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Modelling and forecasting reservoir sedimentation of irrigation dams in the Guinea Savannah Ecological Zone of Ghana

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ABSTRACT

Effective management of reservoir sedimentation requires models that can predict sedimentation of the reservoirs. In this study, linear regression, non-linear exponential regression and artificial neural network models have been developed for the forecasting of annual storage capacity loss of reservoirs in the Guinea Savannah Ecological Zone (GSEZ) of Ghana. Annual rainfall, inflows, trap efficiency and reservoir age were input parameters for the models whilst the output parameter was the annual sediment volume in the reservoirs. Twenty (20) years of reservoirs data with 70% data used for model training and 30% used for validation. The ANN model, the feed-forward, back-propagation algorithm Multi-Layer Perceptron model structure which best captured the pattern in the annual sediment volumes retained in the reservoirs ranged from 4-6-1 at Karni to 4-12-1 at Tono. The linear and nonlinear exponential regression models revealed that annual sediment volume retention increased with all four (4) input parameters whilst the rate of sedimentation in the reservoirs is a decreasing function of time. All the three (3) models developed were noted to be efficient and suitable for forecasting annual sedimentation of the studied reservoirs with accuracies above 76%. Forecasted sedimentation up to year 2038 (2019–2038) using the developed models revealed the total storage capacities of the reservoirs to be lost ranged from 13.83 to 50.07%, with 50% of the small and medium reservoirs filled with sediment deposits if no sedimentation control measures are taken to curb the phenomenon.

Key words: artificial neural network, forecasting, irrigation dams, linear regression, nonlinear exponential regression, reservoir sedimentation modelling

HIGHLIGHTS

- The study developed two mathematical models using linear regression.
- The study developed non-linear exponential regression.
- The study developed an artificial neural network (ANN) model.
- The study forecasted sedimentation up to year 2038 using the developed models.
- The study revealed that the total storage capacities of the reservoirs to be lost ranged from 13.83 to 50.07%.

INTRODUCTION

The development and management of dams have been become a necessity in recent years, due to the seasonality of rainfall and water scarcity in many parts of the world (Yusuf & Yusuf 2012). Dams and their associated reservoirs store water during the rainy season and make it available for humans and animals to use in their immediate environment (Huang *et al.* 2018; Adongo *et al.* 2019). The contribution of irrigation dams towards boosting agricultural production is crucial, especially in dryland environments such as arid, semi-arid and other water-scarce areas in the world (Chihombori *et al.* 2013). As of 2011, the Global Reservoir and Dam estimated about 16.7 million dams with a total storage capacity of about 8,070 km^3 in the world (Lehner *et al.* 2011).

Despite the numerous importance of dams, one of the critical problems in their operation and management is the continuous deposition of sediments in their reservoirs via inflows (Chihombori *et al.* 2013). The construction of a dam and its reservoir on rivers and streams automatically cuts off sediment transport to the downstream side of the dam (Salimi *et al.* 2013), and this development has made the reservoir become a natural means for retention of the transported sediment (Hasan *et al.* 2011). Sedimentation results in loss of reservoir depth, storage capacity and reduction of designed lifespan of reservoirs (Basson 2010) and blocks irrigation canals, damages

power generating turbines, and degrades reservoir water quality (Halcrow 2001). According to White (2001) and Schleiss *et al.* (2016), the existing reservoirs worldwide lose between 0.5% and 1.0% of their total storage capacity yearly with Basson (2010) reporting the global average sedimentation rate as between 0.7% and 0.8% per annum with highest occurrence in arid and semi-arid regions. Adongo *et al.* (2019) reported that reservoirs in northern Ghana are losing their storage capacities to sedimentation at a rate of 0.26 to 0.91% per year.

Modelling and forecasting of reservoir sedimentation has been the subject of several empirical studies since the 1950s (Jothiprakash & Garg 2009). In recent years, the artificial neural network (ANN) technique has shown excellent performance in regression, especially when used for pattern recognition, function estimation, forecasting and modelling (ASCE 2000). Jothiprakash & Garg (2009) noted that ANN is a highly non-linear mathematical model that can capture complex interactions among the input and output variables without any prior knowledge about the nature of these interactions. In the fields of hydrology and water resources engineering, ANNs have been extensively applied because of their ability to model both linear and non-linear systems without the need to make assumptions as are done in most conventional statistical approaches (Nourani 2009). Sarangi & Bhattacharya (2005) compared the performance of ANN models for sediment yield prediction with a linear regression model for the Banha watershed in India. Sarangi *et al.* (2005) developed ANN and linear regression models using watershed geomorphologic parameters to predict surface runoff and sediment yield of the St. Esprit Watershed, Quebec, Canada. Jothiprakash & Garg (2008) found that linear regression techniques sometimes underestimate or overestimate observed values and need modifications. Jothiprakash & Garg (2009) modelled the annual volume of sediment retained in the Gobindsagar Reservoir in India using the ANN and linear regression models. Salimi *et al.* (2013) also applied both ANN and linear regression models to model the sedimentation rate of the Karaj Dam Reservoir in Iran.

In this study, an ANN, linear and non-linear exponential regression models were explored and developed for estimation of annual rate of sedimentation of nine (9) reservoirs in the Guinea Savannah Ecological Zone of Ghana. The novelty of this study is that it used input parameters (Figure 2) that have direct influence in the sedimentation process of reservoirs in the Guinea Savannah Ecological Zone of Ghana in developing the ANN models for estimating and forecasting reservoir sedimentation in the study area and other areas with similar characteristics.

MATERIALS AND METHODS

Description of study area

The study was carried out in nine (9) reservoirs in the Guinea Savannah Ecological Zone (GSEZ) of northern Ghana, namely Daffiama, Karni and Sankana reservoirs in the Upper West Region; Bontanga, Golinga and Libga reservoirs in the Northern Region; and Gambibgo, Tono and Vea reservoirs in the Upper East Region. Figure 1 is a map showing the study reservoirs whilst the principal characteristics of the reservoirs are presented in Table 1. The study reservoirs represent 3% of the number of reservoirs in the GSEZ of northern Ghana with all the three (3) large-sized reservoirs covered and with six (6) being small- and medium-sized reservoirs. Small, medium and large reservoirs are reservoirs with maximum storage capacities of $<1 \, Mm^3$, 1 to 3 Mm^3 and $>3 \, Mm^3$ respectively (Basson 2007; Kolala *et al.* 2015).

