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Research Article

Downscaling Global Weather Forecast Outputs Using ANN for Flood Prediction

Nam Do Hoai, Keiko Udo, and Akira Mano

Disaster Control Research Center, Tohoku University, Aoba 6-6-11, Sendai 890-8579, Japan

Correspondence should be addressed to Nam Do Hoai, nam@potential1.civil.tohoku.ac.jp

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Downscaling global weather prediction model outputs to individual locations or local scales is a common practice for operational weather forecast in order to correct the model outputs at subgrid scales. This paper presents an empirical-statistical downscaling method for precipitation prediction which uses a feed-forward multilayer perceptron (MLP) neural network. The MLP architecture was optimized by considering physical bases that determine the circulation of atmospheric variables. Downscaled precipitation was then used as inputs to the super tank model (runoff model) for flood prediction. The case study was conducted for the Thu Bon River Basin, located in Central Vietnam. Study results showed that the precipitation predicted by MLP outperformed that directly obtained from model outputs or downscaled using multiple linear regression. Consequently, flood forecast based on the downscaled precipitation was very encouraging. It has demonstrated as a robust technology, simple to implement, reliable, and universal application for flood prediction through the combination of downscaling model and super tank model.

1. Introduction

Numerical weather prediction (NWP) has demonstrated its breakthrough in flood forecast recently. In terms of forecast lead time, the flood prediction based upon numerical weather prediction outputs tends to outperform other conventional forecasts which are based on real-time observation, especially in small- to medium-size basins where runoff concentration is relatively short. The forecast lead times given by NWP are ranging from short-term forecast (a couple of hours to few days) to medium-range forecast (up to ten days or more). This allows implementing effective action plans to minimize flood risk. At global scale, even though NWP models have showed significant improvement in terms of spatial resolutions, presently ranging from 25 to 50 km, these spatial resolutions are still far away from the requirement for hydrological simulations or local-scale weather researches that usually require much finer resolutions, of about hundreds meters for small catchments to a couple of kilometers for large basins. Since land surface is averaged within very coarse grid cells; thus, small-scale effects of topography may not be resolved in the global NWP model. As a result, outputs from NWP models, hereinafter called the model outputs, are usually unreliable such as precipitation that is well known as the most unpredictable variable. For that reason, the flood forecast based on model outputs was not what had been expected [1, 2]. Although it is hoped that in the near future the global NWP models might be operational at finer resolutions, downscaling the model outputs from such resolutions to specific sites or area averages for practical uses is essential. Downscaling is a familiar technique used in climate research and weather forecast that aims to utilize information derived from the global NWP model outputs, particularly in the assessment of hydrological implication driven by global climate models or attempting for runoff prediction.

With respect to hydrological simulation and forecasting, though it is a new approach, artificial neural network (ANN) has been reported to give better performance in rainfall-runoff modeling than some other conventional runoff forecasts [3]. The use of (ANN) in runoff prediction is basically divided into two approaches. First, most studies used ANN approach for direct runoff or river stage prediction, as described in literature [4]. The prediction based on ANN is generally considered as an empirical method using mathematic transfer functions that relate stream flow with other weather variables. In this case, the rainfall-runoff process is known as a black box system whose inputs are usually hydrometeorological variables, such as antecedent rainfall and stream flow, and outputs are regularly the runoff or stage prediction. This process apparently omits the effect of physical characteristics of catchment on runoff generation processes. As a result, it sometimes reflects the inconsistency and inefficiency. In addition, this method usually provides the runoff forecast subsequence to the occurrence of rainfall. Therefore, the forecast lead-time is relatively short, especially the quick response catchments, of the order of zero to a couple of hours. To some extent, it is considered insufficient to put in place effective flood mitigation measures. On the contrary, the second approach employs ANN for indirect runoff prediction. The ANN is used to increase the accuracy of precipitation prediction, usually obtained from the model outputs, which is then used as inputs to hydrological models for runoff prediction. This approach is likely to outperform the previous one not only in terms of forecast lead-time extension but also the inclusion of the effects of catchment physical variations and rainfall distribution on the runoff generation process; thus, predictions are more realistic. Recent studies showed that potential predictors used for precipitation prediction are mostly based on outputs from high-resolution weather prediction models or combination of these outputs with other remote sensing information such as images of cloud structures [5, 6]. However, there have been existing limitations that these studies were restricted either just applicable for some in limited areas where are accessible to high-resolution models or at relatively short-term forecast. It means that greater lead times of flood forecast in larger scales are required, particularly in developing countries where globally covered NWP models are available; therefore, its benefit is maximized.

