# Assessment of Rainfall and Climate Change Patterns in the City of Kigali via Machine Learning and IPCC Codex Models and their Impact on Heavy Storms

**Hussein Bizimana** (mutembealhussein@gmail.com)
Rwanda Water Resources Board
**Abdusselam Altunkaynak**
Istanbul Technical University
**Robert Kalin**
University of Strathclyde
**Emmanuel Rukundo**
Rwanda Water
**Mathieu Mbati Mugunga**
Meteo-Rwanda
**Osman Sönmez**
Sakarya University
**Gamze Tuncer**
Sakarya University
**Abdulkadir Baycan**
Sakarya University

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# Assessment of Rainfall and Climate Change Patterns in the City of Kigali via Machine Learning and IPCC Codex Models and their Impact on Heavy Storms

Hussein Bizimana[1,2,3], Abdusselam Altunkaynak[4], Robert Kalin[5], Emmanuel Rukundo[6], Mathieu Mbati Mugunga[7], Osman Sönmez[8], Gamze Tuncer[9], Abdulkadir Baycan[9]

*[1]Postdoctoral Fellow, Istanbul Technical University, Civil Engineering Department, Hydraulic and Water Resources Engineering Division, 34467 Sariyer, Istanbul, Turkey*
*[2]Visiting Lecturer, University of Rwanda, College of Science and Technology, Civil, Environmental and Geomatic Engineering, 3900 Nyarugenge, Kigali, Rwanda*
*[3]Hydraulic Flood Modeling Specialist, Knowledge and Forecasting Hub Department, Rwanda Water Resources Board, 6213 Nyarugenge, Kigali, Rwanda*
*[4]Professor, Istanbul Technical University, Civil Engineering Department, Hydraulic and Water Resources Engineering Division, 34467 Sariyer, Istanbul, Turkey*
*[5]Professor of Environmental Engineering for Sustainability, University of Strathclyde, Civil and Environmental Engineering Department, Glasgow, Scotland, UK.*
*[6]Director General, Rwanda Water Resources Board, 6213 Nyarugenge, Kigali, Rwanda*
*[7]Senior Forecaster, Meteo Rwanda, Kigali, Rwanda*
*[8]Associate Professor of Civil Engineering, Sakarya University, Serdivan, Sakarya, Turkey*
*[9]Research Assistant in Civil Engineering, Sakarya University, Serdivan, Sakarya, Turkey*
*Corresponding Author's email: mutembealhussein@gmail.com*

Rainfall is changing in intensity and abundance for much of the world as a result of global climate change. Rwanda has been negatively affected by a changing climate, exacerbated by human impact on land and water resources. In most parts of the country the rainfall pattern has changed over the last decades resulting in both enhanced flooding and water shortage / scarcity in much of the country, especially in the Capital City of Kigali and peripheries which is the main economic hub of the country with strong links to the East African region. Changes in precipitation have affected agricultural production, hydropower production, and water supplies, and has been a result of increased flash floods in the city. This study developed a new predictive model rainfall patterns in the City of Kigali (CoK) in the Republic of Rwanda using evolutionary methodologies that apply machine learning techniques of Fuzzy Inference Systems (FIS) trained via Genetic Algorithms, Neuro Network Systems and a comparative Support Vector Machine tool, and assessment downscaled climate change combinations with predicted rainfall patterns. The models were calibrated and validated using measured rainfall data in the City of Kigali from 1991 through 2023. The model results show the developed Geno Fuzzy Inference System (GENOFIS) model performed better than the Adaptive Neuro Fuzzy

Inference System (ANFIS) and Support Vector Machine (SVM) models. The Coefficient of Efficiency (CE), and Root Mean Square Error (RMSE) were used as diagnostic measures for model performance evaluation. Models generated with GENOFIS are therefore recommended for rainfall and related prediction pattern in the City of Kigali for climate change adaptation and resilience policy and planning.

**Keywords**: Precipitation; Fuzzy Systems (FS); Support Vector Machine; Machine Learning; Climate change, Resilience.

## INTRODUCTION

Water is the most abundant natural resource on earth (Nafi and Brans, 2019; Aboniyo *et al.*, 2017, Habonimana *et al.*, 2015), but available fresh water resources used to sustain our existence is a small fraction that varies widely in space and time (UNDP, 2020; Ntirenganya, 2018) through anthropogenic development has changed the distribution of available fresh water for production of hydropower and advancement of irrigation and agriculture engineering (Loh and Wackernagel, 2004). Climate change has altered local weather patterns across the globe (Bridgman and Oliver, 2014). In East Africa, El-Nino and La Nina effects impact weather patterns year to year, even though the anomalies originate from the southern Pacific Ocean (Schwing *et al.*, 2002). As well, very dry and hot air from the Sahara can influence weather in Northern Europe (Schwing *et al.*, 2002). These shifting patterns of precipitation have affected East Africa, including Rwanda (USAID, 2014, Ntirenganya, 2018). Sectors such as renewable energy, irrigation, water supply and agriculture production have been impacted in many parts of the country (Karamage *et al.* 2016; NWRMP, 2013). Problems linked to rainfall scarcity have been seen in Rwanda, and especially in Eastern parts of the county which have been facing severe drought for the last decades (Ntirenganya, 2018, REMA, 2010). To adapt and mitigate to the climate change induced changes in precipitation in the City of Kigali, a robust and well-trained rainfall prediction model is of crucial importance. This model will help define policy for more efficient allocation of water resources, and focus during periods of severe flooding and rainfall shortage, thereby guiding investment that will provide sustainable water management measures (Uwera, 2013; USAID, 2014, Theobald *et al.* 2018).

There is a wealth of rainfall prediction models presented in the literature for Central and East Africa, however few research studies have been undertaken in Rwanda. Most of research studies that investigated rainfall fluctuation problems in East Africa (and especially in Rwanda) do not include the stochastic behavior of global climatology and rainfall patterns (Ntirenganya, 2018, UNDP, 2020, USAID, 2014). Recent studies have developed new and high-end approaches to this modelling challenge based on artificial intelligence (Altunkaynak, 2010; Altunkaynak, 2014 Altunkaynak and Nigussie, 2015; REMA, 2010, Rukundo and Dogan, 2016). These methods were used successfully in many parts of the world, and the results have proved reliable when compared to conventional deterministic methods (Munyaneza *et al.* 2013). In 2018 an extended study of the availability of clean water in many provinces of the republic of Rwanda was published by the Ministry of Infrastructure and its stakeholders (MININFRA, 2016). This study highlighted different modeling techniques used to map the availability of fresh water resources in Southern and Eastern Provinces of the country (MININFRA, 2016). These were focused on deterministic models linked to Geographic Information Systems (GIS) (Munyaneza *et al.*, 2013; Rukundo and Dogan, 2016). In this study we present a novel evolutionary method that can be used for rainfall and pattern forecast in the city of Kigali. The model is trained on observed data from the gauge station located at the Kigali International Airport. Geno Fuzzy Inference System (GENOFIS) (Bizimana and Altunkaynak, 2019), Adaptive Neuro Fuzzy Inference System (ANFIS) (Jang, 1993), and Support Vector Machine (SVM) (Jakkula, 2006) were compared. While predictive models are always a challenge for future predictions, artificial intelligence and soft computing based-methods are being adopted for the purposes of this study to evaluate the potential of this non-deterministic approach. To the best of the authors' knowledge, the GENOFIS approach has not been used for rainfall prediction. The GENOFIS approach, as a modelling tool, has previously generated accurate prediction results (Bizimana and Altunkaynak, 2019, 2020), and is recommended for implementation to predict hydrological variables. Here we compared it with widely used ANFIS and linear SVM models using observed rainfall data at Kanombe International Airport, in the City of Kigali.

