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Empirical Evidence for Rainfall Runoff in Southern Nigeria Using a Hybrid Ensemble Machine Learning Approach

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ABSTRACT

Rainfall as an environmental feat can change fast and yield significant influence in downstream hydrology known as runoff with a variety of implications such as erosion, water quality, and infrastructures. These, in turn, impact the quality of life, sewage systems, agriculture, and tourism of a nation, to mention a few. It chaotic, complex and dynamic nature has necessitated studies in the quest for future direction of such runoff via prediction models. With little successes in use of knowledge driven models – many studies have now turned to data-driven models. Dataset is retrieved from Metrological Center in Lagos, Nigeria for the period 1999–2019 for the Benin-Owena River Basin. Data is split: 70% for train, and 30% for test. Our study adapts a spatial-temporal profile hidden Markov trained deep neural network. Result yields a sensitivity of 0.9, specificity 0.19, accuracy of 0.74, and improvement rate of classification of 0.12. Other ensembles underperformed when compared to proposed model. The study reveals annual rainfall is an effect of variation cycle. Models will help simulate future floods and provide, lead time warnings in flood management.

Keywords: Evidence, Rainfall Runoff, Southern Nigeria, Hybrid Ensemble Machine Learning Approach

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1. INTRODUCTION

Rainfall runoff predictions have since become a critical issue with the deluge at the Benin-Owena river basin of Nigeria, from 2015 through 2018; And in 2022. Many states witnessed displacement of her citizens (Abda et al., 2022; Abdulrahim et al., 2021).

Its prediction is a critical component to planning, coordination of farming. Such prediction are possible via the various mathematical models grouped into: knowledge and data driven models (Ojugo, Abere, et al., 2013; Ojugo & Nwankwo, 2021a; Ojugo & Okobah, 2017). Rainfall forecasts always focuses on runoff quantification. Its increased awareness and dynamic nature of environmental issues – have given additional impetus to hydrology. New models must meet new requirements and challenges to deal with associated tasks such as erosion, land degrading, leach, flood resource management, land-use consequence and climate changes etc (Adegede et al., 2014; Adeola et al., 2021; Oyebode et al., 2011). Rainfall has influence in flooding and downstream hydrology with implications and complications of erosion, water quality, and the design of engineering structures – which in turn impacts the quality of life, agriculture, sewage system, and tourism etc (Oludapo Olusola et al., 2022).

For these amongst many other reasons, early warning of rainfall runoff situations is critical in the management of water resources (Obiora-Okeke et al., 2021). The complex, chaotic nature of atmospheric processes that produce rainfall makes rainfall runoff modelling as well as its prediction – a tedious task (Aper et al., 2019; Awotwi et al., 2018; Carter & Parker, 2009). Thus, (Chen et al., 2007; Okafor et al., 2017) in spite of advances in weather forecasting, accurate rain forecasting is the most challenging in operational hydrology.

2. MATERIALS AND MACHINE LEARNING FRAMEWORKS

2.1 Rainfall Runoff Models

Rainfall-Runoff predicts estimates via mathematical models usually grouped into: (a) knowledge models, which has long-standing application, focusing on runoff quantification. The increased awareness, dynamic nature and complex excitation of such environmental problems, has given additional impetus to hydrological modelling (Ojugo et al., 2014; Ojugo, Eboka, et al., 2015; Ojugo & Yoro, 2021). Thus, models must now aim to meet new requirements, as they are to deal with other tasks such as erosion, land degradation, pollutant leaching, irrigation, sustainable flood resource management, land-use possible consequence and climate changes (Panjala et al., 2022). Despite efforts, hydrology is still faced with the fundamental problem of calibration and validation – a consequence of limited data availability and the natural heterogeneity of RR-process (Adeola Fashae et al., 2023; Oseke et al., 2021).

Another form is the Data Driven models that arose from the need to use AI properties to learn feats in time that is not possible via knowledge driven models (Eboka & Ojugo, 2020; Ojugo & Eboka, 2018b, 2018a, 2020b). The need for additional data, more computing power required as added by dimensionality in data and search space, continues to make data models via evolutionary mode in hydrology modelling (Iwara et al., 2019). Study will seek to model runoff via data driven models as educational tools that grants us insight into the task at hand (Ojugo, Yoro, et al., 2013). There are basically 2-types of models (Durowoju et al., 2018):

1. **Knowledge-Driven Model:** Such models have been extensively used assessing the safety of underground disposal of nuclear and toxic waste. Validation is quite impossible as most modelers often provide examples demonstrating the limited accuracy of a model's prediction; and argues that verification and validation are misleading (Ngene & Obianigwe, 2018; Okafor & Ogbu, 2018) – as results often convey an impression of correctness, which cannot be justified scientifically.

