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USING ARTIFICIAL NEURAL NETWORK TECHNIQUE RAINFALL-RUNOFF MODELING IN KHANPUR DAM WATERSHED

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Abstract

The rainfall-runoff analysis is extremely imperative in planning and developing water resources. In the present study, Rainfall-Runoff models based on artificial neural networks were developed for the Khanpur dam watershed Pakistan. The meteorological data used for this model was collected by the Water and Power Development Authority (WAPDA). Seven different types of rainfall-runoff models were designed using a daily meteorological parameter (Rainfall, Evaporation, Temperatures, and discharges). For each case, data sets were trained using fifteen neurons and two no of delays, and the data sets were distributed as (80, 10, 10) percent for training, testing, and validation respectively. These parameters were set using trial and error procedures. The above-constructed models were trained using the ANN lavenberg Marquard (trainlm) function. ANN models were validated using cross validation approach for generalization and best model is calibrated using actual data. All models performed well, the NS and R range between (62%-70%) and (0.69-0.82) respectively. the performance of the all models is in satisfactory to good.

Keywords- ANN, Matlab, Meteorological parameter, Rainfall-Runoff

1. INTRODUCTION

Water resources utilization, planning, designing, and development critically be influenced by Rainfall Run-off. Runoff analyses are also very imperative for the prediction of natural catastrophes like floods and droughts[1]. Accomplished management of water resources significantly distresses hydropower generation, irrigation systems and ecological anxieties as well as nutrition security and boosts the economy [2]. To advance rational water preservation policies it is precarious to pretend the rainfall run-off for ungauged watersheds, under current water crises in addition to tested ones. generally rainfall-runoff models had been categorized into stochastic models[3],lumped conceptual models[4], black-box models[5],and physical-based Models[6]. Physical and conceptual models try to explore the all-physical progressions convoluted in the R-R development, there are some limitations in the use of these models, and these models require catchment specifications and explanations in the overriding equations [7]. The procedure of time-series stochastic simulations is problematic owing to nonlinearity and immobilized manners of the meteorological parameter data. The capability and proficiency of the modelers are required for the efficacious practice of these sorts of models [8].

From the past few decades, for highly multifarious and nonlinear system ANN (Artificial neural networks) has appeared as a power full calculating system [9]. From modeling perspective ANN (Artificial neural networks be appropriate to black-box time-series simulations and deals comparatively malleable and hasty worth of modeling. The ANN (Artificial Neural networks) models can indulgence the malfunctioning of the system due to their parallel architecture [1].In hydrological modeling, ANN(Artificial Neural networks) models are extensively used[7]. For flow prediction in the case of a stream, it consists of the rainfall-runoff transfiguration by proposing input of perceived rainfall and discharge. Earlier researches demonstrate that ANN simulations are sufficient for the accomplishment of statistical Rainfall-Runoff modeling (Nouraniet.al 2014)[8]. Alterations of theoretical rainfall-runoff models were provided by (Tongal and Booij et al., 2018) [9].ANN substantiated as a fabulous instrument for R-R modeling of uninterrupted times; but, a comprehensive assortment of hydro-meteorological datasets is necessary for standardization resolves (Toth and Brath Tealab 2018)[10].The performance of the ANN model is predominantly depend on appropriate structure and input data [11].For rainfall-runoff simulation RBFNN (radial basis function neural network) and MLP (multilayer perceptron are most extensively used[12].

A review of aforementioned studies shows that, in some cases, ANN models consider rainfall variables as the single input [13], while in most studies in addition to rainfall flow (or river stage) and rainfall antecedents data were used as inputs [14].Some studies temperature, evapotranspiration, evaporation also used as input constraints, or amalgamations of these factors in adding to rainfall discharges data are also used as inputs[15].

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2. PROBLEM STATEMENT

The global climate change deeply effects on the climate of Pakistan also effect on hydrological resources of Pakistan increase in temperature and precipitation is predicted in Pakistan [16]. Rainfall Runoff is the conspicuous constituent of the hydrological cycle. The changing climate profoundly influence on the rainfall and rainfall runoff process. Estimate of runoff is crucial for efficient water management. So, numerous researchers 'tries to develop and inspect model by using altered modeling procedures, such as auto regression and artificial intelligence (AI) techniques to deliver a precise forecast of the Rainfall-Runoff.