Reservoir sedimentation modelling approaches

Linear regression and non-linear exponential regression models

Linear regression (LR) and non-linear exponential regression (NER) analyses were performed, relating the output parameter (annual deposited sediment volume) and the input parameters (annual inflow, annual rainfall, annual reservoir trap efficiency and age of reservoir) using Minitab software, version 16.0 and R software, version 3.6.3 respectively.

A general mathematical model of the form (Equation (1)) which provides a linear relation for *SV* with constant variance and good fits to the assembled data is given as:

$$SV = \theta_1 + \theta_2(AR) + \theta_3(AI) + \theta_4(ATE) + \theta_5(Ra) \tag{1}$$

where: SV = predicted annual sediment volume retention (m^3); AR = annual rainfall (mm); AI = annual water inflow (m^3); ATE = annual trap efficiency (%); Ra = age of reservoir (y); θ_1 = model constant; θ_2 to
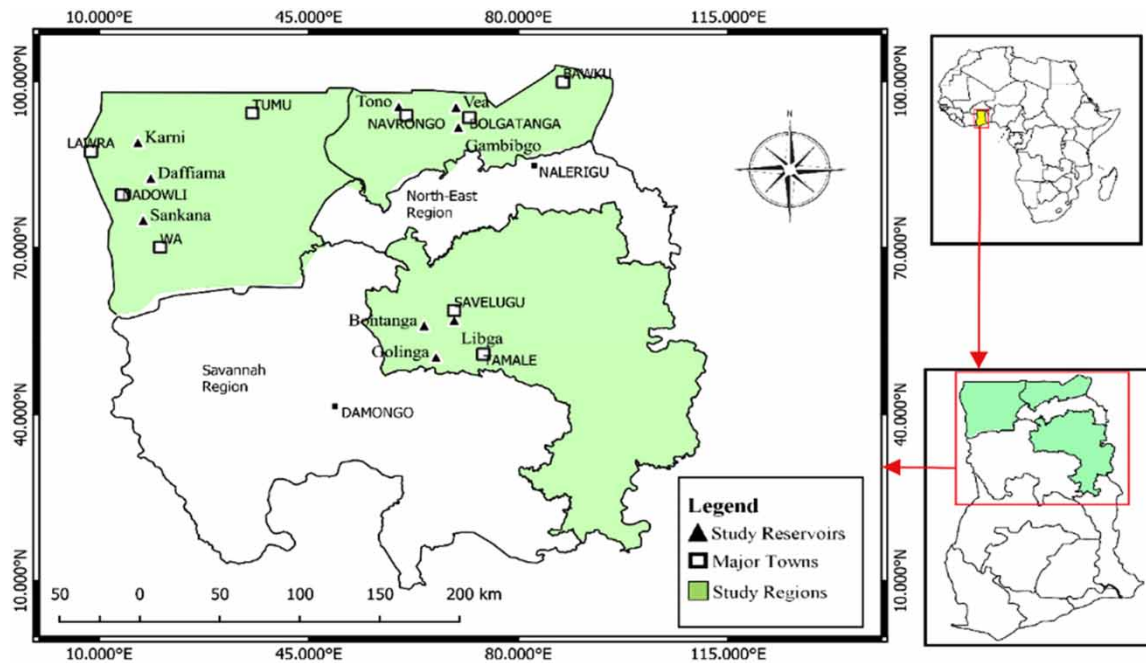
Figure 1 | Map of northern Ghana showing the study reservoirs (Adapted from Adongo *et al.* 2019).

θ_5 = coefficients of predictors. Values of the parameters θ_2 to θ_5 were found using multivariate optimization in Minitab software version 16.

A general mathematical model of the form (Equation (2)) which provides a non-linear exponential relation for *SV* with constant variance and good fits to the assembled data is given as:

$$SV = \theta_1[(AR^{\theta_2})(AI^{\theta_3})(ATE^{\theta_4})(Ra^{\theta_5})] \tag{2}$$

where: SV = predicted annual sediment volume retention (m^3); AR = annual rainfall (mm); AI = annual water inflow (m^3); ATE = annual trap efficiency (%); Ra = age of reservoir (y); θ_1 = model scaling coefficient; θ_2 to θ_5 = scaling exponents of predictors. Values of the parameters θ_2 to θ_5 were found using multivariate optimization in R software.

Artificial neural network (ANN) model

An artificial neural network (ANN) was used to model the rate of reservoir sedimentation in the irrigation dams. ANN is a black box and programmed computational non-linear modelling tool that has an input layer, a hidden layer and an output layer. Each layer consists of several neurons and the layers are interconnected by sets of correlated weights. The neurons receive inputs from the initial inputs or the interconnections and produce outputs by the transformation, using an adequate non-linear transfer function (Sultana & Naik 2016). Four (4) steps were followed in the design and development of the ANN model as described by Vilas *et al.* (2011). Using the input parameters; that is, annual inflows, annual rainfall, reservoir trap efficiency and age of the reservoir and the output parameter; that is, annual deposited sediment volume for each reservoir, the trial-and-error procedure of Jothiprakash & Garg (2009) and Salimi *et al.* (2013) was used to select the appropriate ANN architecture. The input parameters were chosen on the basis of their influence in the reservoir sedimentation process. Also, the trial-and-error approach was used to determine the number of hidden layers and the number of neurons in each hidden layer. The number of neurons in the hidden layer plays an essential role in the performance of the ANN model. Due to the single output nature of the model, the linear transfer function corresponding to the hidden layer and the sigmoid transfer function corresponding to the single output layer (annual deposited sediment volume) were used to select the best ANN architecture. All the considered data set values were pre-processed and normalized using Equation (3) given by Salimi *et al.* (2013) to make the entries standardized. The transformation of the observed data was necessary to make them compatible with the attributes of the transfer

