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ARTIFICIAL NEURAL NETWORK AND PHYSICAL BASED MODELS FOR WATER-LEVEL FORECASTS OF INNER NIGER DELTA IN MALI

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ABSTRACT: The Niger Inner Delta (NID) is a wetland that was selected as an International Important Wetland under the Ramsar Convention (on February 1st, 2004) and can still be considered a hotspot of biodiversity in the Sahel. The Niger River is the main water source for the NID and is also used for urban life and irrigation. Therefore, the sustainable use of water to ensure environmental flow in the NID is under discussion. In this paper, the performance of different models established with empirical approaches (Artificial Neural Network and Regressions) or Conceptual Variable Source Area (Water Balance Method WBM) approaches were evaluated. The results of evaluation and validation based on determination coefficient (R^2), Root Mean Squared Error (RMSE) and Nash-Sutcliffe Efficiency (NSE) show that all the models gave good results, however, the Levenberg Marquardt Artificial Neural Network (with 20 hidden neurons) was the best fit for the validation and testing periods.

Keywords: Niger Inner Delta, Water-level, Wetland, Simulation model

1. INTRODUCTION

For many decades, water shortage has been a dire problem for millions of people living along the southern fringe of the Sahara Desert [1]. A recent international study, published in July 2018, identified the Inner Niger Delta area as the birthplace of African Rice domestication 3000 years ago [2].

The River Niger has its source in the Fouta Djallon Mountains to the south of Guinea (West Africa), it flows northeast through the Upper Niger basin and enters the Niger Inner Delta (NID) in Mali with a large floodplain (ranging from 30,000 to 40,000 km^2) [2] (see Fig 1). The annual flooding of large alluvial plains is a vital resource for many ecosystems, including those serving agriculture, livestock, groundwater recharge, and biodiversity (see Fig 2). The rapid expansion of upstream irrigation, by the diversion dams on the Niger river and its subsidiary (Bani), has made a significant impact on the Water-Level (WL) in the NID downstream [3] as well as the flood area. A smaller flood area means fewer resources and possible friction and even uprisings between different communities and users, described as “The Tragedy of the Commons” by the American Biologist Garrett Hardin in 1968 [4].

The main objective of this study is to develop statistical/stochastic and conceptual/physical models for Niger Inner Delta water level forecasting and make a comparison between these different models. The evaluation and forecasting of water-level fluctuation (WLF) are increasingly important for the NID owing to its close relation to human activity, agriculture production, and socio-economic and environmentally sustainable development.

2. STUDY AREA AND DATA SOURCES

Beyond the town of Ségou, the Niger River forms a vast inland delta with an area of 41,800 km² (Fig 1 & 2); it joins with its main tributary, the Bani, at Mopti and then forms several lakes. The watershed area of this Inner Delta covers 130,000 km² [3]. The NID is extremely flat and contains many lakes and streams of varying morphology. The altitude of the river bed only decreases by approximately 10 m over the 350 km between the entry and exit of the delta [5]. This study uses data from different sources (Table 1). The flow of the River Niger at Mopti and the water level at Akka are taken from the Malian Government Hydraulic Service; the meteorological data are from the Mali-Meteo & Atmospheric Science Data Center (NASA).

Table 1 Data type and data sources

N	Station	Source	Date	Data type
1	Mopti	DNH	1960-2015	Water Flow
2	Mopti	DNH		Water-Level
3	Mopti	DNM		Rainfall
4	Akka	ASDC/NASA		Air Temp.

Note: DNH: Malian National Hydraulic Board, DNM: Malian National Meteorology Board, NASA: Atmospheric Science Data Center of NASA

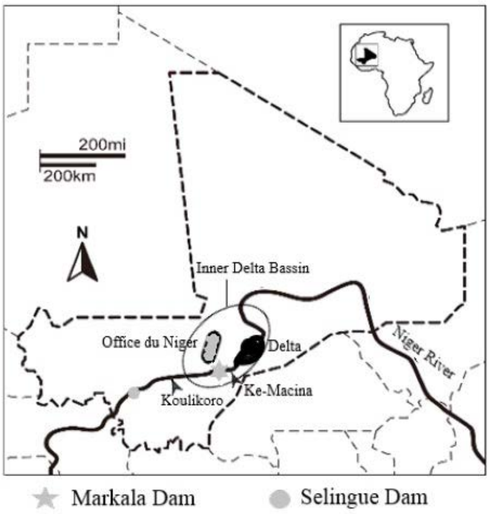

Fig 1. The Niger Inner Delta in Mali

Fig 2. NID during the dry season (Source: Google)