These modeling techniques was developed by using different hydrological and meteorological parameter of long time series data the result obtained from these models perfectly predict the rainfall-runoff. However, some hitches seemed generally associated with prototypical contribution / productivity structure causes problem to insert this into new learning regions that could have a negative impact on the authenticity of the model. One of the most important problems in these types of models is that they depend on elongated time-series facts of quite a few hydrological and climatic factors. Literally, these continuous records are mandatory for the development of a logic model to anticipate the rainfall-runoff. Indeed, this extended time series data provides a consistent model with all the potential shapes desirable to wonderfully intrigue the inputs-outputs of the model's ability to provide a good degree of predictive accuracy.

It is expected that one or more meteorological / hydrological constraints may appear omitted in some case studies, usually in developing regions. Indeed, some factors may be overlooked in many areas of research due to a lack of observational devices to quantify similar characteristics. Absolutely, the omitted data would inevitably disrupt the execution of the model and, therefore, moderate computational skills of the model even if a single input factor is not taken into account. In addition, in developing countries the data collection system is not good and accurate under these conditions, the prediction of ANN-based evaporation models is superlative as it compensates for the effect of the rate of time increase on the level of accuracy of the Model. In this study, Khanpur dam reservoir is under consideration. The study area is located near Islamabad the capital of the Pakistan study investigated the possibility of using ANN technique to produce a rainfall runoff forecasting model with fewer metrological parameter. The anticipated model was designed to predict/estimate rainfall-runoff using daily recorded data of rainfall, evaporation, and temperature (minimum, maximum and average) to predict and estimate the future rainfall runoff.

3. STUDY AREA AND DATA COLLECTIONS

3.1 Study area

Khanpur Dam is located on the Haro River which is almost 50 km away from the capital (Islamabad) of Pakistan. The reservoir of Khanpur dam is located northwest of the Photohar Plateau (longitude 72 ° 53' 30" to 73 ° 26' 20" E; latitudes 33 ° 43' 40" to 34 ° 06' 00" N) shown in Figure 1**.** Its reservoir supplies swallowing water to Rawalpindi and Islamabad and irrigation water to voluminous of the cultivated lands and surrounding industrial areas near by the cities. The groundwater levels in the twin cities (Islamabad/Rawalpindi) are being exploited due to increasing rate of population and there might be future consideration to take more water from Khanpur dam to fulfill the requirement of cities. The rainfall-runoff is one of the major factors which contribute to hydrological cycle. Therefore, for the proper planning and management of watershed, the future prediction of rainfall runoff is a key demand. The main contributor of Khanpur dam watershed is the Haro River that rises from the mountains of Moshpuri and is dammed at Khanpur, north of the capital of Pakistan [16]. The climate of Khanpur dam watershed is semi humid to humid region the temperature range from 2.1°C to 46.6°C by A.R.Ghuman [17].The complete study of the Khanpur dam and water shed was performed (zaheer et al) [16].

3.2 Data Collection

Daily data of following parameters; Perception (Pt), evaporation (Eo), temperature, (To), daily discharge (Qt) data sets were collected from WAPDA (Water and Power Development Authority), Pakistan for a period of 2004 to 2018.

4. METHODOLOGY OF WORK AND ANN

Artificial Neural Networks (ANNs) is a machine learning and works like the brain of humans and animals[18]. ANNs are used for the approximation or evaluations of functions that be subjected to several input considerations, due to these destructions' rainfall runoff is not noticeably replicated or calculated. ANNs obligate the ability to streamline, organize and guess data as of its nature and having the proficiency to hark back to the information putting to them in during the training process. The architecture of ANNs comprises of several layers including input layer, hidden layers and output layer and each layer be made up of different neurons. Input layers neurons receives information from outside as inputs. Then information goes to hidden layers and output layer by using activation function. The architecture of ANN model is shown in Fig.2.

The ANN process had several frameworks, like FFNN, RFB-NN and MLP-NN.Out of which architecture of FFNN (Feed forward neural network), which is currently adopted offer good result by selecting the best number of neurons and hidden layers.

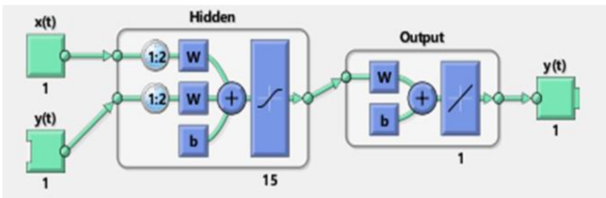

Figure 1 ANNs Architecture.