Validation assess a model's goodness of fit. With groundwater model, some argue that model verification and validation is impossible; and rather, that models can only be confirmed by demonstrating that their simulations agree with observations (Gao et al., 2021; Ojugo & Oyemade, 2021; Ojugo & Yoro, 2013). This confirmation is only partly possible and thus, concludes that the main benefit of models is heuristic – as they yield preliminary hypotheses assisting in gaining better understanding and insight of the task at hand (Ojugo & Otakore, 2018b, 2020b, 2020a, 2021).

2. Data Driven Model: Ojugo et al. (2013) compared validation as predicted versus observed data without specification as to if this data has been used for calibration or not. Validation evaluates confidence in a model's ability to represent the problem entity, and emphasize that a model cannot be expected to be absolutely valid (Ojugo, Yoro, et al., 2013; Ojugo & Yoro, 2013). Rhoda et a. (2017) made 3-classes on runoff validation as: (a) replicative validity agrees that observed data used in model development and estimation of features, (b) predictive validity accurately simulate a variable or time period, which has not been used in model development and calibration, and structurally valid if it reflects the main couplings and behaviour of a real system, and (c) specific validity ensures a generally accepted standard for model validation is adequate for a special purpose (Rhoda et al., 2017). The latter, notes that all models are unrealistic but emphasize that parameter calibration and use of model features makes validation less rigorous – so that even inadequate models is likely to pass tests as provided (Oyerinde et al., 2015).

2.2. Motivation / Statement of Problem

Study is motivated (Ifeka & Akinbobola, 2015; Igwenagu, 2015) as thus:

1. Efforts towards hydrological models are still faced with the fundamental problem of validation due to limited available data and heterogeneity of the runoff process – led to a rise in data-driven model, which are poised on the focal need to learn feats in time that are somewhat not possible via knowledge-driven models (Akazue et al., 2022; Zala & Chaudhari, 2018).
2. Also, many problems are related to model test such that traditional tests like split-sample are often insufficient to evaluate a model validity and assess a variety of the different approaches. Need for additional data, more powerful tests required and the dimensionality of model adopted via data driven models that use evolutionary mode to yield (Allenotor et al., 2015; Allenotor & Ojugo, 2017).
3. The formulation of an optimization task problem requires careful planning and selection of a few design variables as possible – whose outcome procedure indicates whether or not to include more variables in a revised formulation and/or to replace some previously considered design variables with new design variables. Optimization tasks are quite intricate to selected feats, variables, constraints and parameters for a multi-objective function that ultimately yields an optimum solution. These components vary greatly with each problem domain (Yoro, Aghware, Akazue, et al., 2023; Yoro, Aghware, Malasowe, et al., 2023).

To overcome these shortfalls, we adopt a radial basis function neural network for runoff prediction at the Benin-Owena River Basin in Nigeria.

2.3. Data Sampling

The Benin-Owena River Basin Development Agency (BORDA) in Nigeria – has a landmass of 22045km^2 with an annual mean rain of 1023mm, and a perennial discharge of 3.8m/1.5m^3/s respectively for dry and peak periods.