Table 1 | Description of study reservoirs

Name of reservoir		Bontanga	Golinga	Libga	Gambibgo	Tono	Vea	Daffiama	Karni	Sankana
Location	Region	Northern			Upper East			Upper West		
	District/Municipality	Kumbungu	Tolon	Savelugu	Bolgatanga	Kassena-Nankana	Bongo	Daffiama-Bussie-Issa	Lambussie-Karni	Nadowli-Kaleo
	Coordinates	9° 57′N	9° 22′N	9° 59′N	10° 45′N	10° 52′N	10°52′N	10° 27′N	10° 40′N	10° 11′N
		1° 02'W	0° 57'W	0° 85'W	0° 50'W	1° 08'W	0°51'W	02° 34'W	02° 38'W	02° 36'W
Year construction started		1980	1971	1969	1960	1975	1975	1986	1985	1965
Year constructed completed		1986	1974	1980	1963	1985	1980	1989	1988	1970
Maximum storage capacity of reservoirs (10^6 m^3)		25	1.23	0.76	0.30	93	17	0.31	0.33	1.70
Catchment area (km^2)		165	53	31	1.70	650	136	21	35	141
Class of reservoir based on capacity		Large	Medium	Small	Small	Large	Large	Small	Small	Medium
Management		GIDA	GIDA	GIDA	WUA/GIDA	ICOUR	ICOUR	WUA/GIDA	WUA/GIDA	WUA/GIDA
Agro-ecological zone		Guinea Savannah			Guinea/Sudan Savannah			Guinea Savannah		
Geology of reservoir catchment		Precambrian basement rocks and Paleozoic rocks from the Voltaian sedimentary basin			Metamorphic and igneous rocks with gneisss, granodiorite and sandstone			Precambrian, granite and metamorphic rocks		
Soil classes in reservoir catchment		Acrisols, plinthosols, planosols, luvisols, gleysols and fluvisols			Plinthosols, luvisols, vertisols, leptosols, lixisols, and fluvisols			Lixisols, fluvisols, leptosols, vertisols, acrisols and plinthosols		

GIDA, Ghana Irrigation Development Authority; ICOUR, Irrigation Company of Upper Regions; WUA, Water User Association; Small = Storage capacity <1 Mm^3; Medium = Storage capacity from 1–3 Mm^3; Large = Storage capacity >3 Mm^3 Source: GIDA (2017), ICOUR (2017) and Adongo (2019).
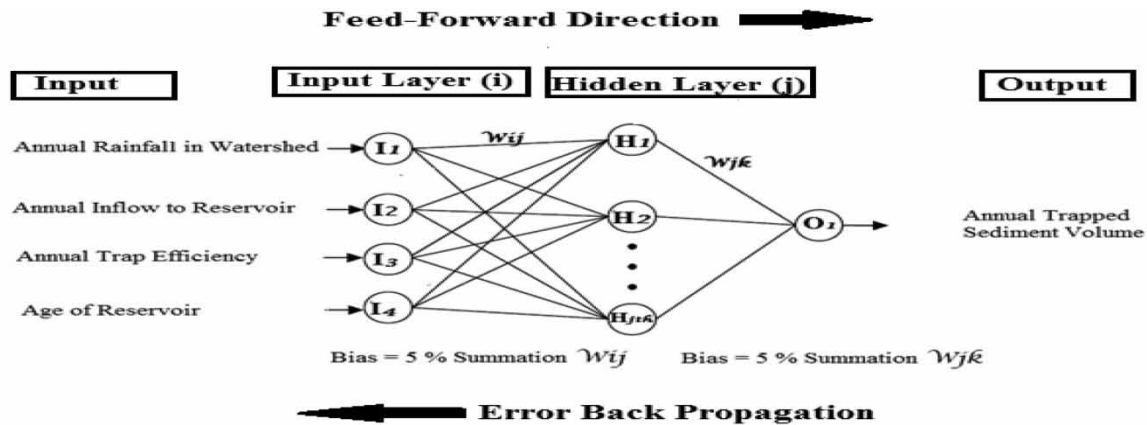
Figure 2 | Detailed artificial neural network architecture of the reservoir sedimentation model. I = input layer (Four input parameters were used), H = hidden layer (dependent on the training algorithm), O = output layer (the annual sediment inflow data were used).

functions:

$$x_n = 2\left(\frac{x_i - x_{\min}}{x_{\max} - x_{\min}}\right) - 1 \tag{3}$$

where: x_n = normalized data; x_i = real amount of data; $x_{\min}$ = minimum entry data and $x_{\max}$ = maximum entry data. Min-max normalization preserves the relationships among the normalized and original data values (Vamsidhar *et al.* 2010).

In order to train and validate the proposed ANN model, the split-sample method was applied, in which 70% of the data was used for training the model and then the remaining 30% was used for validation. This split of dataset (70% training and 30% validation) gave the best accuracies in the training and validation stages. Similarly, Salimi *et al.* (2013) and Sultana & Naik (2016) recorded the highest accuracies using the 70% training and 30% validation split. The feed-forward back-propagation (FFBP) ANN training algorithm presented in Figure 2 was used to model the data.

Acquisition of model input and output parameters
Rainfall data
Twenty (20) years (1999–2018) rainfall data for the catchments of the various study reservoirs was obtained from the Ghana Meteorological Agency.

Estimation of annual water inflows to the reservoirs
The Natural Resource Conservation Service–Curve Number (NRCS-CN) method developed by the United States Department of Agriculture (USDA-NRCS 1985) was used to estimate the water inflows into the study reservoirs. The method has its major input parameters as landuse/landcover classes, hydrologic soil groups, antecedent soil moisture conditions, rainfall, maximum potential soil retention, curve number and weighted curve number (USDA-NRCS 1985). Equations (4)–(6) as developed by USDA-NRCS (1985) were very useful in the estimation of the water inflows into the reservoirs.

$$CN_{wt} = \frac{\sum A_i \times CN_i}{\sum A} \tag{4}$$

where: CN_{wt} = area weighted curve number; CN_i = curve number of each LULC class; A_i = area of each LULC class (km^2) and A = area of the catchment (km^2).

$$Q_d = \frac{(P - 0.2S)^2}{P + 0.8S} \tag{5}$$

where: Qd = runoff depth (mm); P = daily rainfall (mm) and S = potential maximum soil moisture retention after runoff begins (mm).

$$Q_v = Q_d \times A \tag{6}$$

where: Q_v = runoff volume (water inflow) (m^3); Q_d = runoff depth (m) and A = area of reservoir catchment (m^2).

Estimation of trap efficiencies of reservoirs

The trap efficiencies of the large reservoirs; that is, Tono, Vea and Bontanga, were estimated using the empirical model of Gill (1979) for medium-grained sediment given in Equation (7):

$$TE_{Gill} = 100 \left[\frac{\left(\frac{C}{I}\right)}{0.012 + 1.02\left(\frac{C}{I}\right)} \right] \tag{7}$$

where: TE$_{Gill}$ = Gill's trap efficiency for medium-grained sediments (%); C = designed storage capacity (m^3) and I = annual water inflow to the reservoir (m^3).

The trap efficiencies of the small and medium reservoirs; that is, Gambibgo, Libga, Karni and Daffiama and Golinga and Sankana, were determined using the empirical model of Ward (1980) given in Equation (8):

$$TE_{ward} = 100 \left[1 - \frac{0.05}{\sqrt{\left(\frac{c}{I}\right)}} \right] \tag{8}$$

where: TE$_{Ward}$ = ward's trap efficiency (%); C = designed storage capacity of the reservoir (m^3) and I = annual water inflow to the reservoir (m^3).