3. METHODS

The most common methods for river flow and WL forecasting are physical, conceptual and/or statistical rainfall-runoff methods [5-7]. In recent years, Artificial Intelligence (AI) has received a great deal of attention as a modern approach for data series analysis and for hydrology modeling, including Artificial Neural Networks (ANN) and the Adaptive Neuro-Fuzzy Inference System (ANFIS) [7-13]. For our study, six different models were implemented, based on empirical and stochastic approaches.

3.1 Artificial Neural Network (ANN)

An artificial neural network (ANN) is a non-linear, black box statistical/stochastic approach [11]; the main objective is to find the optimum architecture of an ANN that can model the relationship between input and output variables. In this study, the Matlab Neural Network tool® were used to train the different models. For each of the following ANN algorithms, the monthly rainfall, evapotranspiration and the river discharge at Mopti station were designated as predictors and the water level at Akka station was designated as the predicted.

The most commonly used ANN structure is the feed-forward multilayer perceptron (MLP). It is a network formed by simple neurons. The perceptron computes a single output from multiple real-value inputs by forming combinations of linear relationships, according to input weights and even nonlinear transfer functions [6].

Mathematically, the MLP can be express as:

$$\boldsymbol{y}^{(\boldsymbol{k})} = \boldsymbol{f}\left(\sum_{\boldsymbol{i}=\boldsymbol{1}}^{\boldsymbol{n}} \boldsymbol{w}^{(\boldsymbol{k})}{}_{\boldsymbol{i}}\, \boldsymbol{h}^{(\boldsymbol{k})}{}_{\boldsymbol{i}} + \boldsymbol{b}^{(\boldsymbol{k}-\boldsymbol{1})} \right) \quad (1)$$

Where $\boldsymbol{y}$ is the computed value of the maximum monthly water-level ($\boldsymbol{H}_{\mathbf{max}}$); $\boldsymbol{w}_{\boldsymbol{i}}$ is the ith connection weight; and $\boldsymbol{h}_{\boldsymbol{i}}$ represents the input values in each layer.

For the layer $\boldsymbol{k}\mathbf{1}$: $\boldsymbol{ET}_{\mathbf{0}\_\boldsymbol{obs}}, \boldsymbol{Rain}_{\boldsymbol{Obs}}, \boldsymbol{Q}_{\mathbf{max}\_\boldsymbol{obs}}$);

$\boldsymbol{b}$ is the neuron bias, $\boldsymbol{k}$ is the number of layers and $\boldsymbol{f}$ is the activation function. Let us consider the target value of watthe er level to be $\boldsymbol{y}_{\boldsymbol{target}}$.

The Multilayer neural network could have $\boldsymbol{L}$ hidden layers and would be calculated as follows:

The Forward Pass:

→ Layer pre-activation for $k > 0$ ($h^0(x) = x$)

$$\boldsymbol{a}^{\boldsymbol{k}}(\boldsymbol{x}) = \boldsymbol{b}^{(\boldsymbol{k})} + \boldsymbol{w}^{(\boldsymbol{k})} \boldsymbol{h}^{(\boldsymbol{k}-\boldsymbol{1})}(\boldsymbol{x}) \quad (2)$$

→ Hidden layer activation (k $from$ 1 to L)

$$\boldsymbol{y}^{(\boldsymbol{k})}(\boldsymbol{x}) = \boldsymbol{f}(\boldsymbol{a}^{(\boldsymbol{k})}(\boldsymbol{x})) \quad (3)$$

→ Output layer activation ($k = L + 1$)

$$\boldsymbol{y}^{(\boldsymbol{L}+\boldsymbol{1})}(\boldsymbol{x}) = \boldsymbol{g}(\boldsymbol{a}^{(\boldsymbol{L}+\boldsymbol{1})}(\boldsymbol{x})) \quad (4)$$

Where g is the output layer activation function.