Table 1. Detailed Summary Sheet of Rainfall Features for 1999 – 2019

Data	S	de-season	trend	s-trend	residual	fit	SARIMA
75	0.97989	76.5392	83.4223	81.74468	0.917491	1	81.74468
83	0.95718	86.71305	83.46906	79.89491	1.038865	0.91616	73.19653
79	0.97322	81.17384	83.51582	81.27927	0.971958	1.03736	84.31586
79	0.97184	81.2891	83.56258	81.20946	0.972793	0.97055	78.81784
81	0.98179	82.50237	83.60934	82.08681	0.98676	0.97138	79.73749
84	1.02044	82.31743	83.65609	85.36602	0.983998	0.98533	84.1137
89	1.051	84.68126	83.70285	87.9717	1.011689	0.98257	86.43835
89	1.05003	84.75948	83.74961	87.9396	1.012058	1.01022	88.83835
88	1.04681	84.06492	83.79637	87.71888	1.003205	1.01059	88.64782
87	1.02522	84.85983	83.84313	85.95765	1.012126	1.00175	86.10808
79	0.99482	79.41135	83.88989	83.45534	0.946614	1.01066	84.34497
65	0.94775	68.58349	83.93665	79.55096	0.817086	0.94524	75.19475
79	0.97989	80.62129	83.4223	81.74468	0.966424	0.8159	66.69548
83	0.95718	86.71305	83.46906	79.89491	1.038865	0.96502	77.10019
83	0.97322	85.2839	83.51582	81.27927	1.021171	1.03736	84.31586
81	0.97184	83.34705	83.56258	81.20946	0.997421	1.01969	82.80847
84	0.98179	85.55801	83.60934	82.08681	1.023307	0.99597	81.756
85	1.02044	83.2974	83.65609	85.36602	0.995712	1.02182	87.22871
89	1.051	84.68126	83.70285	87.9717	1.011689	0.99427	87.46762
90	1.05003	85.71184	83.74961	87.9396	1.02343	1.01022	88.83835
88	1.04681	84.06492	83.79637	87.71888	1.003205	1.02194	89.64343
88	1.02522	85.83524	83.84313	85.95765	1.02376	1.00175	86.10808
83	0.99482	83.43218	83.88989	83.45534	0.994544	1.02227	85.31389
84	0.94775	88.63097	83.93665	79.55096	1.055927	0.9931	79.00206
87	0.97989	88.78548	83.4223	81.74468	1.064289	1.05439	86.19077
86	0.95718	89.84726	83.46906	79.89491	1.076414	1.06274	84.90752
82	0.97322	84.25639	83.51582	81.27927	1.008867	1.07485	87.36302
83	0.97184	85.405	83.56258	81.20946	1.022048	1.0074	81.81041
83	0.98179	84.53946	83.60934	82.08681	1.011125	1.02056	83.77452
85	1.02044	83.2974	83.65609	85.36602	0.995712	1.00966	86.19066
88	1.051	83.72978	83.70285	87.9717	1.000322	0.99427	87.46762
87	1.04681	83.10964	83.79637	87.71888	0.991805	0.99923	87.65133
85	1.02522	82.90903	83.84313	85.95765	0.988859	0.99036	85.12902
83	0.99482	83.43218	83.88989	83.45534	0.994544	0.98742	82.40547
85	0.94775	89.6861	83.93665	79.55096	1.068497	0.9931	79.00206
82	0.97989	83.68286	83.4223	81.74468	1.003123	1.06694	87.21667
76	0.95718	79.3999	83.46906	79.89491	0.95125	1.00167	80.02834
82	0.97322	84.25639	83.51582	81.27927	1.008867	0.94987	77.20474
81	0.97184	83.34705	83.56258	81.20946	0.997421	1.0074	81.81041
82	0.98179	83.52092	83.60934	82.08681	0.998942	0.99597	81.756
86	1.02044	84.27737	83.65609	85.36602	1.007427	0.99749	85.15175
87	1.051	82.77831	83.70285	87.9717	0.988954	1.00596	88.49601
100	1.05003	95.23537	83.74961	87.9396	1.137144	0.98752	86.84212

Data	S	de-season	trend	s-trend	residual	fit	SARIMA
86	1.04681	82.15435	83.79637	87.71888	0.980405	1.13549	99.60391
88	1.02522	85.83524	83.84313	85.95765	1.02376	0.97898	84.15082
80	0.98179	81.48382	83.60934	82.08681	0.974578	0.99597	81.756
100	1.02044	97.99694	83.65609	85.36602	1.171426	0.97316	83.0748
88	1.051	83.72978	83.70285	87.9717	1.000322	1.16972	102.9023
85	1.05003	80.95007	83.74961	87.9396	0.966572	0.99887	87.84023
89	1.04681	85.0202	83.79637	87.71888	1.014605	0.96517	84.66363
87	1.02522	84.85983	83.84313	85.95765	1.012126	1.01313	87.08628
100	0.99482	100.5207	83.88989	83.45534	1.198246	1.01066	84.34497
80	0.94775	84.41045	83.93665	79.55096	1.005645	1.1965	95.18272
81	0.97989	82.66234	83.4223	81.74468	0.99089	1.00418	82.08637
80	0.95718	83.57885	83.46906	79.89491	1.001315	0.98945	79.05202
83	0.97322	85.2839	83.51582	81.27927	1.021171	0.99986	81.26789
82	0.97184	84.37603	83.56258	81.20946	1.009735	1.01969	82.80847
79	0.98179	80.46527	83.60934	82.08681	0.962396	1.00827	82.76567
84	1.02044	82.31743	83.65609	85.36602	0.983998	0.961	82.03675
86	1.051	81.82683	83.70285	87.9717	0.977587	0.98257	86.43835
90	1.05003	85.71184	83.74961	87.9396	1.02343	0.97617	85.844
86	1.04681	82.15435	83.79637	87.71888	0.980405	1.02194	89.64343

The collected dataset is for the period (1999 – 2019), and was split into 3-sets: ***training*** (45%), ***re-training*** (25%) and ***test*** (30%). All fragment starts at period of constant low rainfall, which agrees with (Ojugo & Eboka, 2021; Ojugo & Ekurume, 2021b, 2021a; Ojugo & Nwankwo, 2021b).