This paper presents the development of an empirical-statistical approach to downscale the precipitation from global NWP outputs to a basin-average scale for flood runoff prediction. The most popular ANN architecture, the feed-forward multilayer perceptron (MLP) using error training back-propagation method, was selected to downscale the large-scale precipitation. The large-scale predictors were obtained from the global NWP outputs, operated by Japan Meteorological Agency, with 0.5° grid point value data. Physical bases of precipitation evolution were analyzed for the optimization of the MLP configuration used in calibration processes because it is very essential to drop out uncorrelated variables that cause overfitting and to overcome the requirement of a long historical record for learning stages as well as to speed up computational skills.

The study point of view targets to use simple approaches which are widely applied and of proven accuracy. Hence, the downscaled precipitation was then used as inputs to the super tank model, a calibration-free requirement rainfall-runoff model, which has been applied in simulating the river flow in a number of basins across various spatiotemporal scales to predict the flood runoff. The case study was conducted for the Upper Thu Bon River, located in Central Vietnam, where floods are considered the most dangerous calamity to human lives. The study results are expected to enhance the existing flood-forecasting technologies and mitigation practices. This is considered valuable for developing countries where ground weather observation is scarce and access to high resolution NWP models is limited.

2. Data and Methodology

2.1. Data and Study Area

Global NWP models are operational at many national meteorological agencies such as in Europe, America, and Japan. These models have been often upgraded; as a result, its spatiotemporal resolution has been quickly increased since the advent of computer technology. However, each agency has its own forecast purposes and is very much dependent on computational capability. The models might be different in terms of physical parameterization, forecast range, forecast issue routine, and spatiotemporal resolution. This study used atmospheric variables derived from the global NWP model outputs, operational at Japan Meteorological Agency, with spatial resolution of 0.5° and 60 vertical layers. It is currently considered the most advanced NWP model, for global scale, that produces 84-hour forecast, issued 4 times per day, at 00, 06, 12, and 18UTC. Precipitation on the surface and other variables are predicted for every 6-hour interval, 00–6, 6–12, 12–18, and 18–24UTC.

This study addressed a convention that precipitation obtained from rain gages was considered as reference rainfall (truth) for the comparison. Given the fact that the global NWP with 0.5° spatial resolution has been operational since late 2007, this analysis was based on archived data for the wet seasons, 2008 and 2009. Inverse distance weighting method was used to interpolate precipitation and related atmospheric parameters either from a point representation (rain-gage) or grid point value representation (NWP) to area-average basis.

In Central Vietnam, it has been highlighted that flood is the most common climate-related disaster. The region has often experienced large-scale floods during the wet seasons, from September to December, annually. These floods were usually caused by extremely widespread intense orographic rainfall that occurred on the windward of the Annam Range, known as the border between Vietnam and Laos. This type of rainfall was basically formulated through the combination of the cold surge from Northern continent and the tropical depression from the Pacific Ocean [7]. The basin selected in this study is the upper reach of Thu Bon River (see Figure 1) with the catchment area of 3,150 km^2. Average basin elevation is about 445 m above the mean sea level. Given the topographical features, rivers in this region are generally very short and steep; therefore, catchment response is rapid, resulted in very short time for people at risk to implement effective flood mitigation measures.

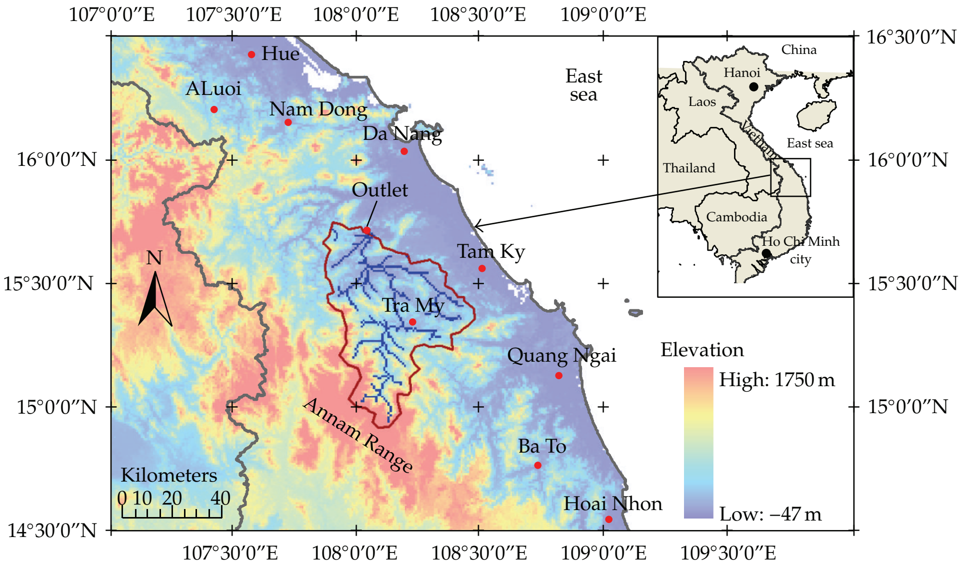

Figure 1: Location of study area and weather observation points (•).

