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Editorial

Use of Meta-Heuristic Techniques in Rainfall-Runoff Modelling

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Abstract: Each year, extreme floods, which appear to be occurring more frequently in recent years (owing to climate change), lead to enormous economic damage and human suffering around the world. It is therefore imperative to be able to accurately predict both the occurrence time and magnitude of peak discharge in advance of an impending flood event. The use of meta-heuristic techniques in rainfall-runoff modeling is a growing field of endeavor in water resources management. These techniques can be used to calibrate data-driven rainfall-runoff models to improve forecasting accuracies. This Special Issue of the journal *Water* is designed to fill the analytical void by including papers concerning advances in the contemporary use of meta-heuristic techniques in rainfall-runoff modeling. The information and analyses can contribute to the development and implementation of effective hydrological predictions, and thus, of appropriate precautionary measures.

Keywords: rainfall-runoff; meta-heuristic; data-driven; modeling; flood; prediction

1. Introduction

Around the world each year, extreme floods, which appear to be occurring more frequently in recent years (owing to climate change), lead to enormous economic damage and human suffering. As such, it is imperative to be able to accurately predict both the occurrence time and magnitude of peak discharge in advance of an impending flood event. The use of meta-heuristic techniques in rainfall-runoff modeling is a growing field of endeavor in water resources management [1–12]. These techniques can be used to calibrate data-driven rainfall-runoff models to improve forecasting accuracies.

The papers contained within this Special Issue entitled Use of Meta-Heuristic Techniques in Rainfall-Runoff Modelling are designed to fill the analytical void by including papers concerning advances in the contemporary use of meta-heuristic techniques in rainfall-runoff modeling. The information and analyses can contribute to the development and implementation of effective hydrological predictions, and thus, of appropriate precautionary measures. The papers cover a number of applications of different novel meta-heuristic techniques in addressing a variety of hydrological modelling problems, tailored for different areas of geography and climatic conditions.

2. Contributors

The correlation between landscape and climate with the data availability is a difficult problem in sub-watershed hydrology. Salas-Aguilar et al.'s work [13] employs a top-down approach to develop a generalized baseflow model in order to assess the annual recession curves and to correlate the recession parameter with hydrological and geographical attributes of twenty-one sub-watersheds in Mexico, covering a variety of climatic conditions. Results indicate that the recession parameter increases with longitude but decreases with latitude and it exhibits a consistent non-linear behavior dependent upon the precipitation rate and evapotranspiration in the sub-watersheds. The non-linear baseflow model is able to separate baseflow from direct flow more accurately in sub-watersheds. It can adequately address the relationship amongst recharge, storage and discharge and can thus be used in basins with insufficient data availability.

The key drawbacks of the conventional curve number model are the vulnerability to instability in the direct runoff results owing to its reliance on the original abstraction level and the absence of the procedure on pre-storm soil moisture accounting for ungauged watersheds. Ajmai et al. [14] integrate the conventional curve number model with a French four-parameter model with a varying original abstraction level, in order to address this issue. Inherent parameters are assigned in the novel parameterization procedure. Its performance is assessed by comparing results with several benchmarking conventional models for observed data in thirty-nine watersheds employing different statistical metrics. Results indicate that the novel model is able to generate better and more consistent outcomes than its counterparts.

It is difficult to optimize the number of calibration sites in hydrologic modeling and, currently, the most often employed method is the trial and error method. Kim et al. [15] put forward an entropy method to attain automatic optimization of the number of calibration sites with application in a Korean river basin. The entropy method is first applied to group different combinations of runoff discharge stations and to determine the best one amongst them. The optimal set of parameters of the developed hydrologic model is then calibrated by employing a genetic algorithm. Calibration results corroborate that the model with the combination and site number recommended by the entropy method outperforms the others. Besides, it is proven to be able to substantially shorten the time required on model calibration.

In real-time discharge forecasting, particularly during typhoon attacks, the difficulties mostly encountered include high uncertainty and long lead time. Huang et al. [16] couple a real-time recurrent learning neural network, an adaptive network-based fuzzy inference system, and some heuristic techniques to address this problem. Heuristic inputs are utilized to enhance the spatial and temporal precision. Results indicate that this proposed model performs much better than the adaptive network-based fuzzy inference system, in terms of both forecasting error at long lead-time and solution stability. The prediction lead-time of the former can be up to forty-nine hours with an average error percentage smaller than 10% while for the latter, the corresponding values are six hours and 20% to 40% respectively.