Estimation of annual sediment volume retention in the reservoirs

The grab sampling method (Mavima et al. 2011) was used to estimate sediment transported into the reservoirs annually via surface runoff with Equation (9) developed by Strand & Pemberton (1982) used in computation of the annual sediment volume in the reservoirs:

$$ARSed = 9.4560 \times 10^{-10} \times TASL \times AI \times ATE \tag{9}$$

where: SV = annual volume of sediment retained in the reservoirs (m^3/y); TASL – total annual sediment concentration in water inflows to reservoir (mg/L); AI = annual water inflow (l) and ATE = annual trap efficiency of the reservoir (%).

RESULTS AND DISCUSSION

Modelling input and output parameters of reservoir sedimentation

The four (4) input parameters used to model the rate of sedimentation of the reservoirs were annual rainfall, annual water inflow, annual trap efficiency and age of reservoir, whilst the output parameter was annual volume of sediment deposit (Table 2). These input parameters were selected because of their high influence in the sedimentation process of a reservoir. Salimi et al. (2013) and Sultana & Naik (2016) noted that reservoir sedimentation cannot occur without the influence of rainfall, water inflows, sediment inflows and the sediment trapping efficiency of the reservoir. As presented in Table 2, the annual rainfall in the reservoirs was found to vary between 617.20 mm and 1,382.30 mm for the period of 2009–2018. The recorded annual water inflows to the reservoirs ranged from 197,836 m^3 at Daffiama to 55,371,500 m^3 at Tono. This variation of annual water inflows among the various catchments was noted to be influenced by catchment size, vegetation cover, antecedent moisture content, rainfall amount, land uses and soil characteristics. The trap efficiency of the reservoirs was found to range from 45.56 to 99.91%, with the least and highest trap efficiencies being recorded at Gambibgo and Tono reservoirs, respectively. The small and medium reservoirs were noted to have lower trap efficiencies

Table 2 | Input and output parameters for modelling of reservoir sedimentation

Period	2009–2018				
	Input parameters				Output parameter
Reservoir	Annual rainfall (mm)	Annual water inflow (m³)	Annual trap efficiency (%)	Age of reservoir (y)	Annual trapped sediment volume (m³)
Bontanga	791.30–1,382.30	9,348,700–13,742,850	54.98–96.05	33	76,389.82–104,548.1
Golinga	817.70–1,357.60	931,085–1,297,063	53.69–89.14	43	7,287.74–10,293.83
Libga	791.30–1,382.30	645,606–1,087,610	50.08–87.54	39	3,449.06–7,308.37
Gambibgo	732.90–1,265.90	114,990–196,434	45.56–78.56	56	1,218.83–2,002.38
Tono	617.20–1,365.00	36,092,500–55,371,500	74.77–99.91	34	216,798.8–355,016.9
Vea	732.90–1,265.90	7,002,800–12,387,040	54.35–93.87	39	53,869.04–82,505.26
Daffiama	811.60–1,292.30	197,836–249,237	51.27–81.50	30	1,594.42–2,027.35
Karni	811.60–1,292.30	217,402–265,600	52.73–83.85	31	2,358.27–2,935.09
Sankana	811.60–1,292.30	1,227,075–1,498,077	57.01–90.77	49	7,021.75–10,327.52

than the large reservoirs and this could be due to their frequent annual spillage, hence higher sediment outflows. In a similar study by Sultana & Naik (2016), a trap efficiency range of 41.80–99.99% for the Sriramsagar reservoir, a large reservoir in Nizamabad was obtained. The annual volume of sediment retained in the reservoirs was estimated to range from 1,594.42 m³ at Daffiama reservoir to 355,016.9 m³ at Tono reservoir. These levels of sediment retention were noted to be influenced by poor land use practices in the catchments and buffer zones of the reservoirs causing high levels of sediment production and inflows into the reservoirs. The reservoirs also lacked the facilities to flush out sediment, hence little sediment outflow from the reservoirs.

Reservoir sedimentation modelling using linear and non-linear exponential regression

Relating the output parameter to the four (4) input parameters in Minitab version 16.0, the overall response of the multi variate linear regression analysis for each of the study reservoirs is presented in Table 3 and the non-linear exponential regression models in Table 4. The linear regression (LR) models recorded an R^2 of 0.763–0.902 (Table 3), thus suggesting that the selected input variables accounted for about 76.3 to 90.2% of the volume of sediment retained in the reservoirs, whilst other factors accounted for about 9.8–23.7%. The results also showed that an increase in the annual rainfall by a unit resulted in an increase in the volume of sediment retention in the reservoirs by 6.05–42.02% (Table 3). A unit increase in annual water inflows also resulted in an increase in volume of sediment retention in the reservoirs by 0.49–1.08%. For annual trap efficiency, the

Table 3 | Response of linear regression model

Reservoir	Linear regression prediction models for annual sedimentation rate of study reservoirs	R^2	Eq.
Bontanga	SV = 0.4156 + 0.2998(AR) + 0.0068(AI) + 0.4046(ATE) + 0.0125(Ra)	0.808	2
Golinga	SV = 0.2336 + 0.4160(AR) + 0.0072(AI) + 0.1228(ATE) + 0.0103(Ra)	0.763	3
Libga	SV = 0.1208 + 0.3115(AR) + 0.0049(AI) + 0.5047(ATE) + 0.0117(Ra)	0.831	4
Gambibgo	SV = 0.9590 + 0.1289(AR) + 0.0102(AI) + 0.1961(ATE) + 0.0161(Ra)	0.852	5
Tono	SV = 0.3535 + 0.4202(AR) + 0.0051(AI) + 0.8560(ATE) + 0.0241(Ra)	0.899	6
Vea	SV = 0.6125 + 0.2304(AR) + 0.0053(AI) + 0.8723(ATE) + 0.0537(Ra)	0.801	7
Daffiama	SV = 0.5032 + 0.0605(AR) + 0.0037(AI) + 0.4641(ATE) + 0.0055(Ra)	0.824	8
Karni	SV = 0.7302 + 0.1894(AR) + 0.0108(AI) + 0.2865(ATE) + 0.0061(Ra)	0.875	9
Sankana	SV = 0.2060 + 0.1036(AR) + 0.0081(AI) + 0.1601(ATE) + 0.0635(Ra)	0.902	10

SV, annual sediment volume (m³); AR, annual rainfall (mm); AI, annual water inflow (m³); ATE, annual trap efficiency (%), and Ra, age of reservoir (y); R^2, coefficient of determination; Eq, equation.