3. THE EXPERIMENTAL FRAMEWORK

Our data-driven model of choice is the radial basis function (RBF) neural network – whose basic form is constructed as a multilayer perceptron (MLP) with I-H-O layers interconnected via weights and bias. The hidden layer sums the weighted input via an activation function as in Eq. 1 to compute output. This output is sent to nodes in hidden layer. $W_{i,j}$ is weight between input and hidden layers, W_oj is bias weight and x_i is rainfall input signal sent via activation function to produce result. Thus, we adopt a hyperbolic tangent or sigmoid function:

$$Zij = w_o j + \sum_{i=1}^{m} x_i * w_o j \quad (1)$$

With output computed, error is fed back to input nodes via error backpropagation, to correct weights. Backpropagation training is used to find weights that estimates target values of output with selected accuracy. Weights are modified by minimizing the errors between target and computed outputs as each forward pass ends. If error is higher than selected value, the steps continue with a reverse pass; Else, training stops. BP updates weights via mean square error continuously until minimal error is achieved. A time-lag recurrent net extends MLP with short-memory, momentum learning that have local recurrent connections – requiring a smaller network to learn temporal problems (unlike in MLP that use extra inputs for past sample).

It is computationally more powerful than other adaptive models. It uses BP in time learning (training algorithm) so that its output at time t is used along with a new input to compute its output at time t+1 in response to dynamism (Akazue, Yoro, et al., 2023).

For non-linear tasks like rainfall, the RBF is constructed by modifying the MLP using extra or an additional 'context layer' to retain in memory data between observations. At each time step, new inputs are fed in and previous contents of the hidden layer are passed into this context layer – to be later, fed back into the hidden layer in the next time step. Context layer is initialized with 0. For any iteration, output from hidden layer is stored in this context layer. Weights are calculated same way for the new connections from and to the context layer from the hidden layer. It yields the Radial Basis Function (RBF) with Euclid distance measures input distance from its centre (Okonta et al., 2013, 2014; Wemembu et al., 2014). It learns by training its weights to best fit the data. The Gaussian activation function assumes approximation influence of data points at centre as the function decreases with distance from its centre as in Eq. 2 to 4 respectively (Ojugo, Aghware, et al., 2015a; Ojugo & Eboka, 2020a; Ojugo & Yoro, 2020):

$$r_j = ||y - Y^{(j)}|| = \sum_{i=1}^{m} ((y_i - w_i.j)^2)^{\frac{1}{2}} \quad (2)$$

Transfer function is applied to r_j to give: $\varphi(r_j) = \varphi \left|\left|y - Y^{(j)}\right|\right| \quad (3)$.

Output layer receives data as the weighted combination as:

$$y^k = w_o + \sum_{i=1}^{m} \left(c_j^k * \varphi(r_j)\right) = \sum_{i=1}^{m} [c_j^k * \varphi\{||y - Y^{(j)}\,] \quad (4)$$

Study adopts unsupervised RBF (BP with momentum learning) with an input-hidden-output structure of 60-18-1 (60 nodes as input, 18nodes as hidden, and 1-node for output) and we use Tansig function to control output. It trains the model to yield results and provide a fail-safe that eradicates noise in the stream in real-time); while we using the Hopfield as a control network. Control parameters are weight and bias with a single output layer that yields the runoff. The ensemble cum model's nonlinearity is identified via input parameter selection at training and cross-validation. The dataset retrieved is split as in fig 2 into: *training*, *cross-validation* and *testing*.

The model aims to predict future flood state and provide lead time warning without other feats such as land-use feats of watersheds. Preliminary results showed that ANN with one hidden layer outperforms those of two/more hidden layers, and to increase the number of parameters by adding more hidden layers, only complicates training and may result in over-training – as the network is complex enough to accurately predict dynamic, nonlinear and complex feats.