4.1 Preparation of data bank for ANN

Before to train ANN models, preparation of data bank is important. The data sets (2004-2018) were prepared to train ANN models in seven different approaches as demonstrated in the table.1. The designed models were trained by using different sets input output combination and neurons by trial and error method. The adopted structure of ANN (1, 2, 15) single hidden layer two no delays and fifteen neurons.

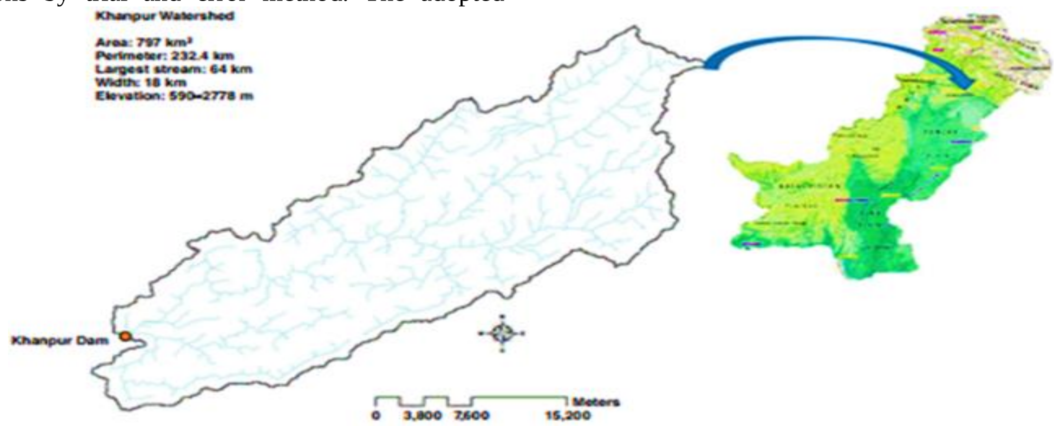

Figure 2 Study area Map.

4.2 Data Normalization

Normalization of parameters play a important contributions in the performance of ANNs models. To circumvent the complications interconnected with the truncated learning rates of the ANNs models, it is obligatory to normalize the constraints concerning a proper higher and lower limit in this work the data is normalized using linear normalization approach and the values are between (0 and 1).

4.3 Architecture of ANN Models

After preparing data bank, ANN models were trained by using MATLAB. The models were constructed in such a way that the output or target value (Runoff/Discharge) remain same for all models, while the input parameters (Perception, Evaporation, Temperature and discharges) were changed. The data set were tested in seven different models. The demonstration of the models and their input/output configuration were represented in Table.1. Each ANN model was consisting of single hidden layers and in every hidden layers 15 neurons were maintained. In every ANN model 80 percent of data was utilized for the training of model, while the remaining 20 percent of data divided into; 10 percent for testing and 10 percent for the validation of model. The All models were verified by means of rehabilitated cross validation approaches [19].

Table 1 Input Parameters

ID	Model	Input Parameters	Output
1	LPtm-1	P(t)	Q(t)
2	LPtm-2	P(t),Eo	Q(t)
3	LPtm-3	P(t), Eo, To	Q(t)
4	LPtm-4	P(t-1)	Q(t)
5	LPtm-5	P(t-2)	Q(t)
6	LPtm-6	P(t-3)	Q(t)
7	LPtm-7	P(t), Eo,To,Qt	Q(t)

Where LPtm linear perception model (1-7), P (t), Eo, To, Q (t) is daily perception, evaporation, Temperature and discharge respectively. Similarly, P (t-1), P (t-2), P (t-3) represent the anticipated perception of 1, 2 and 3 days.

5. MODEL EVALUATION MATRICES.

In general, to assess the conduct of the forecast models, it is essential to scrutinize the models by applying assured concert gauges to understand whether or not the planned models match the actual value. To assess the attainment of the suggested rainfall-runoff prediction models certain statistical gauges were applied to suggested evaporation rate prediction models in this study. The indicators used in this study are presented in the Table.2.