## STUDY AREA

Rwanda has no sea ports, but considerable lake boundaries being located in the great lakes region of East Africa. Countries neighboring Rwanda, are Tanzania in the East, Uganda in the North, Burundi in the South and Democratic Republic of the Congo in the West. The country has an area of 26,338 $km^2$ and population estimated to be 13.4 million as of 2023. The annual population growth rate is estimated at 3.1%. The country has water resources in abundance (rivers, lakes, and swamps). Surface water resources cover 211,000 hectares an equivalent to 8% of the total national land territory, with rivers covering an area of 7,270 hectares and also 22.300 natural springs feeding rivers and lakes (NWRMP, 2013). These incised rivers meander between hills and ridges found across Rwanda and is the reason why Rwanda is famously known as the "country of a thousand hills". Rwanda sits at the catchment boundary between the Congo and Nile river basins in the Western part of the country (Fig. 1).

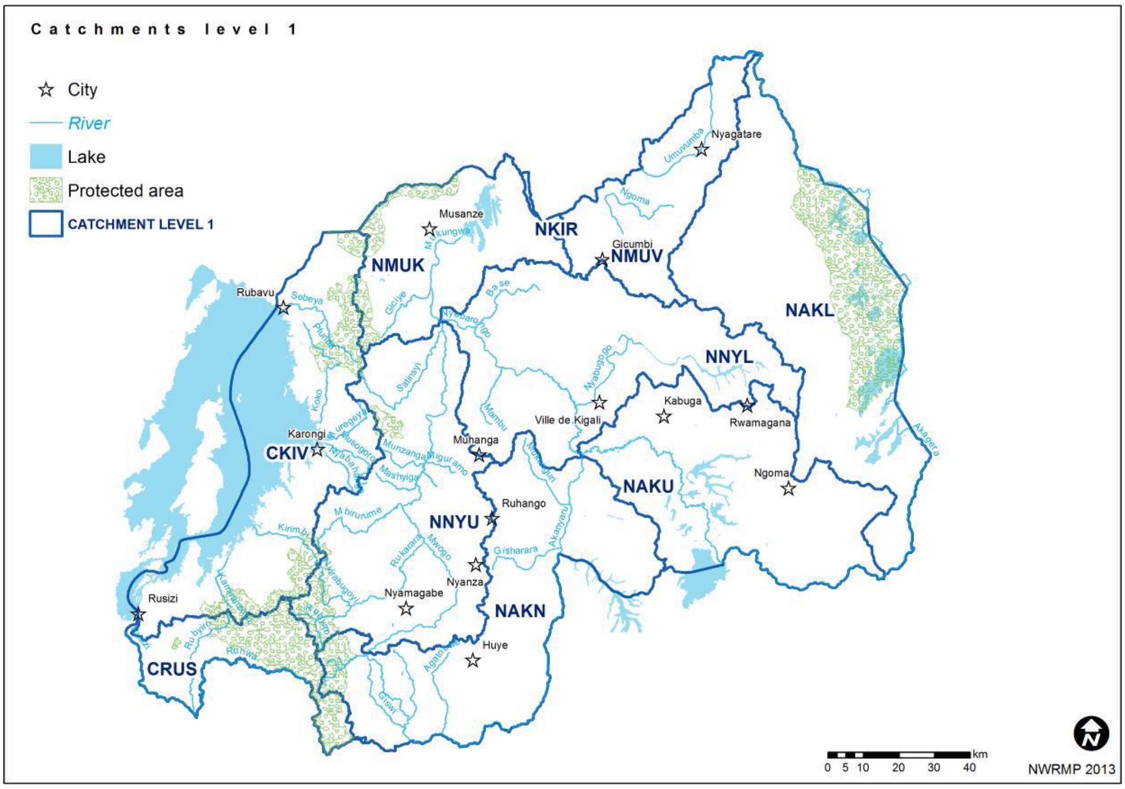


**Fig. 1.** National catchments of level 1 (*NWRMP, 2013*)

The Congo basin occupies 33 % of the country and 10 % of water resources. The Nile basin occupies 67 % of the country and 90 % of water resources. The Nile basin drains towards east where many small streams and rivers converge to the Akanyaru and Nyabarongo rivers. These meet in the southern part of city of Kigali to form the Akagera river that continues towards Lake Victoria. The annual average rainfall ranges from 700 mm to 1400 mm in the Eastern part of the country, to 1200 mm to 1400 mm in central plateau of the country where the City of Kigali is located, and between 1300 mm to 2000 mm in the high-altitude regions of the North. The country water resources is divided in 9 main catchments of level 1, namely, Mukungwa (NMUK), Muvumba (NMUV), NKIR, Lower Akagera (NAKL), Upper Akagera (NAKU), Lower Nyabarongo (NNYL), Upper Nyabarongo (NNYU), Akanyaru (NAKN), Rusizi (CRUS),and Kivu (CKIV) Fig. 1 adapted from the National Water Resources Master Plan

(NWRMP) published in 2013. The City of Kigali is located in NNYL catchment, hydrologically called Lower Nyabarongo.

## THE CITY OF KIGALI

This study was focused on the commercial and political capital of the Republic of Rwanda, the City of Kigali. The city has an area of 730 $km^2$ with a population of more than one million inhabitants. The City of Kigali is located at the center of the country and holds a status of a province being, one of the five provinces in the country. The City of Kigali lies within hilly landscapes spreading across wet valleys. The city is rapidly expanding in terms of structures and modern buildings within its growing economy. Not only is it Rwanda’s most dynamic and important business pivot, but also it is the main port of entry to the country via its international airport. The city holds a moderate high-altitude climate that is associated with its tropical location (Mugiraneza and Ban, 2019; Nduwayezu *et al.*, 2021). Fig. 2a shows the administrative boundaries of the City of Kigali.