In their paper Estimation of Rainfall Associated with Typhoons over the Ocean Using Tropical Rainfall Measuring Mission (TRMM)/TRMM Microwave Imager (TMI) and Numerical Models, Yeh et al. [17] couple much numerical weather research and forecasting as well as radiative transfer models with the Tropical Rainfall Measuring Mission/ Precipitation Radar data from 2002 to 2010 to predict rainfall resulting from a typhoon in the northwestern Pacific Ocean. A microwave radiative transfer model is developed to mimic fifteen typhoons and to generate a posterior probability distribution function. The precipitation rate resulting from a typhoon can then be determined by entering the TMI with attenuation indices at specific frequency into the posterior probability distribution function. Results show that the locations of the simulated rainband with the heaviest precipitation agree well with field observations. This paper contributes towards a feasible solution in providing a quick and accurate prediction of rainfall resulting from a typhoon.

The paper by Wu and Lin [18] entitled An Hourly Streamflow Forecasting Model Coupled with an Enforced Learning Strategy documents how to enhance the accuracy of hourly streamflow prediction by integrating an enforced learning strategy with four different neural network-based models, namely, the support vector machine, radial basis function network, back propagation network, and self-organizing map. The performances of these neural network-based models, with and without the enforced learning strategy, are compared under real-life application. Results indicate that, among different neural network-based models, the support vector machine and self-organizing map outperform the radial basis function network and back propagation network. Besides, the incorporation of the enforced learning strategy is able to enhance the performance of all types of neural network-based models in hourly streamflow prediction. As such, it is concluded that the proposed methodology is promising in enhancing neural network-based streamflow prediction models.

It is important to be able to predict the long-term power production of small hydropower plants for successive integration with power production of large to medium hydropower plants. However, a recognized prediction model for this purpose does not exist. Li et al. [19], in their paper Applying a Correlation Analysis Method to Long-Term Forecasting of Power Production at Small Hydropower Plants, employ a correlation analysis method to predict the power production of small hydropower plants. Analysis is performed on the correlation between small hydropower plants and large to medium hydropower plants which reveals that they have similar interval inflows. As such, a regression model is built to predict the power production of small hydropower plants on the basis of the inflows of large to medium hydropower plants. The proposed method is successfully applied to small hydropower plants in the Yunnan Power Grid.

The prediction of reservoir monthly inflow is significant owing to the purposes of water resource management as well as the stability of long-term reservoir operation. In their paper Heuristic Methods for Reservoir Monthly Inflow Forecasting: A Case Study of Xinfengjiang Reservoir in Pearl River, China, Cheng et al. [20] employ two heuristic prediction methods, namely, artificial neural networks and the support vector machine, to predict reservoir monthly inflow. In these models, a genetic algorithm is used to select and calibrate the optimized set of model parameters. A hybrid prediction two-stage model coupling the above two methods is also developed in this study. In the first stage, each method is employed to predict the reservoir monthly inflow values, both of which are used as the input variables of a second artificial neural network model for refined prediction in the second stage. These three models are applied to predict monthly reservoir inflow in Xinfengjiang reservoir from 1944 to 2014. Results indicate that the hybrid method outperforms both artificial neural networks and the support vector machine in terms of five performance evaluation metrics.

Whilst the artificial neural network has been proven to be one of the most effective methods in daily discharge prediction, its drawbacks of slow training speed and vulnerability to being trapped in the local optimum cannot be neglected in real-life application. Cheng et al. [2], in their paper Daily Reservoir Runoff Forecasting Method Using Artificial Neural Network Based on Quantum-behaved Particle Swarm Optimization, address this problem by investigating the use of the artificial neural network model based on quantum-behaved particle swarm optimization in daily discharge prediction. In this model, quantum-behaved particle swarm optimization is utilized to determine the optimal set of synaptic weights and thresholds of the artificial neural network. The hybrid model is able to couple the advantages of both methods and thus to improve the performance of the prediction model. It is applied to Hongjiadu reservoir in China for the period from 2006 to 2014. Results illustrate that the proposed hybrid model outperforms the original artificial neural network model and hence proves its feasibility in daily discharge prediction.

Wang et al. [21], in their paper Daily Runoff Forecasting Model Based on ANN and Data Preprocessing Techniques, examine the effect of applying a data preprocessing technique, namely, singular spectrum analysis, to the input data on the performance of the artificial neural network model for daily discharge prediction. Benchmark comparison is then made with the original artificial neural network model as well as a nonlinear perturbation model based on the artificial neural network. Field data of eight real watersheds are used for model calibration and comparison. Results show that the artificial network model with singular spectrum analysis outperforms both benchmarking models whilst the integration of a nonlinear perturbation model to the artificial neural network can also induce some performance enhancement, though to a lesser extent. Besides, models with the input combination comprising both rainfall and previous runoff perform better than their counterparts with the input combination considering rainfall solely.