Table 2 Performance Classifications

Statistical Indicator	Assessment	Performance Classification	Ref.
Root mean square error (RMSE) RMSE=$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(oi-si)^2}$ RSR=$\frac{RMSE}{STDEVobs}$	Below half of the STDEV value 0.00≤ RSR ≤0.50 0.50< RSR ≤ 0.60 0.60<RSR≤0.70 RSR>0.70	Satisfactory Very Good Good Satisfactory Unsatisfactory	[20] [21]
Nash–Sutcliffe efficiency (NS) NS=$1-\frac{\sum_{i=1}^{i=n}(\mathbf{oi-si})^2}{(\mathbf{mi-mi(mean)}}$	0.75 to 1.00 0.65 to 0.75 0.50 to 0.65 0.4 to 0.50 NSE ≤ 0.4	Very Good Good Satisfactory Acceptable Unsatisfactory	[22] [21]
Mean Bias Error MBE=$\frac{1}{n}\sum\lvert oi-si\rvert$	MBE>0 Positive MBE<0 Negative	Overestimated Forecast Underestimated Forecast	[23]

6. RESULT AND DISCUSSION

In this study seven different models were designed using ANN techniques to estimate the rainfall runoff of selected watershed. We set seven different input combination to find correlation between the input and output. The linear rainfall-runoff ANN models configuration, Rainfall, rainfall and evaporation, rainfall, evaporation and temperatures, rainfall, evaporation, temperatures and discharges data had been used to find correlation with runoff/discharge. The performance of ANN models was dignified by using Root mean square error (RMSE), RSR and (NS) Nash Sutcliff efficiency statistical criteria and their equation of calculation are given as equation. Table. 3. Shows the values of the performance measures (RSR, NS MBE and R) for Different model configurations.

Table 3 Performance measures

ID	RSR	Performance	NS	Performance	MBE	Status	R	Status
1	0.52	Good	0.69	Good	0.00010	OEF	0.81	Good
2	0.56	Good	0.68	Good	-0.00024	UEF	0.78	Good
3	0.59	Good	0.65	Good	-0.00013	UEF	0.79	Good
4	0.62	Satisfactory	0.62	Satisfactory	0.000311	OEF	0.78	Good
5	0.63	Satisfactory	0.61	Satisfactory	-0.00111	UEF	0.82	Good
6	0.61	Satisfactory	0.70	Good	-0.00069	OEF	0.80	Good
7	0.57	Good	0.68	Good	-0.00065	UEF	0.79	Good

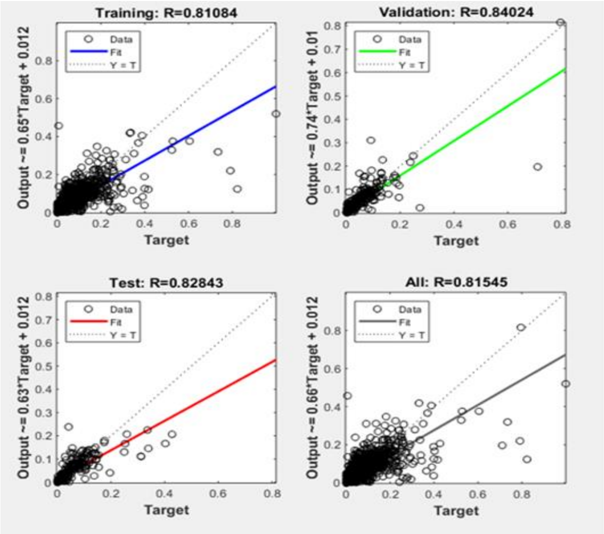

Figure 3 Data Comparison

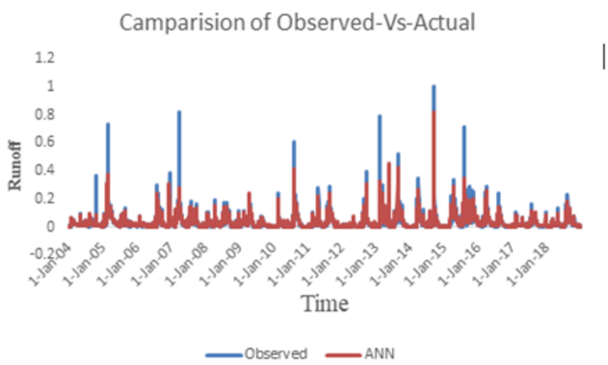

Figure 4 Data Comparison

Where OEF, UEF is overestimated forecast and underestimated forecast. From the above model ID-1 is selected as best model.it is calibrated using actual data their comparison is given in Figure.3 Their regression analysis for testing training and validation are also given in Figure.3

7. CONCLUSION

This study was concentrated on comparing meteorological parameters with rainfall-runoff of Khanpur dam watershed. Rainfall-Runoff was calculated from 2004 to 2018 and precipitation, temperature, evaporation and discharges were used as meteorological constraints to develop a relation with rainfall-runoff, ANN modeling techniques were used for runoff calculations.