2.2. *Downscaling*

It is expected that in the near future global NWP models may be operational at very fine resolution; however, there will still be a requirement to refine these models outputs to individual sites or local scales for weather research and application [8]. Downscaling is a common technique used in climate research and weather forecast that tries to utilize global atmospheric variables such as precipitation information for the use of impact assessment, hydrological simulation, and forecasting at subgrid or small scales. Downscaling methods are simply classified into dynamical approach and empirical-statistical approach [9].

The dynamical downscaling normally refers to limited area models (LAMs), or the so-called nested grid models, embedded with global NWP fields at its lateral boundaries. This type of models is usually based on fundamental physical principles and is able to take into account considerations of small-scale effects of land surface on weather patterns. Thus, outputs from LAM are expected to be realistic. However, it requires cost-effective evaluation regarding the selection of downscaling methods. First, it is costly to run LAM because of massive computational requirements, known as super computer systems. As a result, not many nations, especially the developing countries, are able to establish its own LAM for the purpose of weather forecast and hydrological simulations. This type of model is currently available only in such regions as North America (North Atlantic Model), Japan (Mesoscale Model), and some regions in Europe (COSMO Model for Germany). Second, the LAM are also subject to systematic biases as their accuracy is very much dependent on the veracity of the global weather model outputs that are used to derive the boundary conditions of the LAM [9]. In addition, in some cases finer-grid data might not be well reflected in the hydrological model if the details are aggregated over time and space [10].

In line with the scope of this study that simple approaches across a wide range of application are preferable the present study used statistical downscaling method that is considered as one of the most cost-effective methods in local-impact assessments of climate scenarios and weather forecast. The statistical downscaling is cheap to run and universally applicable. Various statistical tools for weather downscaling have been proposed and were clearly reviewed by Wilbey and Wigley [8]. The statistical downscaling is fundamentally based on the formulation of either linear or nonlinear relationships between large-scale atmospheric variables and local or single-site scale variables. These relationships are then used to correct the outputs of the NWP models. The weakness of the method is that it requires a long historical weather observation record for the calibration processes. However, in the context of the present study, this problem can be avoided by taking into account the physical bases regarding the evolution processes of storm events in the study area. These storms are widespread orographic rainfall, typically following tropical depressions and typhoons in wet seasons.

Model output statistic (MOS) has been well known for a long history as a statistical downscaling tool for operational weather forecast [11]. Multiple linear regression is commonly used in the formulation of relationships between variables (predictors) derived from global NWP outputs and local or small-scale variables (predictants) such as downscaling precipitation. This method has been accepted in many meteorological centers for operational weather forecast, for example, in the USA. Nonetheless, precipitation is one of the most unpredictable variables, in terms of learning skill; a review of empirical downscaling techniques indicated that ANNs are generally observed to perform a better learning ability than the other regression-based downscaling techniques [4, 12]. Consequently, the present study employed ANN to downscale the large-scale precipitation derived from the global NWP model outputs.

Ground weather analysis based on downscaling global NWP outputs is typically conducted for individual points, subgrid scale or area-average bases. The NWP outputs are provided as a grid-point-value format, at very coarse spatial resolution. Using area-average downscaling approach apparently tends to reduce small-scale effects, in particular when the catchment size is larger than the size of grid cells (approximate 2,500 km^2). Information from neighbor grid points was preliminarily interpolated to the study basin using inverse distance weighting method. The same procedure was conducted for the ground rainfall observation points in order to compare with those obtained from the model outputs.

2.3. Artificial Neural Network (ANN)

Artificial neural network is simply understood as a nonlinear statistical data modeling tool that presents complex relationships between predictors (input layer) and predictants (output layer) through a synapse system (hidden layers) connecting predictors with predictants, or the so-called required outputs. As a result, ANN has demonstrated its wide range of application to solve complicated problems in many fields, for instance, engineering and environment.

