows a three-dimensional curve that represents the mapping from distance and  
501 previous radiation density to actual radiation density.

#### 502 503 Conclusion

504 An ANFIS model was used to developed a forecast rainfall from the year 2008-2017. It is  
505 observed that, the actual and the forecasted rainfall followed the same pattern from 2008  
506 to 2010 with slightly decrease in 2011. A high amount of rainfall in 2012 was forecasted  
507 to be flooded during that year and tally with the forecasted rainfall in 2012. From 2014 to  
508 2017 gives a constant flow between the actual and forecasted rainfall. However, the

509 prediction accuracy using Mean Absolute Percentage Error (MAPE) was determined as  
510 4.0% and the absolute percentage error shows that the model efficiency was validated to  
511 be 96.0% (that is  $100\% - 4.0\% = 96.0\%$ ) which shows excellent prediction accuracy with  
512 no any flood possibility in the year ahead.

513

UNDER PEER REVIEW

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