→ Calculating the error using squared error function gives:

$$\boldsymbol{E} = \sum \frac{1}{2}(\boldsymbol{y_{target}} - \boldsymbol{y}^{(L+1)})^2 \quad (5)$$

The back-forward Pass:

The goal with back-propagation is to update each of the weights ($\boldsymbol{w^k}$) in the network so that they cause the actual output to be closer to the target output, thereby minimizing the error for each output neuron and the network as a whole. For details about the procedure refer to [14].

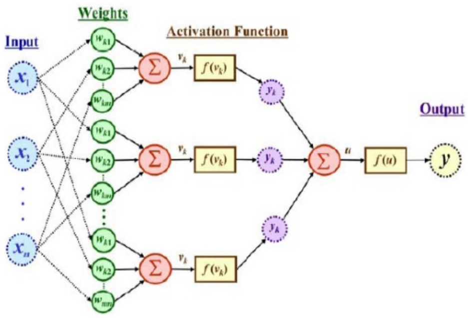

Fig 3. Multilayer Neural Network Architecture (Source: Almad Aljebaly refer to [10])

Previous studies indicated that the Levenberg-Marquardt algorithm produces reasonable results for most ANN applications [6,15]. For the present study, the three algorithms available in Matlab® (Levenberg-Marquardt (LM), Bayesian Regularization (BR) and Scaled Conjugate Gradient (SCG) algorithms) were considered and the number of hidden layers was fixed.

3.1.1. Levenberg-Marquardt Algorithm (LM)

Levenberg-Marquardt (LM) is the most popular alternative to the Gauss-Newton method for finding the minimum of the function $F(x)$ that is a sum of:

$$F(x) = \frac{1}{2}\sum_{i=1}^{m}[f_i(x)]^2 \quad (6)$$

Let the Jacobian of $f_i(x)$ be denoted $J_i(x)$, then the LM method searches in the direction given by the solution p of the equation:

$$(J_k{}^T J_k + \lambda_k I)p_k = -J_k{}^T f_k \quad (7)$$

where λ_k are non-negative scalars and I is the identity matrix [14].

3.1.2. Bayesian Regularization Algorithm (BR)

This algorithm uses David MacKay's Bayesian techniques to optimize regularization and requires the computation of the Hessian matrix [16]. Typically, training aims to reduce the sum of squared errors E_D and the regularization adds an additional term E_W [17]. The objective term becomes

$$F = \beta E_D + \alpha E_w \quad (8)$$

where β and α are the objective function parameters.

3.1.3. Scaled Conjugate Gradient Algorithm (SCG)

The Scaled Conjugate Gradient (SCG) method, is based on the gradient descent algorithm (as are most of the feed-forward neural networks) and is well known in optimization theory [18]. The SCG avoids the line search per learning iteration by using an LM approach in order to scale the step size.

3.2. Gaussian Process Regression (GPR) model with MatLAB regression learner

Gaussian process regression (GPR) models are kermel-based, probabilistic models [19,25]. A linear regression model is of the form:

$$y = x^T \beta + \varepsilon \quad (9)$$

where $\varepsilon \sim N(0, \sigma^2)$. A GPR model explains the response by introducing the latent variable. The GPR model was fit using a squared, exponential kernel (covariance) function, which is defined as:

$$k(x_i, x_j|\theta) = \sigma_f^2 exp\left[-\frac{1}{2}\frac{(x_i - x_j)^T(x_i - x_j)}{\sigma_l^2}\right] \quad (10)$$

It is expected that points with similar predictor values x_i, naturally have close response (target) values y_i. In other words, it determines how the response at one point x_i is affected by responses at other points x_j, $i \neq j$, $i = 1, 2, \ldots, n$, where σ_l is the characteristic length scale and σ_f is the signal standard deviation.