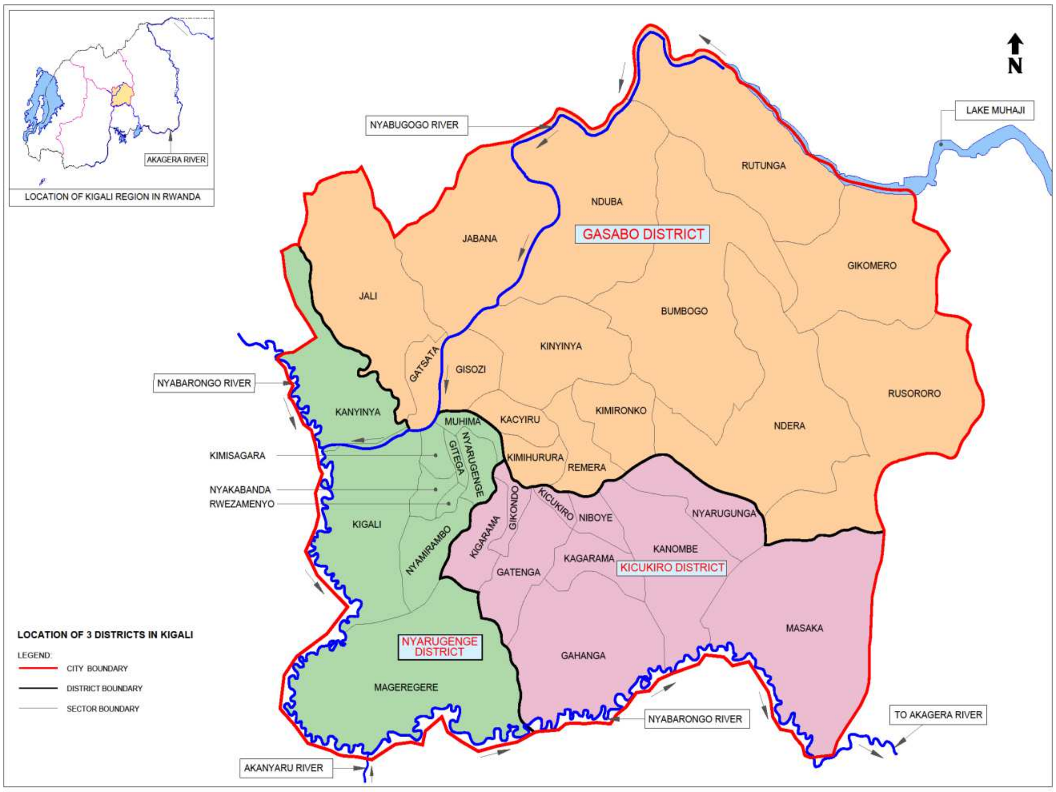


**Fig. 2a:** The city of Kigali Administrative boundaries

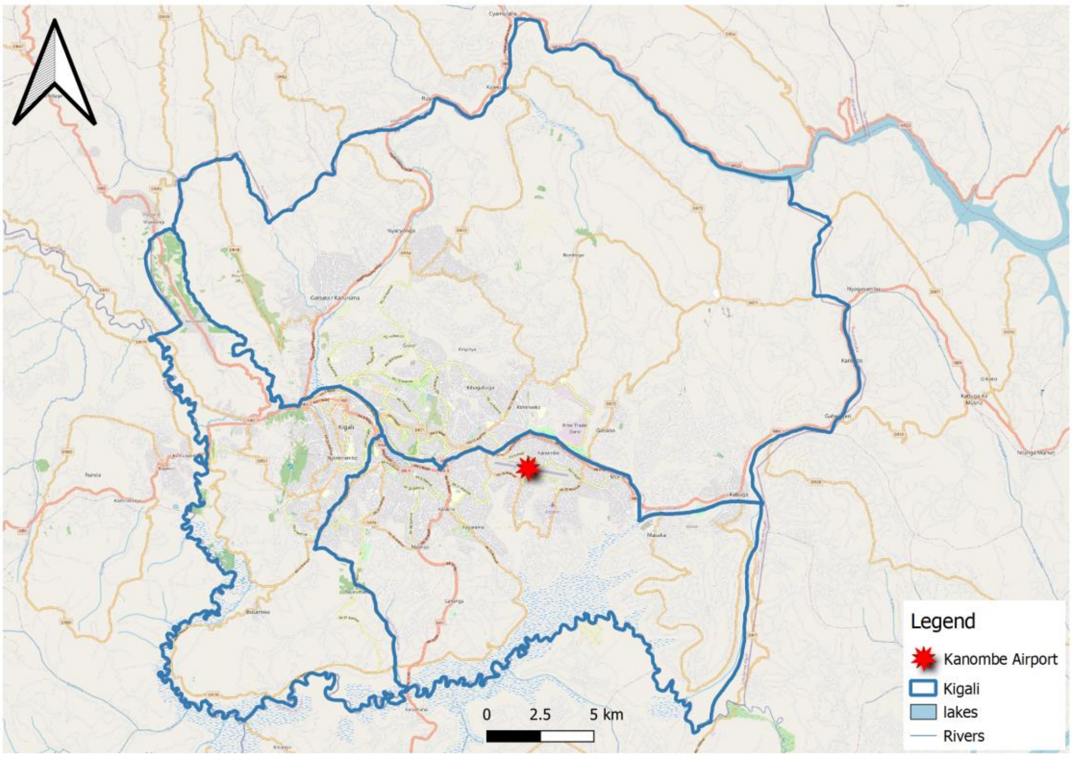


**Fig. 2b:** The location of Kanombe Airport and rain gauge station

The City of Kigali has three districts, Nyarugenge, Kicukiro and Gasabo (**Fig. 2a**). The city's one of the long-term rainfall gauging station is at the Kanombe International Airport located in and its updated data has been used in this study. The maintenance and recording of rainfall data are managed and monitored by the Rwanda Meteorological Agency. The city has an averagely temperature between 17–31°C with monthly wind speed ranging between of 4 m/s – 8 m/s (Henninger, 2013a, b; Loknath *et al.* 2015).

## MODELLING METHODS

### Geno Fuzzy Inference System Model

The Geno Fuzzy Inference System Model (GENOFIS) is a hybrid evolutionary technique proposed by Bizimana and Altunkaynak (2019). GENOFIS is an improvement of the conventional and widely accepted Sugeno Fuzzy Inference System, and is a robust compromise between computational complexity and high accuracy. With the Sugeno-ANFIS structure, for $n$ inputs and $f$ membership functions, $k$ input parameters that are given to each input and membership function, should have the total number of fitting parameters equalized to $F(n,f,k) = nf.k + fn.\ (n+1)$**.** Bizimana and Altunkaynak (2019) proposed in detail the advantages and disadvantage of the GENOFIS versus conventional Sugeno Adaptive Neuro-Fuzzy Inference System (ANFIS) approaches. GENOFIS was developed combining the method proposed by Jovanovic (2004) and a technique to represent the consequent part of the Sugeno Fuzzy Inference System as any favorable type of mathematical function, and if required, a combination of two or more of them. Sugeno FIS is a conventional approach that utilizes constant or linear functions, never a combination. The GENOFIS technique defines the total number of fitting parameters as $G\ (n, f, k) = n \text{ x } f \text{ x } k + n \text{ x } f\ (n+1) = n \text{ x } f \text{ x } (n+k+1)$. This approach increased accuracy and reduced computation complexity for linear problems

(Bizimana and Altunkaynak, 2019,2020a, 2020b). IF/THEN rules for evolutionary GENOFIS approach were introduced by Bizimana and Altunkaynak (2019) as follows;

***Rule 1***: If $Q_i \in [1991 - 1995]$ then $Q_i^n = a_1(Q_i)^n + b_1(Q_i{}^*)^{n-1} + c_1(Q_i)^{n-2} + d_1(Q_i)^{n-n} + e_1$

***Rule 2***: If $Q_i \in [1995 - 2000]$ then $Q_i^n = a_2(Q_i)^n + b_2(Q_i)^{n-1} + c_2(Q_i)^{n-2} + d_2(Q_i)^{n-n} + e_2$

***Rule 3***: If $Q_i \in [2000 - 2023]$ then $Q_i^n = a_3(Q_i)^n + b_3(Q_i)^{n-1} + c_3(Q_i)^{n-2} + d_3(Q_i)^{n-n} + e_3$

where $Q_i^n$ and $Q_i$ define the normalized rainfall data and the rainfall records, respectively. The Genetic Algorithms (GAs) technique was applied to optimize parameters, $a_1$, $b_1$, $c_1$, $d_1$, $e_1$, $a_2$, $b_2$, $c_2$, $d_3$, $e_3$, $a_3$, $b_3$, $c_3$, $d_3$, and $e_3$ as consequent parameters. Details on the optimization process of the novel GENOFIS models are found in Bizimana and Altunkaynak (2019).