Table 4 | Response of non-linear exponential regression model

Input parameter(s)	NER prediction models for annual reservoir sedimentation of study reservoirs	R^2	Eq.
Bontanga	$SV = 0.3011[(AR^{0.37})(AI^{0.39})(ATE^{0.82})(Ra^{0.09})]$	0.858	11
Golinga	$SV = 0.1380[(AR^{0.23})(AI^{0.42})(ATE^{0.79})(Ra^{0.07})]$	0.797	12
Libga	$SV = 0.2131[(AR^{0.27})(AI^{0.34})(ATE^{0.74})(Ra^{0.12})]$	0.845	13
Gambibgo	$SV = 0.4423[(AR^{0.21})(AI^{0.31})(ATE^{0.59})(Ra^{0.18})]$	0.872	14
Tono	$SV = 0.2415[(AR^{0.25})(AI^{0.44})(ATE^{0.91})(Ra^{0.09})]$	0.913	15
Vea	$SV = 0.5102[(AR^{0.38})(AI^{0.48})(ATE^{0.77})(Ra^{0.11})]$	0.841	16
Daffiama	$SV = 0.1771[(AR^{0.19})(AI^{0.38})(ATE^{0.81})(Ra^{0.08})]$	0.879	17
Karni	$SV = 0.2216[(AR^{0.16})(AI^{0.41})(ATE^{0.69})(Ra^{0.10})]$	0.892	18
Sankana	$SV = 02944[(AR^{0.24})(AI^{0.31})(ATE^{0.84})(Ra^{0.19})]$	0.910	19

NER, non-linear exponential regression; SV, annual sediment volume (m^3); AR, annual rainfall (mm); AI, annual water inflow (m^3); ATE, annual trap efficiency (%), and Ra, age of reservoir (y); R^2, coefficient of determination; Eq, equation.

model established that a unit increase resulted in an increase in volume of sediment retention in the reservoirs by 16.01–87.23%. A unit increase in age of reservoir resulted in a 0.55–6.35% increase in volume of sediment retention in the reservoirs. Equations (2)–(10) presented in Table 3 can be used as the models for estimating annual volume of sediment retention in reservoirs with accuracy between 76.3 and 90.2%.

Table 4 presents the expression for *SV*, which indicates that reservoir capacity loss increases with an increase of the independent variables; that is, *AR*, *AI*, *ATE*, and *Ra*. The exponent of *Ra* in Equations (11)–(19) is less than one, thus indicating that the rate at which sediment is retained in the reservoirs is a decreasing function of time. This is expected because those areas of the reservoir that are conducive to settlement of fine sediments will fill quickly in the early years and then no longer be available for deposition. Shrinkage of deposited silt also takes place from weathering action and the superimposed loads of additional sediment, thereby reducing the sedimentation rate with time (Froehlich *et al.* 2017).

The study developed Generalised Linear Regression (GLR) and Non-linear Exponential Regression (NER) models for application on different reservoirs in the Guinea Savannah Ecological Zone (GSEZ) of northern Ghana using the data of the nine (9) study reservoirs. The details of the GLR model are presented in Table 5, whilst the details of the NER model are presented in Table 6. It can be observed that the accuracy of the models increased with increased number of input parameters. The models with the highest R^2 are Equation (28) for the GLR model and Equation (37) for the NER model. These models were therefore considered the best models for predicting annual rate of reservoir sedimentation in the GSEZ. The R^2 of 0.913 for the GLR model and 0.941 for the NER model indicate that the input parameters account for about 91.3% and 94.1%, respectively, of the variations in annual reservoir sedimentation in the GSEZ. Both models show that annual

Table 5 | Linear regression models for estimating annual reservoir sedimentation in the GSEZ

Input parameter(s)	LR prediction models for annual reservoir sedimentation	R^2	Eq.
ATE	$SV = 0.2086 + 13.5011(ATE)$	0.276	20
AI	$SV = 0.1523 + 0.0019(AI)$	0.291	21
AR, AI	$SV = 0.3420 + 0.3870(AR) + 0.0071(AI)$	0.384	22
AR, ATE	$SV = 15.8402 + 12.3022(AR) + 13.7110(ATE)$	0.427	23
AI, ATE	$SV = 0.2434 + 0.0068(AI) + 0.5801(ATE)$	0.495	24
AR. ATE, Ra	$SV = 19.1401 + 13.0740(AR) + 13.3801(ATE) + 0.3102(Ra)$	0.539	25
AR, AI, ATE	$SV = 0.0970 + 0.8940(AR) + 0.0057(AI) + 0.8912(ATE)$	0.644	26
AI, ATE, Ra	$SV = 0.2845 + 0.0087(AI) + 0.7340(ATE) + 0.0104(Ra)$	0.705	27
AR, AI, ATE, Ra	$SV = 0.4201 + 0.0864(AR) + 0.0068(AI) + 0.8370(ATE) + 0.0047(Ra)$	0.913	28*

LR, linear regression; SV, annual sediment volume (m^3); AR, annual rainfall (mm); AI, annual inflow (m^3); ATE, annual trap efficiency (%), and Ra, age of reservoir (y); R^2, coefficient of determination; Eq, equation, * - Developed and proposed model for application on different reservoirs in the Guinea Savannah Ecological Zone of northern Ghana.

Table 6 | Non-linear exponential regression models for estimating annual reservoir sedimentation in the GSEZ

Input parameter(s)	NER prediction models for annual reservoir sedimentation	R^2	Eq.
ATE	$SV = 0.6186 ATE^{2.6}$	0.326	29
AI	$SV = 0.7042 AI^{0.70}$	0.341	30
AR, AI	$SV = 0.4549[(AR^{0.39})(AI^{0.56})]$	0.402	31
AR, ATE	$SV = 0.6944[(AR^{0.89})(ATE^{1.18})]$	0.431	32
AI, ATE	$SV = 0.5709[(AI^{0.57})(ATE^{0.53})]$	0.445	33
AR. ATE, Ra	$SV = 0.6432[(AR^{0.96})(ATE^{1.37})(Ra^{0.36})]$	0.558	34
AR, AI, ATE	$SV = 0.7998[(AR^{0.77})(AI^{0.14})(ATE^{0.81})]$	0.653	35
AI, ATE, Ra	$SV = 0.5194[(AI^{0.53})(ATE^{0.77})(Ra^{0.08})]$	0.772	36
AR, AI, ATE, Ra	$SV = 0.3801[(AR^{0.13})(AI^{0.17})(ATE^{0.62})(Ra^{0.05})]$	0.941	37*

NER, non-linear regression; SV, annual sediment volume (m³); AR, annual rainfall (mm); AI, annual inflow (m³); ATE, annual trap efficiency (%), and Ra, age of reservoir (y); R^2, coefficient of determination; Eq–equation, * - Developed and proposed NER model for application on different reservoirs in the Guinea Savannah Ecological Zone of northern Ghana.

volume of sediment retention increases as all the independent variables (*AR, AI, ATE* and *Ra*) increase. In Equation (37), as presented in Table 6, the exponent of *Ra* is less than one (1) and this indicates that the rate of sedimentation is a decreasing function of time. This is because those areas of the reservoir that are conducive for settlement of fine sediments will fill quickly in the early years and then no longer be available for deposition. Also, shrinkage of deposited silt takes place from weathering action and the superimposed loads of additional sediments thereby reducing the sedimentation rate with time.