3.3. Water Balance Model using Variable Source Area (WBM/VSA)

The water depth in the NID may be obtained using the Water Balance Model (WBM) with Variable Source Area (VSA), see Eq. (11). The concept of Variable Source Area was introduced for the first time by Hewlett and Hibbert in 1967 [20]. Dunne (1975) [21] is also known for his contribution to the fundamental concept of the VSA. The VSA develops when the soil profile becomes saturated from below after the water table rises towards the land surface.

$$H_{i+1} = Max(H_i + (Q_{i+1} - Q_{out})\frac{D}{A_1} + (R_{i+1} - ET_{0_{i+1}}D)\frac{(A_1+A_2)}{A_1}, \gamma) \quad (11)$$

The outflow is $Q_{out} = \beta Max(H_i, 0)^{\alpha}$ (12)

The wet soil area is given as $A_2 = \delta\sqrt{A_1}$ (13)

Time, maximum monthly inflow from the upstream Mopti station (Q_i), monthly rainfall (R) the daily potential evapotranspiration (ET_0), the number of days in each month (D), and pond water surface (A_1) data were fed into the spreadsheet. To estimate the maximum water level (H_i) at various time-steps, Eq. (11) is used, based on parameters α, β, γ and δ. The Generalized Reduced Gradient (GRG) nonlinear solving method was used to identify the parameters in Excel Solver ®.

3.4. Multiple Linear Regression (MLR)

As opposed to simple linear regression models, which describe the linear function relationship between a single explanatory variable X (inflow, Rainfall, ET_0) and the response variable Y (NID Water-Level), multiple linear regression models comprise the use of a collection of explanatory variables for describing the behaviour of Y [22-23].

In formal terms:

$$y = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} \quad (14)$$

Parameter estimation in multiple linear regression is based on the least squares method and can be computed using the Excel ® Data Analysis Regression Toolbox. The equation to estimate the maximum monthly water level of the NID will be:

$$H_{max} = \beta_0 + \beta_1 ET_0 + \beta_2 Rain + \beta_3 Q_{max} \quad (15)$$

4. RESULTS

The monthly data from 1960 to 2010 (612 datasets) were used for the model training and validations and the monthly data from 2011 to 2015 (60 datasets) were used for testing. In order to validate and evaluate the models, the Correlation Coefficient (r), squared R (R^2), Root Mean Squared Error (RMSE) and Nash-Sutcliffe Efficiency (NSE) were used (Table 2). The plots of the maximum monthly WL (H_{max}) variation for different models are shown in Fig 4.