## Adaptive Neuro Fuzzy Inference System

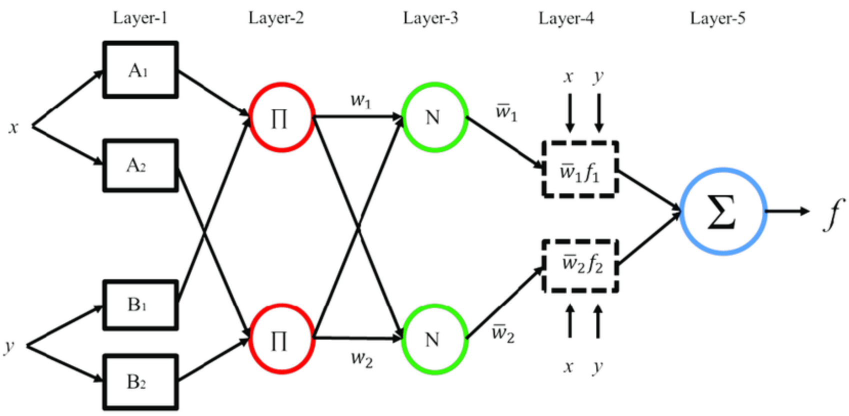


***Fig. 3***: *Neuro-Fuzzy Inference System structure*

The Adaptive Neural Fuzzy Inference System (ANFIS) is based on the Takagi-Sugeno Fuzzy Inference System (FIS) (Sugeno and Kang, 1988). The Neuro-fuzzy approach was proposed by Jang (1992) who utilized two inputs and generated one output by using two fuzzy if-then rules as follows;

***Rule 1***: If $x$ is $A_1$ and $y$ is $B_1$ then $f_1=p_1x+q_1y+r_1$

***Rule 2***: If $x$ is $A_2$ and $y$ is $B_2$ then $f_2=p_2x+q_2y+r_2$

As shown in **Fig.3**, five structure layers of the ANFIS approach are defined as follows:

**Layer 1:** Every node available in this layer has a node function

$O_{\mathrm{I}}^1 = \mu_{A_i}(X) \quad for\ i = 1{,}2$ or;

$O_i^1 = \mu_{B_{i-2}}(Y) \quad for\ i = 3{,}4$

In the formulae above, $X$ and $Y$ are the inputs to node $i$, and $A_i$ and ( $B_{i-2}$ ) stand for the linguistic label (Great, little, Far, close, etc.) together with the node function. The function depicts the magnitude to which $X$ (and $Y$) reaches the quantifier A, (or $B_{i-2}$) and also named as *the membership function* of $A_i$ and ($B_{i-2}$), respectively. The FIS provides considerable freedom in representing the type of membership functions in accordance to one's needs in terms of simplicity, speed, efficiency, and convenience. Takagi and Sugeno (1985) showed the only condition that should be met is that a membership function has to vary between 0 and 1. In **Fig.3** the ANFIS architecture is depicted as suggested by Jang (1992).

The membership function is a function of its parameters, as a result changing its parameters modifies the membership function shape. Parameters represented in the first layer define the premise (antecedent) parameters. In Jang (1993) and Bizimana and Altunkaynak (2019), the fabrics and functionality of the ANFIS have been explained in details.

To reach best performance, Adaptive Neuro Fuzzy Inference System utilizes the least-square optimization approach to find the consequent parameters and back-propagation technique to generate the antecedent (premise) parameters. The learning process is informed by two steps: (1) calibration data set is utilized as the input, the antecedent or boundary parameters are considered as stationary values and the optimized consequent parameters are calculated by an iterative least-square approach, and (2) designs are spread, but in this step the consequent variables are assumed to be fastened and back-propagation is used to modify the antecedent parameters. Adaptive Neuro Fuzzy Inference System (ANFIS) represents the optimized consequent output only as a linear or constant function whilst many problems behave to a great extent as irregular functions. As a result, a novel and evolutionary technique called GENOFIS was used to predict rainfall time series data. This approach is specified as an integration of the optimized Genetic Algorithms (GAs) and Sugeno FIS (Bizimana and Altunkaynak, 2020). Furthermore, the novel GENOFIS technique allows the characterization of the consequent part as a linear, non-linear and constant functions or combination of all simultaneously. The novel GENOFIS also provides the optimized consequent parameters via generated Genetic Algorithms (GA) (Bizimana and Altunkaynak, 2020).

***Support Vector Machine***

The Support Vector Machine (SVM) is utilized in machine-learning-based systems (Jakkula, 2006). SVM works as a supervised machine learning algorithm for classification and/or regression defiance (Jakkula, 2006). SVM performs this task via direct control of noise and advanced propagation to large dimensional data, offering advanced integrity. **Fig. 4** depicts the SVM hyperplane.

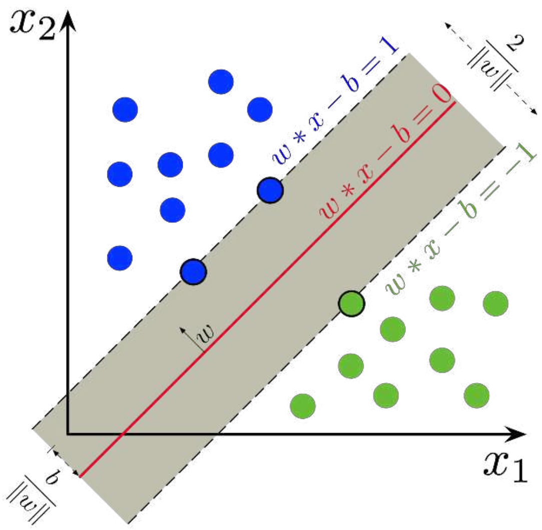


***Fig.4*** *Support Vector Machine hyperplane*

SVM increases the margins between categories by generating hyperplanes (Huang *et al.*, 2018). The most optimal result of *r* which the coefficient of correlation is reached by lessening the cost function between the nearest calibration data points, and the hyperplane as follows;

Reduce: $\frac{1}{2} \parallel \omega \parallel^2 + C \sum_{i=1}^{n} \xi_i$ (1)

Subject to $y_i(\omega^T x_i + b)^3 \geq 1\text{-}\xi_i, \xi_i \geq 0$ (2)

Where $\omega^T, x_i \in R^2$ and b $\in R^1$, $\parallel \omega \parallel^2 = \omega^T$ , $\omega$ is defined as the training weight, $C$ is the tradeoff parameter between noise and margin, $\xi_i$ is the measure of calibration data, and $y_i$ is the class label for the *i*th specimen. The adaptive advantage of SVM is that it can be used for linear as well as nonlinear data classification. To generate a greater accuracy in predicting rainfall precipitation in the City of Kigali, a nonlinear classifier (Sern *et al.*, 2020) was utilized in this study. This classifier operates with a third-order kernel function (Said *et al.*, 2015).

## MODEL PERFORMANCE EVALUATION CRITERIA

The evaluation criteria Coefficient of Efficiency (CE), proposed by Nash-Sutcliffe (1970) and used by Bizimana & Altunkaynak (2019) and Altunkaynak & Kartal (2019), was used to measure the prediction performance of the GENOFIS, ANFIS and SVM models. The root mean square error (RMSE) was used to assess the prediction error generated by the aforementioned models in predicting the rainfall availability in the City of Kigali. According to Moriasi *et al.* (2007), if CE is greater than 0.5, the performance of a model is acceptable. Donigan & Love (2003) and, Altunkaynak & Nigussie (2019) detailed all the acceptable ranges for CE where CE values greater than 0.85 indicate high accuracy of a predictive model.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Q_{i\ (o)}^{n} - Q_{i\ (p)}^{n}\right)^{2}} \tag{3}$$

$$CE = \left[1 - \frac{\sum_{i=1}^{n}\left(Q_{i\ (o)}^{n} - Q_{i\ (p)}^{n}\right)^{2}}{\sum_{i=1}^{n}\left(Q_{i\ (o)}^{n} - Q_{i\ (av)}^{n}\right)^{2}}\right] \tag{4}$$

where, $Q_{i\ (\mathrm{av})}^{n}$ defines the average rainfall depth observed at a gauge station, $Q_{i\ (o)}^{n},\ and\ Q_{i\ (p)}^{n}$ are observed rainfall and predicted rainfall at Kanombe Airport station.