4. FINDINGS AND RESULT DISCUSSION

4.1. Proposed Ensemble Evaluation

We compute misclassification error rate, and improvement percent for train and test scenarios denoted by Eq. 8 and 9 respectively to yield table 2 as thus:

$$Classification\ Rate\ \frac{No.of\ Incorrect\ class}{No.of\ Sample\ set} \quad (8)$$

$$Improvement\ \frac{MR(A)-MR(B)}{MR(A)}\ x\ 100 \quad (9)$$

Table 2. Summary Sheet For Benchmark Models

Model	Classification Error Rate		Improvement Percentage	
	Training	*Testing*	*Training*	*Testing*
PHMM	0.137	0.102	0.075	0.845
GANN	0.213	0.197	0.063	0.646
DNN	0.112	0.032	0.0789	0.901
RBF	0.0129	0.010	0.921	0.983

Results in table 2 indicates that the hybrid RBF outperforms other heuristics. This can be attributed to the fact that RBF has a rule support. It yields a classification error rate of 1.29% (i.e. model's inability to capture false-positives and true-negatives error rate); while for PHMM, GANN and DNN stood at 13.7%, 21.3% and 11.2% respectively. However, the benchmark models (i.e. PHMM, GANN and DNN) promises an improvement of 84.5%, 64.6% and 90.1% respectively; while, our RBF yields an improvement of 98.3%. This is in agreement with (Ibor et al., 2023; Ojugo, Aghware, et al., 2015b; Ojugo, Oyemade, et al., 2015; Yoro & Ojugo, 2019b, 2019a).

4.2. Findings and Discussion

Table 3 are performance values for the RBF and Hopfield networks are as thus:

Table 3: The proposed RBF versus Existing Hopfield Model Performance

Model	*Training / Cross Validation Phase*				
	COE	r^2	MSE	MAE	MRE
RBF	0.723	0.21	0.910	0.710	1.328
Hopfield	0.832	0.34	0.945	0.623	0.789
	Testing Phase				
RBF	0.714	0.11	0.723	0.628	0.108
Hopfield	0.833	0.28	0.756	0.512	1.310

The RBF network yield a performance that is feasible for prediction. Its inaccuracy is clarified via longer training and larger dataset (as long as overtraining does not occur). Table 2 has the structure of 18-inputs, a single hidden layer with 18 nodes and a single output (18-18-1).

It implies improved performance at testing with greater efficiency (proper training and parameter selection – void of overfit, over-parameterization and over-train) (Akazue, Asuai, et al., 2023; Omede & Okpeki, 2023). Predicted values yielded better result for stations with larger size, and result also indicates that RBF is more easily trained to learn data feats and consistently outperforms other techniques used – though ANN's performance is not impaired by non-linearity and data selection.

Number of nodes in hidden layer influences network's performance. If it is small, network may not achieve its accuracy. If it is too many, may result in overtraining. The general pattern of rainfall over the period, and annual totals indicates spatial and temporal variability from cohesive relations between rainfall and runoff. Factors affecting runoff are more uniform in smaller area of catchments, and its coefficient determination increased with a decrease in the area.

Conflicts must be adequately resolved in to effectively harness the benefits therein the model, exploit the numeric data and explore the domain problem space to yield an optimal solution (Ojugo & Eboka, 2018c; Ojugo & Otakore, 2018a; Okobah & Ojugo, 2018). Modelers must select needed feature(s) to avoid model over-fit (Oyemade & Ojugo, 2020, 2021). Encoded via model's learning helps to address the issues of statistical dependencies between the various heuristics used, highlight implications of such a multi-agent populated model as well as resolve conflicts in data feats of interest. Thus, as agents creates and enforce their own rules on the dataset (Akazue, Debekeme, et al., 2023; Muslikh et al., 2023; Oladele et al., 2024).

5. CONCLUSION

Models are useful to represent reality as their primary value is to serve as educational tools for insight to help us better understand and reflect upon reality (Aghware et al., 2023b, 2023a). They compile knowledge and are vehicles to communicate hypotheses. Its sensitivity analysis help modelers to reflect on a variety of system theories (Malasowe et al., 2023; Ojugo, Akazue, Ejeh, Ashioba, et al., 2023; Ojugo, Akazue, Ejeh, Odiakaose, et al., 2023). Thus, a detailed model should be applicable on a grand scale. For runoff, it is used to examine hypotheses, and investigate which input features are most crucial to be estimated accurately.

We must thus, be keen to a model's feedback mechanism; rather than its accuracy of numeric agreement between its prediction and observation (Ojugo, Odiakaose, et al., 2023). Also, ensembles are valuable to help us understand runoff processes, as only understood models can be used. There must be a balance for complexity and simplicity, which is crucial for studying runoff (Yoro & Ojugo, 2019a). Thus, we recommend: (a) parameters are a major source of uncertainty. Model should have input ranges via Monte-Carlo methods, (b) a multi-criteria training with adequate data can help to reduce parameter uncertainty, and (c) prediction is of limited practical use, without data about reliability and accuracy.

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