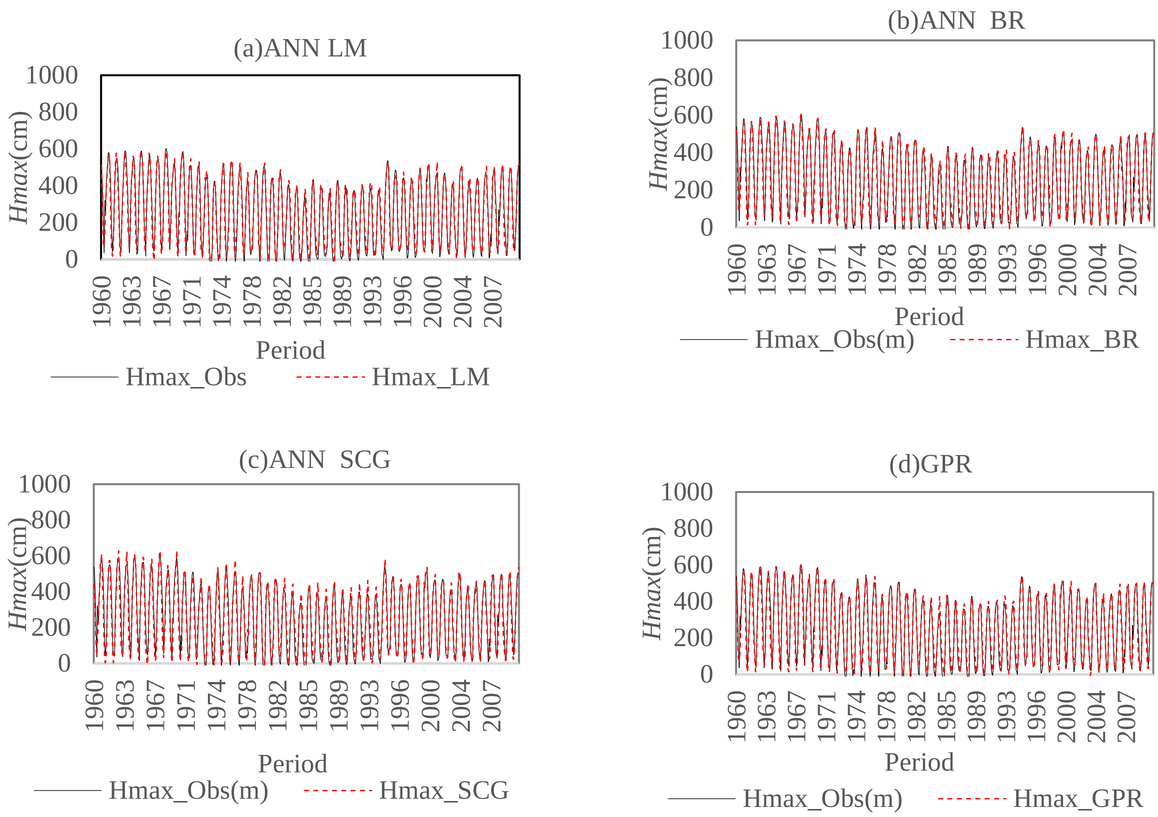

Fig 4a-d. Validation scatter plots of observed versus modeled water level. (a) Levenberg-Marquardt (ANN ML), (b) Bayesian Regularization (ANN BR), (c) Scaled Conjugated Gradient (ANN SCG), (d) Gaussian Process Regression (GPR)

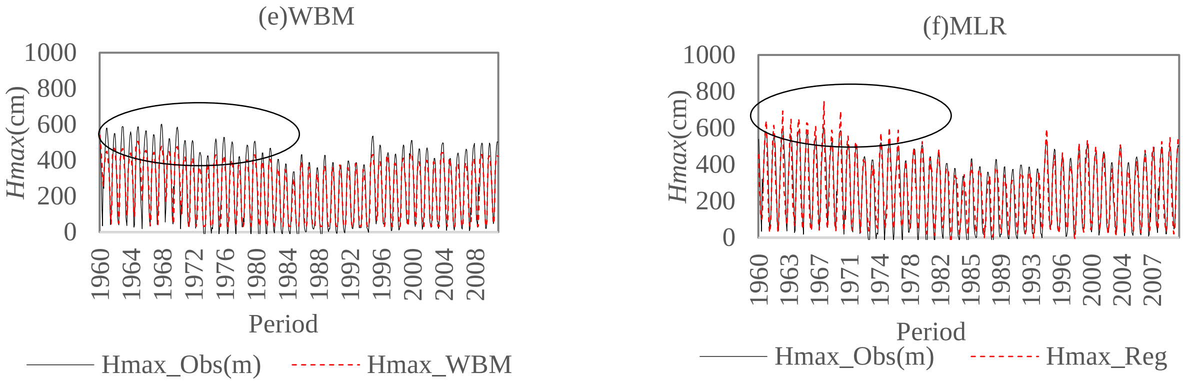

Fig 5e,f. Validation scatter plots of observed versus modeled water level. (e) Water Balance Model (WBM), (f) Multilinear Regression model (MLR).

Table 1 Model validation and evaluation statistics

	Model	Validation (1960-2010)				Evaluation (2011-2015)			Methods/Parameters
		r	R^2	*RMSE* (cm)	*NSE*	*r*	R^2	*RMSE* (cm)	
a	ANN LM	0.97	0.94	41.47	0.95	0.97	0.95	38.36	Mathworks (Levenberg-Marquardt)
b	ANN BR	0.97	0.89	59.00	0.94	0.97	0.95	38.20	Mathworks (Bayesian Regularization)
c	ANN SCG	0.96	0.92	52.05	0.91	0.96	0.92	46.99	Mathworks (Scaled Conjugate Gradient)
d	MLR-GPR	0.97	0.93	46.88	0.91	0.97	0.95	37.51	Mathworks (Regression Learner GPR)
e	WBM-	0.95	0.91	60.00	0.84	0.96	0.93	50.80	Excel (SOLVER GRG) α=1.29,β=228.73,δ=59.19,γ=0.32
f	MLR-GRG	0.93	0.87	65.02	0.853	0.96	0.92	46.68	Excel (Data Analysis) β_0=1070.2, β_1=-156.65,β_2=-1.14 , β_3=0.12

5. DISCUSSION

The models' performance from R^2, RMSE and NS are given in Table 2 and Fig 5. It can be seen from the validation results that the ANN (LM, BR and SCG) perform much better for each of the algorithms, followed by Gaussian Process Regression; the Water Balance Model and the Multilinear Regression Model have the worst performance.