### Modeling Data

For this study, rainfall records from 1991 through 2023 recorded at Kanombe International Airport's gauging station in the south of the City of Kigali (Fig.2b) were used as inputs to GENOFIS, ANFIS and SVM models (Table 1 – 4). Observed rainfall data were divided into three periods, [1991-1995], [1995-2000] and [2000-2023]. These periods were chosen to optimize uncertainty and scattering in the rainfall records by utilizing short periods and avoiding stochastic abnormalities in the datasets (e.g. jump and trends). The normalized observed rainfall data were used as outputs of those models. The normalization was performed as follows;

$$Q_i^n = 0.8\,\frac{Q_i - Q_{i_{min}}}{Q_{i_{max}} - Q_{i_{min}}} + 0.1 \tag{5}$$

***Table 1:*** *ANFIS-based If-Then rules and parameters*

| | *Rule no.* | *Antecedent* | *Consequent* |
|---|---|---|---|
| | | $Q_i$ | $Q_i^n$ |
| ANFIS ($Q_i \in [1991 - 1995]$) | *1* | *L1* | $Q_i^n$ = *0.22(*$Q_i$*)- 0.12* |
| | *2* | *L2* | $Q_i^n$ = *0.04(*$Q_i$*)- 0.08* |
| | *3* | *L3* | $Q_i^n$= *0.12(*$Q_i$*)- 0.04* |
| | *4* | *T1* | $Q_i^n$ = *0.02(*$Q_i$*)- 0.004* |
| | *5* | *T2* | $Q_i^n$ = *0.0035(*$Q_i$*)- 0.02* |
| | *6* | *T3* | $Q_i^n$= *0.048(*$Q_i$*)- 0.001* |
| | *7* | *R1* | $Q_i^n$ = *0.05(*$Q_i$*)- 0.002* |
| | *8* | *R2* | $Q_i^n$ = *0.06(*$Q_i$*)- 0.003* |
| | *9* | *R3* | $Q_i^n$ = *0.11(*$Q_i$*)- 0.014* |
| ANFIS ($Q_i \in [1995 - 2000]$) | *1* | *L1* | $Q_i^n$ = *0.025(*$Q_i$*)- 0.11* |
| | *2* | *L2* | $Q_i^n$ = *0.16(*$Q_i$*)- 0.10* |
| | *3* | *L3* | $Q_i^n$= *0.18(*$Q_i$*)- 0.04* |
| | *4* | *T1* | $Q_i^n$= *0.06(*$Q_i$*)- 0.004* |
| | *5* | *R1* | $Q_i^n$ = *0.064(*$Q_i$*)- 0.004* |
| ANFIS ($Q_i \in [2000 - 2023]$) | *1* | *L1* | $Q_i^n$= *0.14(*$Q_i$*)- 0.038* |
| | *2* | *L2* | $Q_i^n$ = *-0.17(*$Q_i$*)+ 0.51* |
| | *3* | *L3* | $Q_i^n$= *-0.12(*$Q_i$*)- 0.15* |
| | *4* | *T1* | $Q_i^n$ = *-0.20(*$Q_i$*)- 0.13* |
| | *5* | *T2* | $Q_i^n$ = *0.025(*$Q_i$*)- 0.0065* |
| | *6* | *T3* | $Q_i^n$ = *0.0068(*$Q_i$*)- 0.008* |
| | *7* | *R1* | $Q_i^n$ = *- 0.086(*$Q_i$*)+ 0.046* |

| | | |
|---|---|---|
| *8* | *R2* | $Q_i^n = 0.018(Q_i) - 0.06$ |
| *9* | *R3* | $Q_i^n = 1.6x10^{-7}(Q_i) + 4.9.10^{-7}$ |

***Table 2:*** *GENOFIS-based If-Then rules and consequent parameters*

| | Rule no. | Antecedent $Q_i$ | Consequent $Q_i^n$ |
|---|---|---|---|
| GENOFIS ($Q_i \in [\mathbf{1991-1995}]$) | *1* | *1991-1992* | $Q_i^n = a_1(Q_i)^6 + b_1(Q_i)^5 + c_1(Q_i)^4 + d_1(Q_i)^3 + e_1(Q_i)^2 + f_1(Q_i) + g_1$ |
| | *2* | *1992-1994* | $Q_i^n = a_2(Q_i)^6 + b_2(Q_i)^5 + c_2(Q_i)^4 + d_2(Q_i)^3 + e_2(Q_i)^2 + f_2(Q_i) + g_2$ |
| | *3* | *1994-1995* | $Q_i^n = a_3(Q_i)^6 + b_3(Q_i)^5 + c_3(Q_i)^4 + d_3(Q_i)^3 + e_3(Q_i)^2 + f_3(Q_i) + g_3$ |
| GENOFIS ($Q_i \in [\mathbf{1995-2000}]$) | *1* | *1995-1997* | $Q_i^n = b_1(Q_i)^5 + c_1(Q_i)^4 + d_1(Q_i)^3 + e_1(Q_i)^2 + f_1(Q_i) + g_1$ |
| | *2* | *1997-1998* | $Q_i^n = a_2(Q_i)^6 + b_2(Q_i)^5 + c_2(Q_i)^4 + d_2(Q_i)^3 + e_2(Q_i)^2 + f_2(Q_i) + g_2$ |
| | *3* | *1998-2000* | $Q_i^n = a_3(Q_i)^6 + b_3(Q_i)^5 + c_3(Q_i)^4 + d_3(Q_i)^3 + e_3(Q_i)^2 + f_3(Q_i) + g_3$ |
| GENOFIS ($Q_i \in [\mathbf{2000-2023}]$) | *1* | *2000-2010* | $Q_i^n = f_1 Q_i + g_1$ |
| | *2* | *2010-2017* | $Q_i^n = e_2(Q_i)^2 + f_2 Q_i + g_2$ |
| | *3* | *2017-2023* | $Q_i^n = d_3(Q_i)^3 + e_3(Q_i)^2 + f_3 Q_i + g_3$ |

*__Table 3:__ Consequent parameters for the GENOFIS model*

| Rainfall records | [***1991-1995***] | | | | | | | [***1995-2000***] | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $Q_i \in$ | **a$_1$** | **b$_1$** | **c$_1$** | **d$_1$** | **e$_1$** | **f$_1$** | **g$_1$** | **a$_2$** | **b$_2$** | **c$_2$** | **d$_2$** | **e$_2$** | **f$_2$** | **g$_2$** |
| [1991-1995] | 0 | 0 | 0 | 0 | 0 | -0.016 | 0.14 | 0 | 0 | 0 | 0 | 0.3 | -0.31 | 0.41 |
| [1995-2000] | 0 | -0.03 | 0.01 | 0.11 | -0.05 | 0.1 | 0.53 | -74.2 | 23.1 | -132.5 | 145.8 | 630.5 | 195.15 | -192 |
| [2000-2023] | -0.021 | 5.10$^{-5}$ | 0.12 | 0.21 | -0.34 | -0.03 | -0.07 | 28.14 | -107.02 | 27.72 | 54.8 | 410.23 | 58.1 | 105 |

*__Table 4:__ Consequent parameters for the GENOFIS model (__continued__)*

| Rainfall records | [***2000-2023***] | | | | | | |
|---|---|---|---|---|---|---|---|
| $Q_i \in$ | **a$_3$** | **b$_3$** | **c$_3$** | **d$_3$** | **e$_3$** | **f$_3$** | **g$_3$** |
| [1991-1995] | 0 | 0 | 0 | 0.013 | -0.063 | 0.145 | -5.45 |
| [1995-2000] | 75 | 23.8 | -2.18 | 45.07 | 53.5 | 38.43 | 84.5 |
| [2000-2023] | 63.14 | 161.7 | 5.4.10$^{4}$ | 4.1.10$^{7}$ | 10$^{2}$ | 10$^{4}$ | 7.5.10$^{2}$ |

The fuzzy Inference System rules are shown in Table 1 and 2 respectively for the ANFIS and GENOFIS models, and the consequent parameters for the ANFIS and GENOFIS models are provided in *Table 3* and *4*, respectively.