Reservoir sedimentation modelling using artificial neural network (ANN)

A Multi-layer Perceptron (MLP) ANN architecture model consisting of three (3) layers was developed for each reservoir using the R tool. Since there was a large variation among the data sets, all the data were normalised between a range of 0 and 1. The model was trained using 70% of the data and the remaining 30% was used for validation. A satisfactory model was selected based on the minimum *MSE* values and the optimum values of R^2 generated during the training and validation stages. Performance statistics for the ANN model for each reservoir are presented in Table 7.

Table 7 | Performance statistics of the ANN model for predicting annual reservoir sedimentation

Reservoir	ANN structure	Mean square Error (*MSE*)		Coefficient of determination (R^2)		Average accuracy of model (%)
		Training stage	Validation stage	Training stage	Validation stage	
Bontanga	4–9–1	0.1430	0.1865	0.8570	0.8135	83.53
Golinga	4–8–1	0.1180	0.1030	0.8820	0.8970	88.95
Libga	4–10–1	0.1020	0.1250	0.8980	0.8750	88.65
Gambibgo	4–7–1	0.1260	0.1137	0.8740	0.8863	88.02
Tono	4 –12–1	0.0930	0.0899	0.9070	0.9101	90.86
Vea	4–10–1	0.1120	0.1210	0.8880	0.8790	88.35
Daffiama	4–10–1	0.0790	0.0714	0.9210	0.9286	92.48
Karni	4–6–1	0.0340	0.0690	0.9660	0.9310	94.85
Sankana	4–8–1	0.0890	0.0825	0.9110	0.9175	91.43

Based on the minimum *MSE* values of 0.034–0.143 during the training stage and 0.069–0.187 during the validation stage (Table 7), it was found that the *Feed Forward, Back Propagation* (BP ANN) models with structures ranging from 4–6–1 at Karni reservoir to 4–12–1 at Tono reservoir generated the best trend of the observed volume of sediment retained in the reservoirs. The detailed architecture of the proposed models are illustrated in Figure 3. According to Jothiprakash & Garg (2009), the best ANN prediction model is the ANN structure
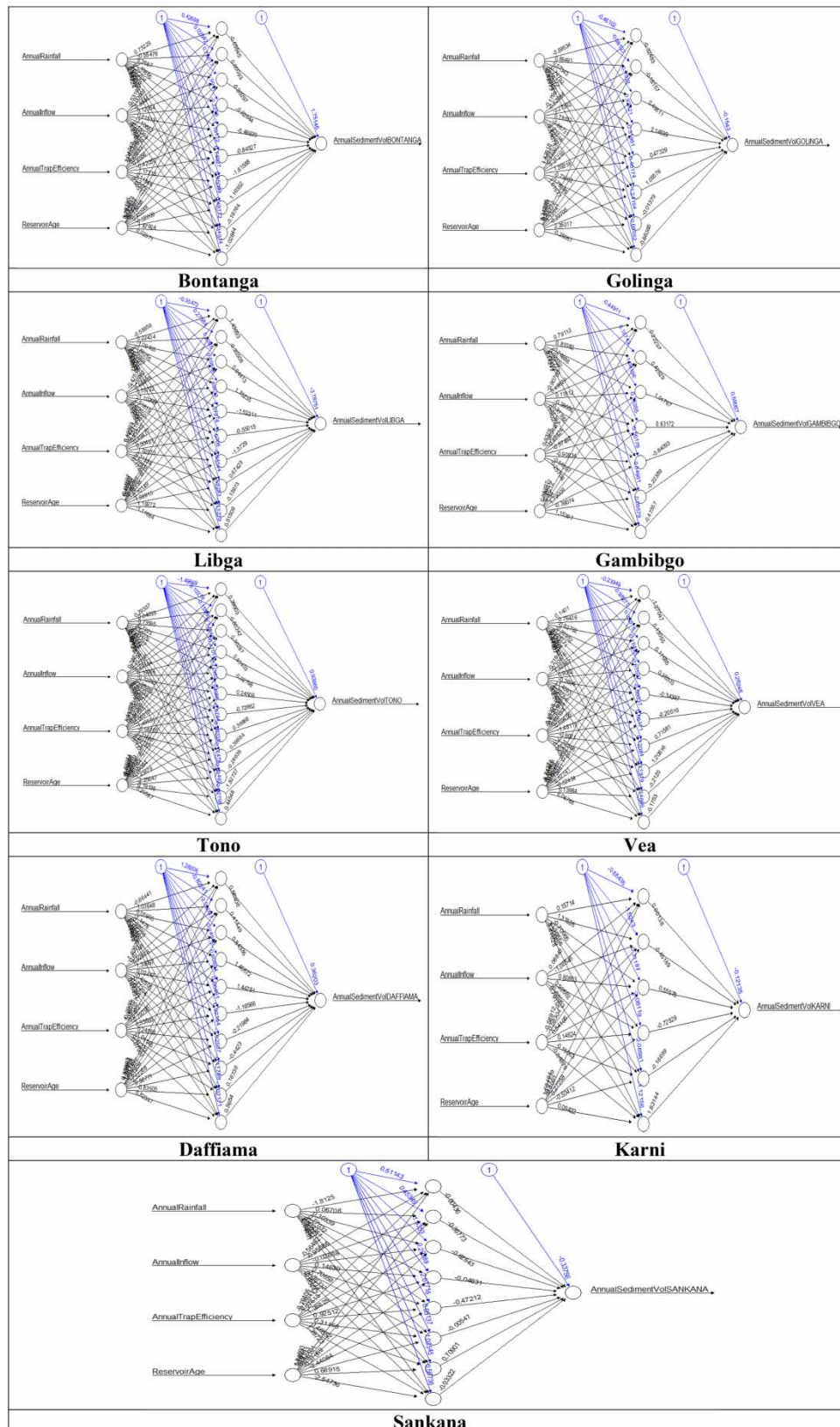
Figure 3 | Detailed architecture of artificial neural network (ANN) model for the study reservoirs.