In this study seven different types of models were trained relating meteorological parameter with rainfall-runoff all the models produced satisfactory result according to the statistic given in Table.2. Based on the above statistic it can be concluded that ANN models, are proved to be a powerful modeling tools in modeling of hydrological process which are generally considered as black box models. ANN is a prominent substitute to the deterministic and theoretical model for the rainfall runoff analyses. It is comparatively simple to establish and do not involve the comprehensive exploration of the watershed geological and hydrological constraints as are crucial for the solicitation of deterministic, conceptual and other types of physically based simulations.

8. RECOMMENDATIONS

The performance of the models can be increased by using other hydrological parameter like hydraulic connectivity, land use and land cover further models can be trained using different weekly and monthly average data of the meteorological parameter.

The performance of the can be calibrated by using other physical based model like Soil water Assessment tool (SAWAT), HEC-HMS. The ANN model can be established for sediment discharge and reservoir levels estimations.

REFERANCES

[1] A. R. Ghumman, Y. M. Ghazaw, A. R. Sohail, and K. Watanabe, "Runoff forecasting by artificial neural network and conventional model," *Alexandria Eng. J.*, vol. 50, no. 4, pp. 345–350, 2011, doi: 10.1016/j.aej.2012.01.005.

[2] A. R. Ghumman, I. S. Al-Salamah, S. S. AlSaleem, and H. Haider, "Evaluating the impact of lower resolutions of digital elevation model on rainfall-runoff modeling for ungauged catchments," *Environ. Monit. Assess.*, vol. 189, no. 2, 2017, doi: 10.1007/s10661-017-5766-0.

[3] M. Tu Pham, H. Vernieuwe, B. De Baets, and N. E. C. Verhoest, "A coupled stochastic rainfall-evapotranspiration model for hydrological impact analysis," *Hydrol. Earth Syst. Sci.*, vol. 22, no. 2, pp. 1263–1283, 2018, doi: 10.5194/hess-22-1263-2018.

[4] S. Nauman, Z. Zulkafli, A. H. Bin Ghazali, and B. Yusuf, "Impact assessment of future climate change on streamflows upstream of Khanpur Dam, Pakistan using Soil and Water Assessment Tool," *Water (Switzerland)*, vol. 11, no. 5, 2019, doi: 10.3390/w11051090.

[5] Z. M. Yaseen, M. F. Allawi, A. A. Yousif, O. Jaafar, F. M. Hamzah, and A. El-Shafie, "Non-tuned machine learning approach for hydrological time

series forecasting," *Neural Comput. Appl.*, vol. 30, no. 5, pp. 1479–1491, 2018, doi: 10.1007/s00521-016-2763-0.

[6] US Army Corps of Engineers Institute for Water Resources Hydrologic Engineering Center, "Hydrologic Modeling System Technical Reference Manual," *Hydrogeol. J. Hydrol. Model. Syst. Tech. Ref. Man.*, no. March, p. 145, 2000.

[7] K. W. Chau, "A split-step particle swarm optimization algorithm in river stage forecasting," *J. Hydrol.*, vol. 346, no. 3–4, pp. 131–135, 2007, doi: 10.1016/j.jhydrol.2007.09.004.

[8] L. Chen, V. P. Singh, S. Guo, J. Zhou, and L. Ye, "Copula entropy coupled with artificial neural network for rainfall–runoff simulation," *Stoch. Environ. Res. Risk Assess.*, vol. 28, no. 7, pp. 1755–1767, 2014, doi: 10.1007/s00477-013-0838-3.