## Climate Change Projections Downscaled on the City of Kigali

## Climate Change Projections

### *NEX-GDDP-CMIP6*

The NEX-GDDP-CMIP6 dataset was used to analyse future trends in terms of temperature and precipitation for Rwanda. Thrasher et al. (2022) have discussed in details the NEX-GDDP-CMIP6 data set. The NEX-GDDP-CMIP6 dataset is comprised of global downscaled climate scenarios derived from the General Circulation Model (GCM) runs conducted under the Coupled Model Intercomparison Project Phase 6 (CMIP6) and across four greenhouse gas emissions scenarios known as Shared Socioeconomic Pathways (SSPs). The dataset compiles climate projections from 35 CMIP6 GCMs and four SSP scenarios, for the period 2015-2100, as well as the historical experiment for each model, for the period 1950-2014. Each of these climate projections is downscaled to a spatial resolution of 0.25 degrees x 0.25 degrees.

Two SSP scenarios (SSP2-4.5 and SSP5-8.5) are analysed to provide a range of future climate projections (Nazarenko et al. 2021). SSP2-4.5 represents a “stabilisation scenario”, in which greenhouse gas emissions peak around 2040 and are then reduced. Although often used as ‘business as usual’, the SSP5-8.5 is above the business-as-usual emission scenarios and designed as a worst-case scenario. We include this scenario as an upper limit to the possible future climate. These scenarios are selected as they represent an envelope of likely climate changes and hence cover a plausible range of possible future changes in temperature and precipitation relating to project implementation. Fig. 5 depicts the projected changes in climatic means in Rwanda.

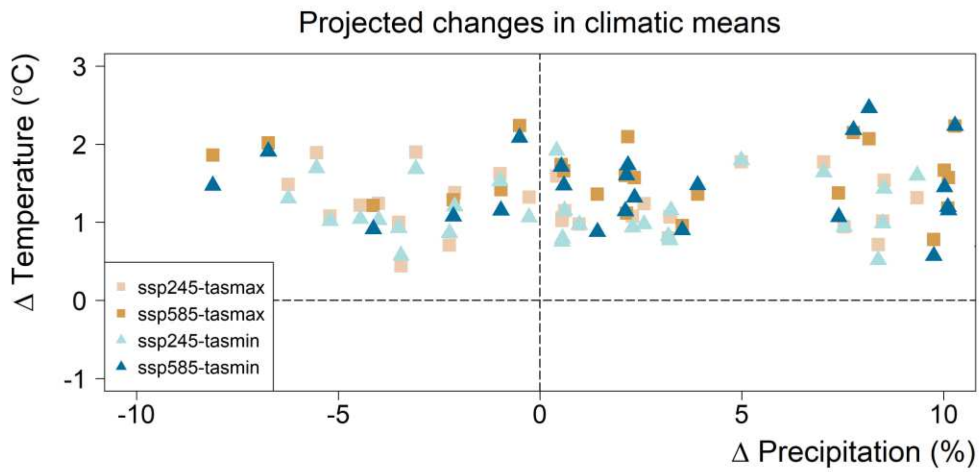


**Fig. 5.** Projected temperature (max and min) and precipitation changes for Rwanda derived from NEX-GDDP-CMIP6.

A 20-year window was selected as appropriate for deriving average climate changes, effectively considering interannual variations in temperature and precipitation, and robust comparison.

- Reference period [2015]: 2000 – 2019.
- Future period [2050]: 2040 – 2059.

From Fig. , temperature and precipitation trends for Rwanda can be summarised, as derived from the ensemble mean of the considered GCMs. Under both SSP scenarios (SSP2-4.5 and SSP5-8.5), precipitation is expected to vary considerably across individual GCMs, but the ensemble mean indicates that precipitation is to increase by 2.4% to 7.6%, respectively. Mean temperatures are expected to increase on average by about 1.1 °C to 1.4 °C, respectively.

## Climate projection for Rwanda under CMIP5

Meteo-Rwanda regional climate projections were used to provide an analysis of future trends for temperature and precipitation. The dataset, provided by Meteo-Rwanda, was obtained from the Coordinated Regional Climate Downscaling Experiment (CORDEX Africa 0.44), and based on CMIP5. The data is available from 2021 to 2070 and downscaled to 0.22 km pixel size. All data were bias-corrected, set to standard calendar. Table 5 provides an overview of the GCM and RCM model combinations used to derive the data. For each variable the Representative Concentration Pathways (RCP) 4.5 and 8.5 was used for the analysis.

**Table 5.** Details Meteo-Rwanda regional climate projections

| *Variable* | *GCM* | *RCM* |
|---|---|---|
| Precipitation | MPI | REMO 2009 |
| Tasmax | MOHC | CCLM 4-8-17 |
| Tasmin | ICHEC | CCLM 4-8-17 |

## Coupling Rainfall Modelling with Climate Change Projections

Using trained and calibrated GENOFIS, ANFIS and SVM models, the results for predicted rainfall were analysed for the two projected climate scenarios, RCP 4.5 and 8.5. To quantify the impact, the baseline scenario was used as a reference to obtain relative and/ or absolute changes directly. The results thus present the change in monthly average from the baseline period (1991 – 2023), to the future period (2040 – 2059). 2020 and 2050 are selected as representative years for both baseline, and future projections, respectively.

## Results and Discussion

Our aim was to provide a more robust and accurate prediction for Kigali rainfall data. The model calibration results against the observed rainfall records from 1991 to 2009 (obtained from the

Rwanda Meteorological Agency) corresponding to 60% of all rainfall records for the GENOFIS, ANFIS, and SVM models are shown in Figure 5.

Model parametric results for the three models are depicted in Table 6. A relatively good agreement was found between the results of the GENOFIS model and observed rainfall data when compared to those of the ANFIS and SVM (Fig. 5). The model and parametric results of the ANFIS and SVM performed with nearly the same prediction error during calibration (Fig. 2).