In their paper Parameter Automatic Calibration Approach for Neural-Network-Based Cyclonic Precipitation Forecast Models, Lo et al. [22] propose a neural network-based precipitation prediction model coupled with a parameter automatic calibration approach in determining the training parameters of the neural network. It is applied to Dawu station in Taiwan, with data on a typhoon and ground weather as model inputs. A multiple linear regression model and a multilayer perception neural network model are employed as the benchmark for comparison of the performance of the proposed model. For the multilayer perception neural network model, the trial-and-error method is used for tuning and calibrating the training parameters manually. Results demonstrate that the neural network-based model with a parameter automatic calibration approach outperforms all the benchmarking models. Results also show that, if the increment number in the parameter ranges increases, the computing efficiency of the proposed model will decrease but its accuracy will increase.

The paper by Kim and Singh [23] entitled Spatial Disaggregation of Areal Rainfall Using Two Different Artificial Neural Networks Models presents the development of two artificial neural network models, namely, the multilayer perceptron and Kohonen self-organizing feature map, for spatial disaggregation of areal precipitation in the Wi-stream catchment in South Korea. For the three-layer multilayer perceptron model, three training algorithms, namely, Levenberg–Marquardt, conjugate gradient and quickprop, are employed to compute areal precipitation. Results show that the Levenberg–Marquardt training algorithm is more sensitive to the number of hidden nodes than the other two training algorithms. The network architectures of 11-3-1 for the Levenberg–Marquardt algorithm and 11-5-1 for both the conjugate gradient and quickprop algorithms perform the best amongst all tried structures. As such, their corresponding inverse networks represent the best multilayer perceptron model for spatial disaggregation of areal precipitation. Results also indicate that both the multilayer perceptron and Kohonen self-organizing feature map are feasible for spatial disaggregation of areal precipitation.

In nonlinear hydrologic processes, spatial variability has a very significant role. In most grid-based rainfall-runoff models, the often assumed uniform subgrid variability results in scale-dependence. In their paper Subgrid Parameterization of the Soil Moisture Storage Capacity for a Distributed Rainfall-Runoff Model, Guo et al. [24] study the effect of scale on the Grid-Xinanjiang model at Yanduhe Basin and propose a subgrid parameterization method in order to integrate the subgrid variability of the soil moisture storage capacity, which has significant effects on discharge partitioning and generation in the model. Correlation is performed between the soil moisture storage capacity and the topographic index because their spatial patterns are quite similar. Results illustrate that the proposed method outperforms the original Grid-Xinanjiang model in terms of consistency and precision. It is able to eliminate the recalibration process when there is any change to the resolution of the digital elevation model and enhance the use of the model even in an ungauged basin.

Previous research indicates that adaptive algorithms are key in deterministic flood prediction models owing to the intrinsic non-stationary nature of the rainfall-runoff process. Ho and Lee [25], in their paper Grey Forecast Rainfall with Flow Updating Algorithm for Real-Time Flood Forecasting, develop a real-time flood prediction system by coupling a precipitation prediction model, a geomorphology-based discharge model and an updating algorithm. Observed hourly precipitation data are employed in the grey precipitation prediction model. The watershed discharge model is able to mimic the effects of changing geo-hydrological conditions. Validation of the system is performed at two watersheds in Taiwan and one in the United States. Results demonstrate that the proposed system is promising in simulating the observed hydrographs in several sets of rainfall-runoff cases covering different conditions and will be useful in reducing human and economic losses in advance of flooding incidents.

3. Conclusions

The fourteen papers contained in the Special Issue entitled Use of Meta-Heuristic Techniques in Rainfall-Runoff Modelling cover a wide range of applications of different novel meta-heuristic methodologies and techniques in addressing a variety of hydrological modelling problems, tailored for different areas of geography and climatic conditions in order to resolve both local and regional pertinent issues as well as in different time scales. They are demonstrated to be able to fill the analytical void by enriching the advances in the contemporary use of meta-heuristic techniques in rainfall-runoff modeling. It is apparent, from the abovementioned collection of papers, that novel applications of meta-heuristic techniques in rainfall-runoff modeling will be required for proper water resources management. The information and analyses can certainly contribute to the development and implementation of effective hydrological predictions, and thus, of appropriate precautionary measures.

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