that best captured the pattern of the observed data set. Also, the R^2 values of 0.857–0.996 and 0.814–0.931 during the training and validation stages, respectively, suggest that averagely, about 81.35 to 96.60% of the variables are explained by the output of the models during the training and validation stages. The average accuracy of the

models ranged from 85.53 to 94.85%. In modelling the annual sedimentation rate of the Gobindsagar Reservoir in India, Jothiprakash & Garg (2009) observed that a *Feed Forward Back Propagation* ANN model with a structure of 3–5–1 with R^2 values of 0.970 (training stage) and 0.965 (validation stage) best followed the pattern of the observed sediment volume. Salimi *et al.* (2013) also had an ANN structure of 3–3–1 with R^2 values of 0.972 for training and 0.988 for testing in the Karaj reservoir in Iran while Sultana & Naik (2016) recorded an ANN structure of 3–10–1 with R^2 value of 0.922 for the Sriramsagar reservoir in Nizamabad. ANN structure indicates the stage at which high prediction accuracy can be attained.

Comparison of reservoir sedimentation prediction models

The three (3) reservoir sedimentation prediction models were compared based on their accuracies (Table 8). The accuracy of the linear regression (LR) model ranged from 76.3 to 90.2%, non-linear exponential regression model ranged from 79.7 to 91.3% and the ANN model ranged from 83.5 to 94.9%. The results from the ANOVA showed no significant difference among the models, as can be seen in Figure 4. Therefore, all the models were observed to be efficient and suitable for predicting the annual sedimentation of the reservoirs, as they recorded accuracies above 76% (Table 8).

Table 8 | Accuracy of reservoir sedimentation prediction models

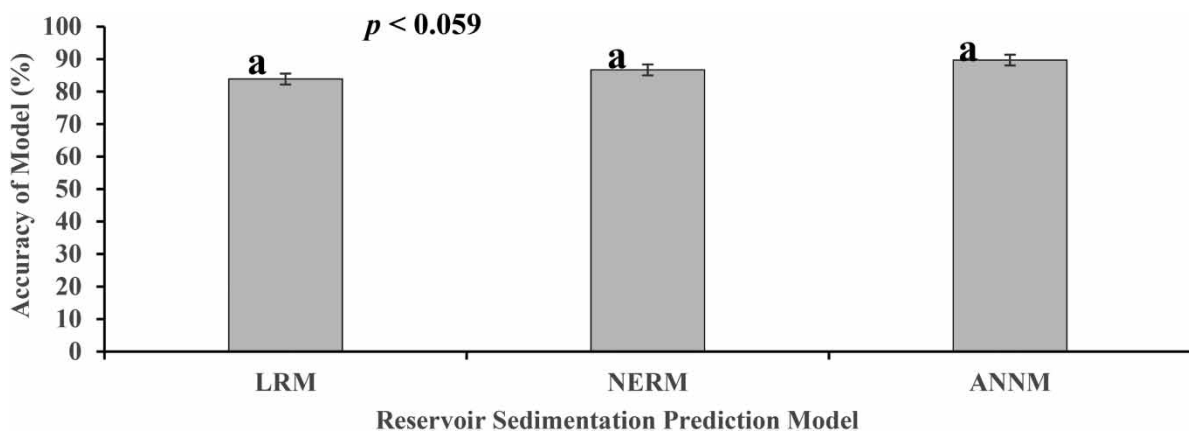| Reservoir	Accuracy of model (%)		
	Linear regression model (LRM)	Non-linear exponential regression model (NERM)	Artificial neural network model (ANNM)
Bontanga	80.8	85.8	83.5
Golinga	76.3	79.7	88.9
Libga	83.1	84.5	88.6
Gambibgo	85.2	87.2	88.0
Tono	89.9	91.3	90.8
Vea	80.1	84.1	88.4
Daffiama	82.4	87.9	92.5
Karni	87.5	89.2	94.9
Sankana	90.2	91.0	91.4

Figure 4 | Level of accuracy of reservoir sedimentation prediction models. Bar values (means $\pm$ SD, $n = 9$); SD, standard deviation; LRM, linear regression model; NERM, non-linear exponential regression model; ANNM, artificial neural network model.

Forecast of annual sediment volume retention in the study reservoirs

The developed linear regression (LR), non-linear exponential regression (NER) and artificial neural network (ANN) models were used to forecast the volume of sediment that would be retained in the reservoirs within the next 20 years; that is, by year 2038 and the results presented in Table 9 and Figure 5.

Table 9 | Forecasted total storage capacity loss in the study reservoirs up to year 2038

Reservoir	Class of reservoir	Age of reservoir in 2038 (y)	Current volume of sediment deposits (m³) 2018	Forecasted total storage capacity loss (%) by year 2038		
				Linear regression (LR) model	Non-linear exponential regression (NER) model	Artificial neural network (ANN) model
Bontanga	Large	52	2,522,000	18.42	20.81	19.07
Golinga	Medium	62	400,000	46.97	50.07	48.33
Libga	Small	58	220,000	44.88	47.01	45.94
Gambibgo	Small	75	100,000	44.22	48.22	46.18
Tono	Large	53	7,940,000	13.83	15.54	14.32
Vea	Large	58	2,290,000	20.81	23.10	21.94
Daffiama	Small	49	60,000	40.61	41.30	39.44
Karni	Small	50	90,000	42.04	44.63	42.92
Sankana	Medium	68	580,000	45.64	47.51	44.59