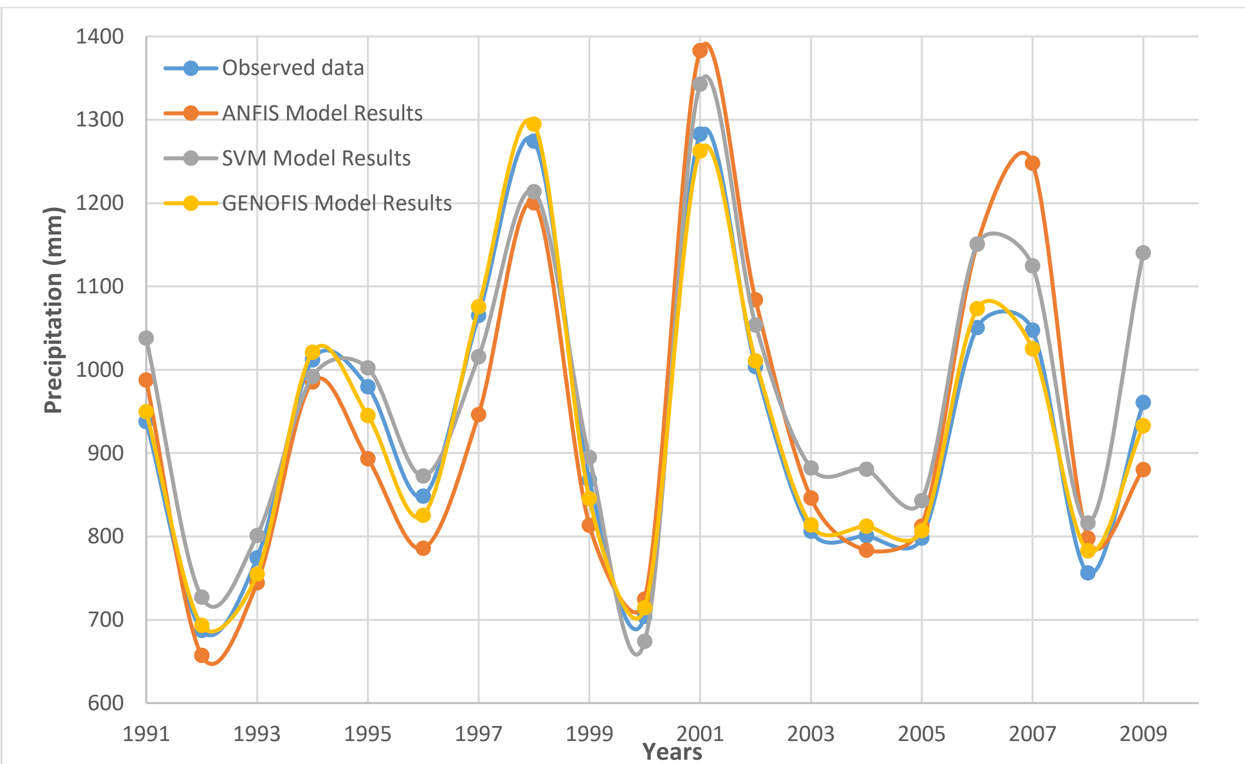


**Fig. 5:** Model results of GENOFIS, ANFIS and SVM during training and calibration for the baseline

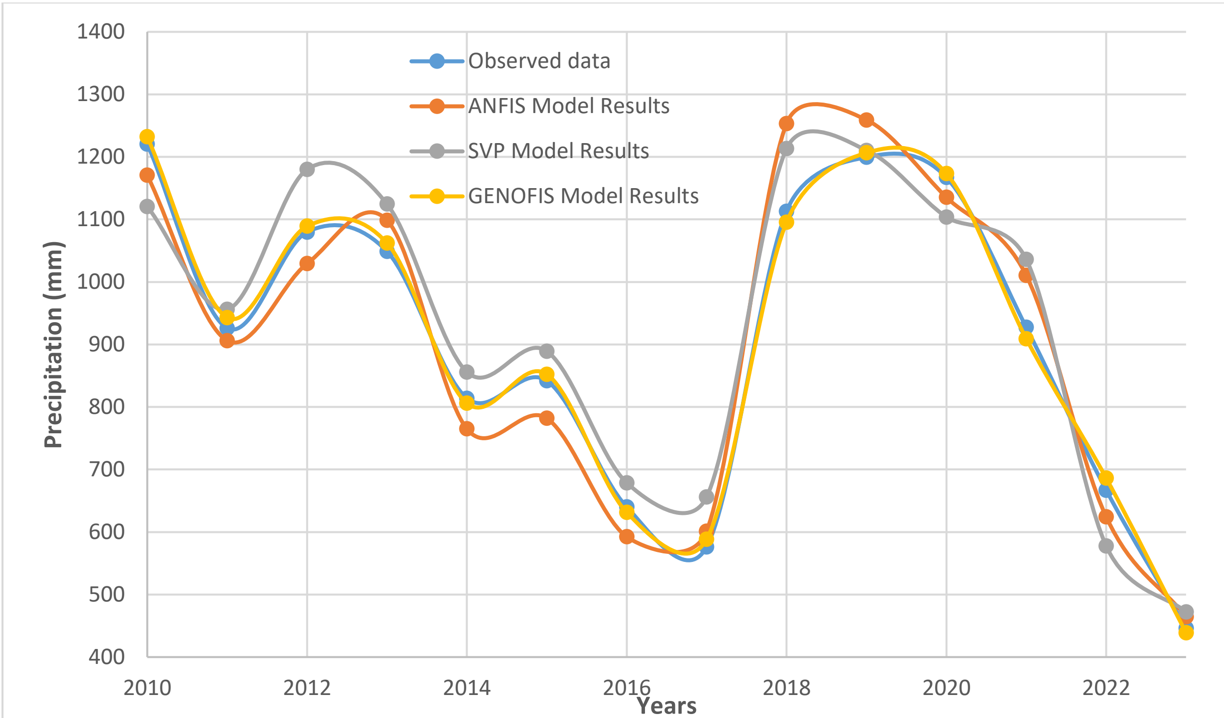


**Fig. 6**: Model results of GENOFIS, ANFIS and SVM during testing for the baseline

The GENOFIS, ANFIS and SVM models were validated with observed rainfall data from 2010 through 2023, corresponding to 40% of the rainfall records (Fig. 6). Once again, the GENOFIS model outperformed the other models for fitting of rainfall variation.

The calculated RMSE and CE values of GENOFIS, ANFIS and SVM models for calibration (training) and validation (testing) phases are presented in Table 6. For the calibration phase, RMSE values of GENOFIS, ANFIS and SVM models were calculated as 2.3 x $10^{-4}$, 6.8 x $10^{-3}$, and 9.3 x $10^{-3,}$ respectively. It can be seen that the GENOFIS has a smaller prediction error than ANFIS and SVM. During the validation (testing) phase of the modeling, the RMSE values for the GENOFIS, ANFIS and SVM models were 1.9 x $10^{-4,}$ 3.8 x $10^{-3,}$ and, 7.3 x $10^{-3}$, respectively. Again, the RMSE of the GENOFIS model was less than those of ANFIS and SVM. Table 6 shows the CE values of GENOFIS, ANFIS and SVM prediction results were 0.98, 0.93, and 0.95 for the calibration (training) phase and, 0.96, 0.91 and 0.93 for the validation (testing) phase, respectively. According to Donigan and Love (2003) and Altunkaynak (2019), if the CE value is greater than 0.85, the model performance good. All models have reproduced the rainfall data variance, but it is clear the GENOFIS model outperformed the others.

***Table 6:*** *Parametric modeling results*

| MODELS | Calibration | | | Validation | | |
|---|---|---|---|---|---|---|
| | ANFIS | GENOFIS | SVM | ANFIS | GENOFIS | SVM |
| Number of inputs | 1 | 1 | 1 | 1 | 1 | 1 |
| Processing time | 586 | 936 | N/A | 476 | 742 | N/A |
| IF-THEN rules | 9 | 3 | N/A | 5 | 3 | N/A |
| RMSE | $6.84\text{x}10^{-3}$ | $2.33\text{x}10^{-4}$ | $9.33\text{x}10^{-3}$ | $3.77\text{x}10^{-3}$ | $1.93\text{x}10^{-4}$ | $7.33\text{x}10^{-3}$ |
| CE | 0.93 | 0.98 | 0.95 | 0.91 | 0.98 | 0.95 |

[*]**RMSE** is dimensionless and [*]Processing time is in seconds

Figures 7 and 8 present the GENOFIS, ANFIS and SVM model values with the observed rainfall data during calibration and validation. These results are plotted against the **1:1** line. It is obvious the GENOFIS model prediction results followed the corresponding observed rainfall data more closely than those of the ANFIS and SVM models. In summary, both the calculated values of diagnostic measures RMSE and CE show an increased accuracy when matching rainfall variation using the GENOFIS model when compared with ANFIS and SVM models, and therefore increases confidence is using these results as input to hydrologic models to manage urban flooding and sediment transport challenges.