For all the models, the NSE values of validation are close to 1, which is in the range of acceptable levels (between 0 and 1, where 1 is the optimal value) according to Moriasi et al. [24], however, the ANN Levenberg-Marquardt algorithm gives the best result for each performance index.

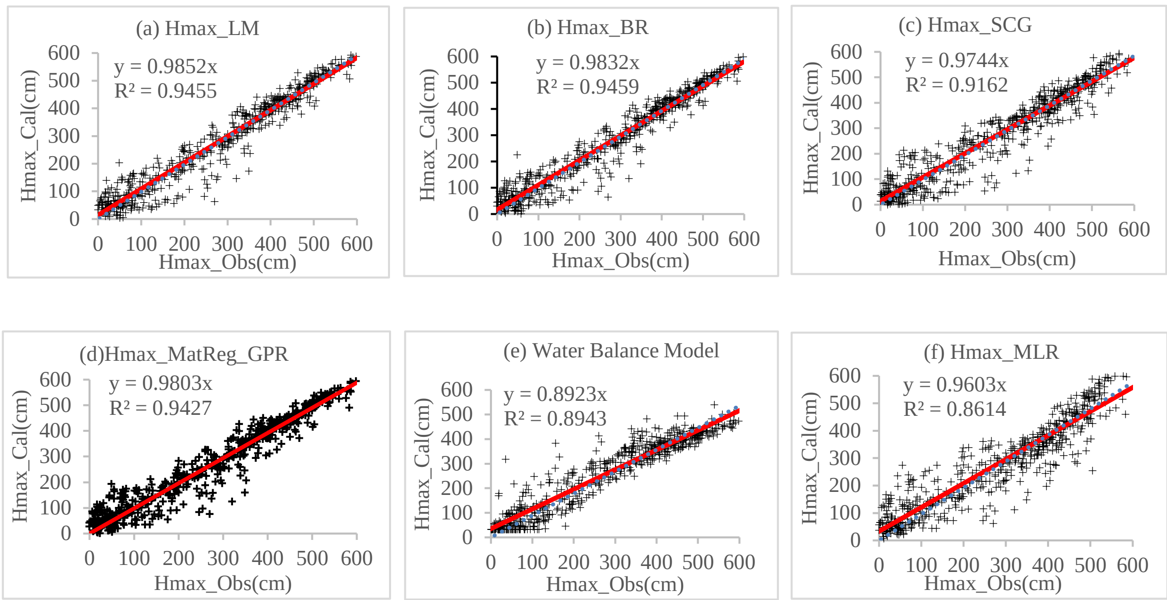

Fig 6: (a) Levenberg-Marquardt (ANN ML), (b) Bayesian Regularization (ANN BR) (c) Scaled Conjugated Gradient (ANN SCG), (d) Gaussian Process Regression (GPR), (e) Water Balance Model (WBM), (f) Multilinear Regression model (MLR).