The ages of the reservoirs at 2038 (Table 9) would be 49 to 75 years with the least and highest being the Daffiama and Gambibgo reservoirs, respectively. The total volume of sediment predicted by the ANN model to be retained in the reservoirs by the year 2038 ranged from 122,264 m³ at Daffiama to 13,317,600 m³ at Tono, whilst the LR model predicted sediment volume deposits ranging from 125,891 m³ also at Daffiama and 12,861,900 m³ at Tono (Figure 5). This variation could be due largely to size of catchment and annual sediment inflows. The total storage capacities of the reservoirs forecasted to be lost within this time period ranged from 14.32 to 48.33% by the ANN model, 13.83 to 46.97% by the LR model and 15.54 to 50.07% by NER model (Table 9). The results from the three (3) models indicate that the storage capacities of the Golinga, Libga, Gambibgo, Daffiama, Karni and Sankana reservoirs would almost be 50% filled with sediment deposits by year 2038 if no sedimentation control measures are taken to curb the phenomenon. In all three (3) models, it was noted that the predicted storage capacity losses in the small and medium reservoirs were quite higher than those of the large sized reservoirs, as can be observed in Table 9. Across all the reservoirs, the trend of the observed sedimentation data was best followed by the ANN model than the LR and NER models, as illustrated in Figure 5. This suggests that the ANN model gives more accurate and efficient predictions when compared with the LR model. In forecasting the trap efficiency of the Sriramsagar reservoir (Nizamabad), Sultana & Naik (2016) observed that the pattern of the observed trap efficiencies was better followed by the ANN model than the LR model. Similarly, Jothiprakash & Garg (2009) and Salimi et al. (2013) found that the ANN model estimated the volume of sediment retained in the Gobindsagar Reservoir (India) and Karaj reservoir (Iran), respectively, with higher accuracy and less effort compared to the LR model.

CONCLUSIONS

The study developed two mathematical models using linear regression (LR) and non-linear exponential regression (NER) and artificial neural network (ANN) models with input parameters as annual rainfall, annual water inflows, annual trap efficiency and age of reservoir, for the forecast of annual sedimentation in the study reservoirs and other reservoirs in the Guinea Savannah Ecological Zone (GSEZ) of Ghana. The models revealed that annual sediment volume retention increases as all four (4) independent variables (input parameters) increased and the rate of sedimentation in the reservoirs also decreased with time. The developed mathematical models provide a straightforward and rapid means of predicting the annual storage capacity loss of reservoirs in the GESZ of Ghana. The feed-forward, back-propagation algorithm Multi-Layer Perceptron ANN model structure, which best captured the pattern in the annual sediment volumes retained in the reservoirs, ranged from 4–6-1 at Karni to 4–12-1 at Tono.

Based on the accuracies of the models, the results from the ANOVA showed no significant difference among the models and therefore, all the three (3) models developed are noted to be efficient with accuracies above 76% and suitable for forecasting the annual sedimentation of reservoirs with characteristics like those in the GSEZ of Ghana.
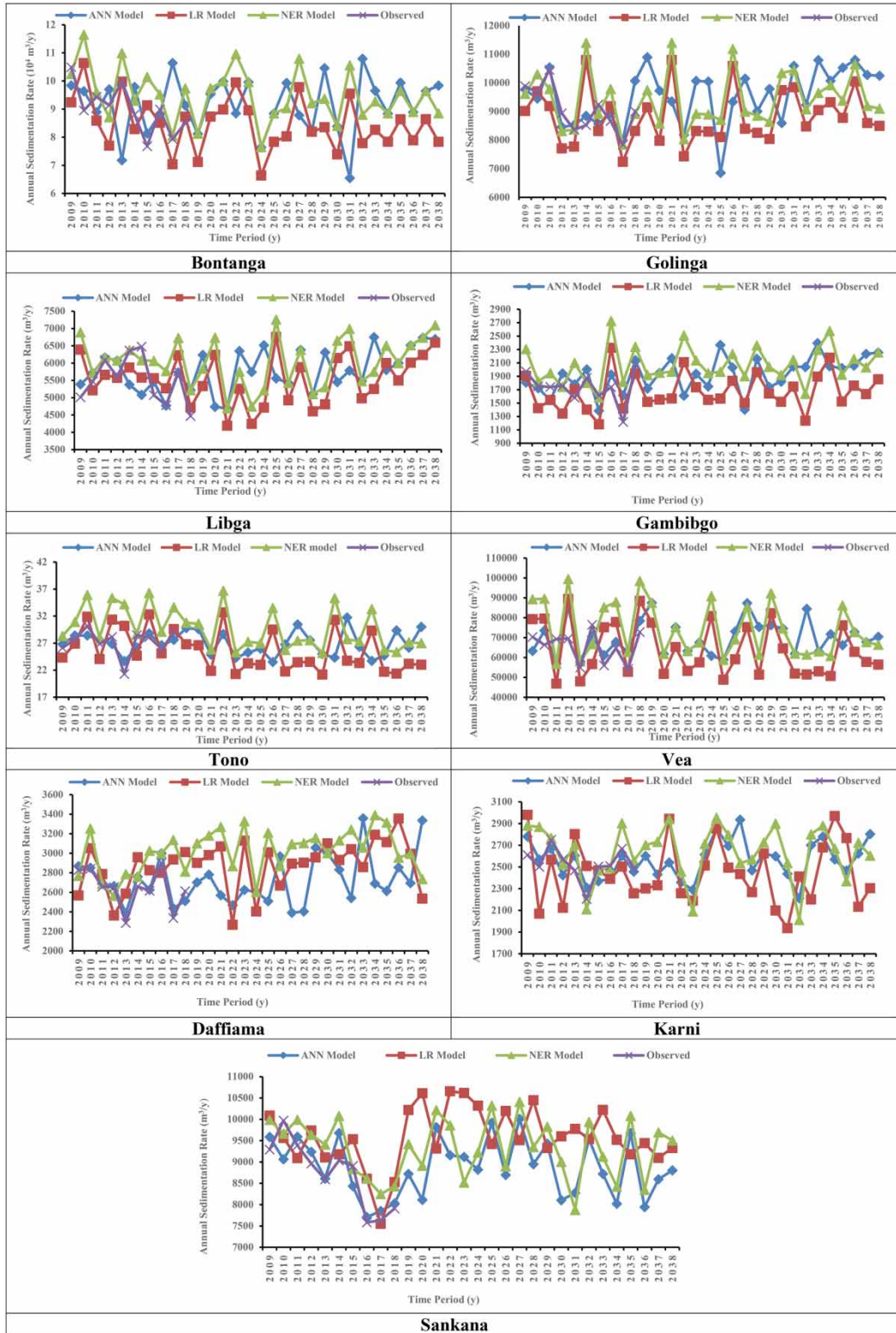
Figure 5 | Annual observed and predicted sedimentation rates for the study reservoirs.

Forecasted sedimentation up to the year 2038 using the developed models revealed that the total storage capacities of the reservoirs that would be lost ranged from 13.83 to 50.07%, with all three (3) models indicating that the small and medium reservoirs would almost be 50% filled with sediment deposits if no sedimentation control measures are taken to curb the phenomenon.

DECLARATION OF CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest. They have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Also, no financial support was received for the conduct of the research and/or preparation of the article.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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