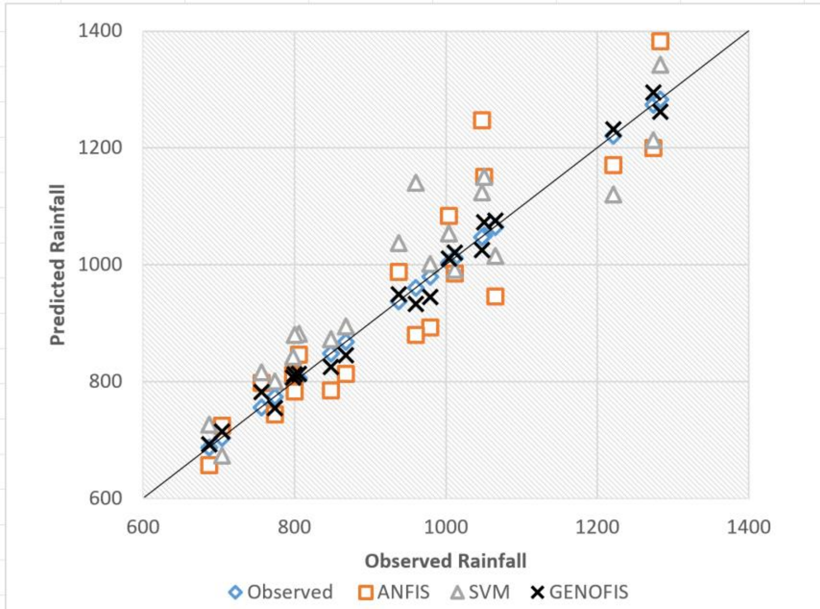


**Fig. 7:** $45^0$ exact model (1:1) line for rainfall modeling results in calibration process for the baseline

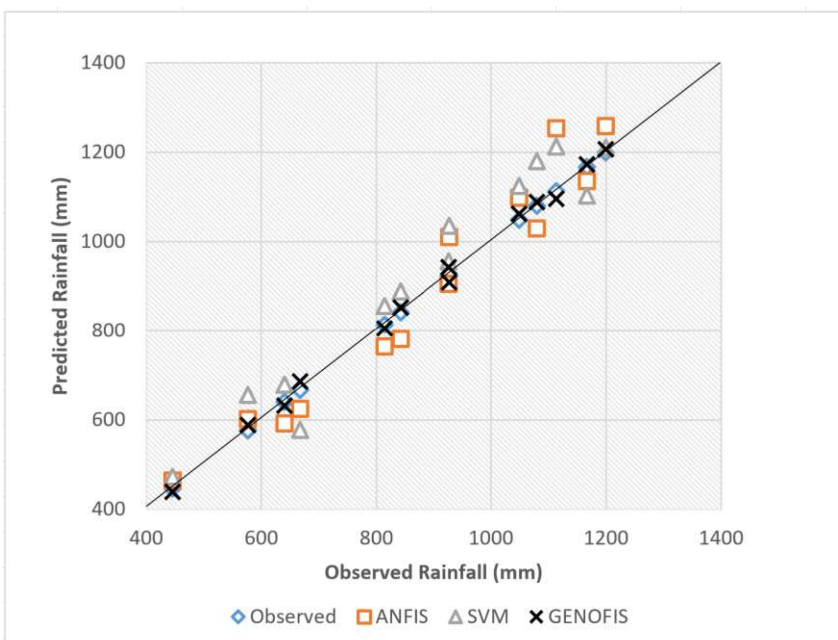


**Fig. 8:** $45^0$ exact model (1:1) line for rainfall modeling results in validation phase for the baseline

Predicted rainfall with GENOFIS was evaluated using RCP 4.5 and 8.5 models, and **Error! Reference source not found.** shows the expected relative changes in average precipitation under both climate scenarios in all main catchments of the country. Under RCP 4.5 the predicted precipitation trends are quite comparable across the nine catchments, precipitation is expected to remain relatively stable though a decrease by about -1.2% is expected (range between -4.2% decrease and 2.3% increase) taking 2050 year as the representative projection year. Under RCP 8.5, there is more variability expected in predicted precipitation changes. Looking at the national picture, the highest decreases in precipitation are expected for Lake Kivu catchment (CKIV, -16.8%) and Upper Nyaborongo (NNYU, -10.7%) catchments. In contrast, the highest increases in precipitation are expected for Lower Akagera (NAKL, 5.1%) and Muvumba (NMUV, 3.7) catchments. On average, the Meteo-Rwanda regional climate projections foresee an average decrease in precipitation of about 5%. The NNYL which is Lower Nyabarongo within which the City of Kigali is located will display a stable climate by 2059 but is most likely going to be influenced by micro climate that could affect Northwest and Central region of the country, and the Upper Nyabarongo, where much of increased intensity of rainfall will be observed.

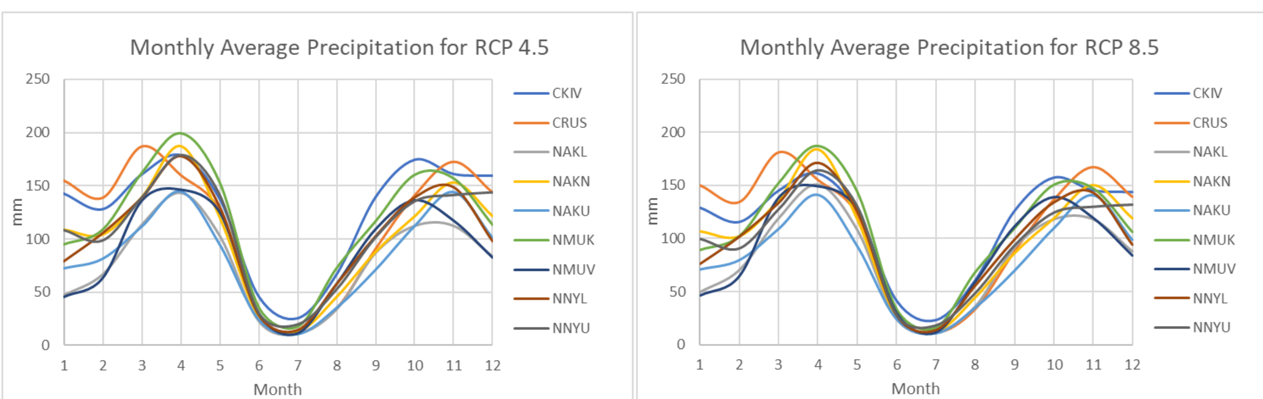


**Fig. 9**1. Monthly average precipitation for RCP 4.5 and RCP 8.5 for the period 2040 – 2059.

## CONCLUSIONS AND RECOMMENDATIONS

The results of the enhanced GENOFIS prediction model using the incomplete rainfall data in the city of Kigali can now be used as a continuous input function for evaluation of hydrologic challenges such as flooding and sediment transport affecting key flood hotspots in the City of Kigali. Novel GENOFIS coupled with climate change projections with RCP 4.5 and 8.5 have revealed accurate prediction of the future rainfall trends, and this is a tangible tool that can be integrated in Climate Smart National Water Resources Management as the country and the region keep building a more climate change resilient environment.

## Declarations:

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**Conflicts of interest/Competing interests**

The authors declare that there is no conflict of interest regarding publishing this article.

**Availability of data and material**

The gauged rainfall data used in this study will be available upon request from the corresponding author.

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