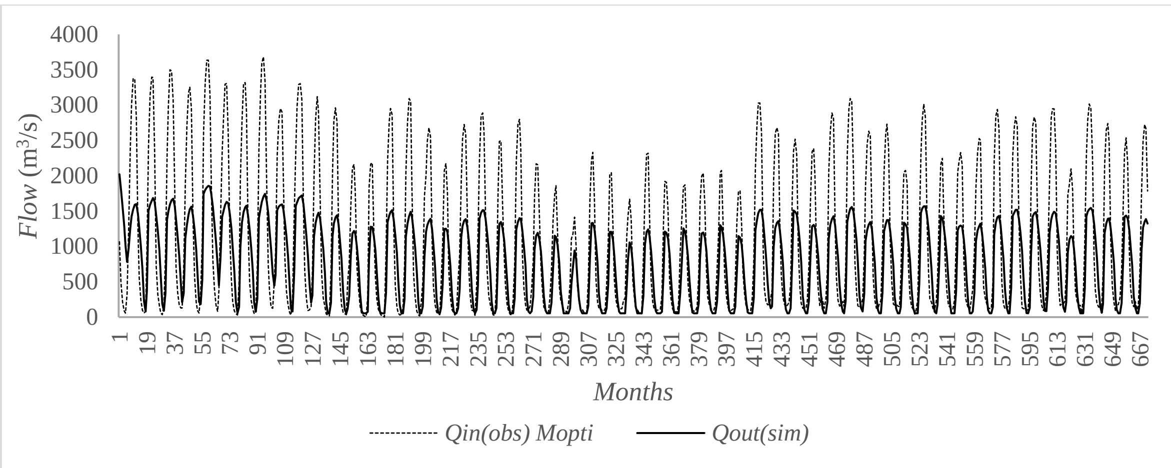

Fig 7: Comparison between the measured incoming flow $Qin_{(obs)}$ and calculated outgoing flow $Qout_{(sim)}$

Although the ANN Levenberg-Marqardt gives the best fitting results, it does not allow us to estimate all of the internal processes that occurred in the watershed, like the physically-based Water Balance Model using Variable Source Area does. From WBM, the wet area surrounding the water body of the delta ($\boldsymbol{A_2 = 5,900 \sim 9,381\ km^2}$) and the monthly outflow ($\boldsymbol{Q_{out}}$) were estimated as shown in Eq (12) and Fig 6.

The inflow fluctuated much more than the outflow due to the presence of several lakes in the delta.

Owing to the lack of climate data throughout the large area of the NID (with only one station serving 40,000 km^2), the WBM could not compute accurately, therefore the ANN is the best alternative to overcome this issue.

6. CONCLUSIONS

The accuracy of different models for forecasting the maximum monthly water level of the Niger River Inner Delta was investigated using different statistical/stochastic methods with input data of the water inflow discharge from the Mopti station, the rainfall and the $\boldsymbol{ET_0}$. From the results, the Artificial Neural Network Levenberg-Marquardt was the best model for predicting the water level of the Inner Niger Delta. However, the ANN Bayesian Regularization, the ANN Scaled Conjugate Gradient and the Gaussian Process Regression can also be applied with minimal error. Although the WBM does not fit that well, it can still be used to estimate the wet area surrounding the waterbody of the delta and the outflow.

7. ACKNOWLEDGMENTS

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8. REFERENCES

[1] Zwart L., Beukering P. V., Kone B. and Wymenga E., The Niger, a Lifeline. Effective Water Management in the Upper Niger Basin, Leo Zwarts (RIZA), Pieter van Beukering (IVM), Bakary Kone (Wetlands International) and Eddy Wymenga (A&W), Eds., Sevare (Mali), Amsterdam (Netherlands): Wetlands International/Institute for Environmental Studies (IVM)/A&W Ecological, 2005, p. p. 169-190.

[2] Cubry P., Tranchant-Dubreuil C.,. Thuillet A.-C, Monat C., Ndjiondjop M.-N., Labadie K., Cruaud C.,Engelen S, Scarcelli N., Rhone B.,Buregarella C., Dupuy C., Larmande P., Wincker P.,Francois O., Sabot F. and Vigouroux Y., “The Rise and Fall of African Rice Cultivation Revealed by Analysis of 246 New Genomes,” Current Biology, vol. 28, 2018, pp. 2274-2282.

[3] Mariko A., Mahe G., Orange D.,Royer A., Nonguierma A., Amani A. and Servat E., “Suivi des zones d inondation du Delta Interieur du Niger, Perspective avec les donnees de basse resolution NOAA/AVHRR,” Gestion Integree en zones inondables tropicales, 2002, pp. 231-244.

[4] Kassambara B., Ganji H. and Kajisa T., “Impact of Agricultural Water Allocation on the Ecosystems in the Inner Niger River Delta,” GEOMATE, vol. 14, no. 42, 2018, pp. 164-170.

[5] Garrett H., “The Tragedy of the Commons,” American Association for the Advancement of Science, vol. 162, no. 3859, 1968, pp. 1243-1248.

[6] Ibrahim M, Wisser D., Ali A.,Diekkrüger B., O. Saidou, Mariko A. and Alfouda A., “Water Balance Analysis over the Niger Inland Delta-Mali: Spatio-temporal Dynamics of the Flood Area Water Losses,” MDPI-Hydrology, vol. 4, no. 40, 2017, pp. 1-23.