[9] M. Tayyab, J. Zhou, X. Dong, I. Ahmad, and N. Sun, "Rainfall-runoff modeling at Jinsha River basin by integrated neural network with discrete wavelet transform," *Meteorol. Atmos. Phys.*, vol. 131, no. 1, pp. 115–125, 2019, doi: 10.1007/s00703-017-0546-5.

[10] T. K. Chang, A. Talei, C. Quek, and V. R. N. Pauwels, "Rainfall-runoff modelling using a self-reliant fuzzy inference network with flexible structure," *J. Hydrol.*, vol. 564, pp. 1179–1193, 2018, doi: 10.1016/j.jhydrol.2018.07.074.

[11] E. Toth and A. Brath, "Multistep ahead streamflow forecasting: Role of calibration data in conceptual and neural network modeling," *Water Resour. Res.*, vol. 43, no. 11, pp. 1–11, 2007, doi: 10.1029/2006WR005383.

[12] A. Guven and Ö. Kişi, "Daily pan evaporation modeling using linear genetic programming technique," *Irrig. Sci.*, vol. 29, no. 2, pp. 135–145, 2011, doi: 10.1007/s00271-010-0225-5.

[13] F. Granata, R. Gargano, and G. de Marinis, "Support vector regression for rainfall-runoffmodeling in urban drainage: A comparison with the EPA's storm water management model," *Water (Switzerland)*, vol. 8, no. 3, pp. 1–13, 2016, doi: 10.3390/w8030069.

[14] A. Talei, L. H. C. Chua, C. Quek, and P. E. Jansson, "Runoff forecasting using a Takagi-Sugeno neuro-fuzzy model with online learning," *J. Hydrol.*, vol. 488, pp. 17–32, 2013, doi: 10.1016/j.jhydrol.2013.02.022.

[15] Z. X. Xu and J. Y. Li, "Short-term inflow forecasting using an artificial neural network model," *Hydrol. Process.*, vol. 16, no. 12, pp. 2423–2439, 2002, doi: 10.1002/hyp.1013.

[16] M. Zaheer, Z. Ahmad, and A. Shahab, "Hydnological modeling and characterization of the Khanpur watershed, Pakistan," *J. Am. Water Works Assoc.*, vol. 108, no. 5, pp. E262–E268, 2016, doi: 10.5942/jawwa.2016.108.0043.

[17] A. R. Ghumman, "Assessment of water quality of Rawal Lake by long-time monitoring," *Environ. Monit. Assess.*, vol. 180, no. 1–4, pp. 115–126, 2011, doi: 10.1007/s10661-010-1776-x.

[18] P. S. Kumar, T. V. Praveen, and M. A. Prasad, "Artificial Neural Network Model for Rainfall-Runoff -A Case Study," *Int. J. Hybrid Inf. Technol.*, vol. 9, no. 3, pp. 263–272, 2016, doi: 10.14257/ijhit.2016.9.3.24.

[19] A. Moghaddamnia, M. Ghafari Gousheh, J. Piri, S. Amin, and D. Han, "Evaporation estimation using artificial neural networks and adaptive neuro-fuzzy inference system techniques," *Adv. Water Resour.*, vol. 32, no. 1, pp. 88–97, 2009, doi: 10.1016/j.advwatres.2008.10.005.

[20] J. Singh, H. V. Knapp, J. G. Arnold, and M. Demissie, "Hydrological modeling of the Iroquois River watershed using HSPF and SWAT," *J. Am. Water Resour. Assoc.*, vol. 41, no. 2, pp. 343–360, 2005, doi: 10.1111/j.1752-1688.2005.tb03740.x.

[21] D. N. Moriasi, J. G. Arnold, M. W. Van Liew, R. L. Bingner, R. D. Harmel, and T. L. Veith, "M e g s q a w s," vol. 50, no. 3, pp. 885–900, 2007.

[22] I. Boskidis, G. D. Gikas, G. K. Sylaios, and V. A. Tsihrintzis, "Hydrologic and Water Quality Modeling of Lower Nestos River Basin," *Water Resour. Manag.*, vol. 26, no. 10, pp. 3023–3051, 2012, doi: 10.1007/s11269-012-0064-7.

[23] A. V. M. Ines and J. W. Hansen, "Bias correction of daily GCM rainfall for crop simulation studies," *Agric. For. Meteorol.*, vol. 138, no. 1–4, pp. 44–53, 2006, doi: 10.1016/j.agrformet.2006.03.009.