[7] Mohammad Kalteh A., “Monthly river flow forecasting using artificial neural network and support vector regression models coupled with the wavelet transform,” ELSEVIER, vol. 54, 2013, pp. 1-8.

[8] Rezaeianzadeh M., Tabari H., Arabi Yazdi A., Isik S. and Kalin L., “Flood flow forecasting using ANN, ANFIS and regression models,” Springer, vol. 25, no. 1, 2014, pp. 25-37.

[9] Marquardt D. W., “An Algorithm for Least-Squares Estimation of Nonlinear Parameters,” J. Soc. Industry. Appl. Math., vol. 11, no. 2, pp. 431-441, 1963.

[10] Aljebaly A., “Western Michigan University Computer Science,” 20 November 2016. [Online]. Available: https://wmich.edu/cs. [Accessed 05 December 2016].

[11] MacKay D. J. C., “Bayesian Interpolation,” Computation and Neural Systems, vol. 4, 1992, pp. 415-447.

[12] Foresee F. D. and Hagan M. T., “Gauss-Newton Approximation to Bayesian Learning,” in International Conference on Neural Network, Houston, TX, USA, 1997.

[13] Moller M. D., “A Scaled Conjugate Gradient Algorithm for Fast Supervised Learning,” Neural Networks, vol. 6, 1993, pp. 525-533.

[14] Rasmussen C. E. and Williams C. K. I., Gaussian Processes for Machine Learning, Cambridge, Massachusetts: The MIT Press, 2006.

[15] Hewlett J. D. and Hibbert A. R., “Factors affecting the response of small watersheds to precipitation in humid areas,” Progress in Physical Geography, vol. 33, no. 2, 1967, pp. 288–293.

[16] Dunne T., Moore T. R. and Taylor C. H., “Recognition and Prediction of Runoff-Producing Zones in Humid Regions,” Hydrological Science, vol. XX, no. 3, 1975, pp. 305-325.

[17] Moriasi D. N., Arnold J. G., Vanliew M. W., Binger R. L., Harmel D. R.and. Veith T. L, “Model Evaluation Guidelines for Systematic Quantification of accuracy in Watershed Simulations,” ASABE Soil & Water Division, vol. 50, no. 3, 2007, pp. 885-900.

[18] Rosenberg E. A., Wood A. W. and Steinemann A. C., “Statistical applications of physically based hydrologic models to seasonal streamflow forecasts,” Water Resources Research, vol. 47, no. W00H14, 2011, pp. 1-19.

[19] Risley J. C., Gannett M. W., Lea J. K. and Roehl E. A. Jr, Scientific Investigation Report, An Analysis of Statistical Methods for Seasonal Flow Forecasting in the Upper Klamath River Basin of

Oregon and California, Reston, Virginia: U.S. Geological Survey (USGS), 2005.

[20] Dawson C. and Wilby R., “Hydrological modeling using Artificial Neural Networks,” Progress in Physical Geography, vol. 25, no. 1, 2001, pp. 80-108.

[21] Xiong L., O'Connor K. M., and Guo S., “Comparison of three Updating Shemes Using Artificial Neural Network in Flow Forecasting,” Hydrology and Earth System Sciences, vol. 8, no. 2, 2004, pp. 247-255.

[22] Dawson C. W. and Wilby R., “An artificial neural network approach to rainfall-runoff modeling,” Hydrological Sciences Journal, vol. 43, no. 1, 2009, pp. 47-66.

[23] Khan M. S. and Coulibaly P., “Application of Support Vector Machine in Lake Water Level Prediction,” Journal of Hydrologic Engineering, vol. 11, no. 3, 2006. , pp. 199-205

[24] Özgür K., “Streamflow Forecasting Using Different Artificial Neural Network Algorithms,” Journal of Hydrologic Engineering, vol. 12, no. 5, 2007, pp. 532-539.

[25] Costa V., Chapter 9 Fundamentals of Statistical Hydrology,edition Naghettini M Belo Horizonte, Brazil: Springer, 2016, pp.391-440

[26] Yu Z., Lei G., Jiang Z., and Liu F., “Arima Modelling and Forecasting of Water Level in the Middle Reach of the Yangtze River,” Conference proceedings, in ICTIS, Banff(Canada), pp. 172-177, 2017.