Given many types of ANN have been extensively developed so far, as stated in literature [4], especially since the error back-propagation training algorithm was explored [13] it is very important regarding the selection of an appropriate ANN configuration and training method. In many cases, cost-effective analysis should be considered. Present study approach, for example, to employ a simple and reliable technology is preferable. One of the most simple and popular ANN architectures which was mostly used in hydrological modeling, approximately 89% [4], the feed-forward multilayer perceptron (MLP) using error back-propagation weight update rule, was employed for calibration processes. Presently,

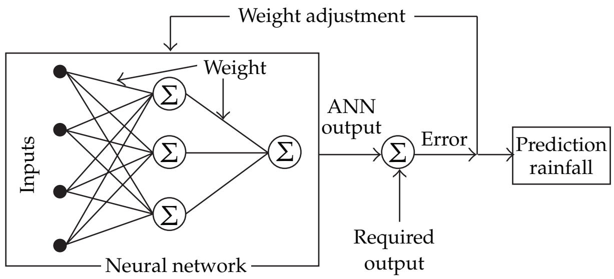

Figure 2: ANN architecture with back-propagation algorithm.

the MLP neural network was found to outperform radial basis function neural network and other multiple linear regression methods. The feed-forward MLP configuration selected here includes an input layer, a single hidden layer which has been selected by most researches [4], and an output layer that is interconnected by synapse weights (Figure 2). The number of nodes of the hidden layer was selected ranging from $(2n + 1)$ to $(2n^{0.5} + m)$, where n is the number of input nodes and m is the number of output nodes [14]. The training phase of the ANN is to adjust the weights so that the difference between the network outputs (predictants) and the expected outputs is minimized. For each node at a given layer, the outputs of n neurons in the previous layer provide the input to that node. These outputs are multiplied by the respective weights of connections between nodes, and then the summation function adds together all these products to produce the input that is processed by the activation function. The selection of activation functions is dependent on the type of network and learning algorithm; however, logistic sigmoid and hyperbolic tangent functions have been mostly employed, up to 64% and 13%, respectively [4]. Approximation used for the weight change is given in (2.1) by the delta rule [15]

$$w_{\text{new}} = w_{\text{old}} - \eta \frac{\partial E^2}{\partial w}, \tag{2.1}$$

where η is the learning rate parameter, w is the weights, and E^2 is the squared error.

2.4. Optimization of Predictors

It has been already addressed in [4], with respect to data handling for ANN, in which the determination of appropriate predictors for the input layer is very important. This process tends not only to drop out those variables that have less influence on the output to avoid overfitting but also to overcome the shortage of historical record used for calibration processes. For that reason, this study takes into account the physically based consideration regarding the precipitation evolution. As addressed in the previous sections, the study area is dominated by the orographic rainfall that intense rainfall is prevailing on the windward side (to the East) of the Annam Range of about 1500 m, that is, approximately equal to the geopotential height of 850 hPa pressure level, and very little precipitation falls on the leeward side (to the West). Therefore, among hundreds of variables provided by the global NWP outputs, only variables which are driving factors for the orographic rainfall evolution were selected in the calibration processes. It includes momentum variables of pressure levels of

700 hPa and 850 hPa such as wind-field velocities and changes in vertical pressure and the rainfall prediction on the surface. Additional predictors screening was conducted to finalize a good set of predictors based on "stepwise regression" or known as forward regression.

2.5. Hydrological Model

With respect to hydrological modeling, the tank model is considered a very simple model that has been widely used in rainfall runoff-analysis. This feature is in line with the standpoint of the study that simplified approaches are preferable. However, as a conceptual model, the tank model has many parameters that are required for calibration; it might not be an appropriate selection to assess the rainfall-runoff processes for poor observation basins. The super tank model used in this study aims to overcome this issue. The super tank is also based on the original tank model, being attributed to some physical-base features [16]. Thus, the super tank model is nearly calibration-free requirement, because model parameters are internally calibrated based on catchment geotopographical information. Additionally, the super tank model is semidistributed; therefore, it is assumed to outperform lumped hydrologic models in terms of spatial variation consideration. As a result, the super tank model has demonstrated its robustness and reliability in rainfall-runoff modeling, across a wide range of spatial and temporal scales as described in [2], especially the scarce observation catchments. Evaluation of runoff model performance is based on two criteria, Nash Sutcliffe Index (NSI), or the so-called coefficient of efficiency and the relative error of predicted runoff (η), as expressed in (2.2) and (2.3), respectively

$$\mathrm{NSI} = 1 - \frac{\sum \left(Q_{\mathrm{obs}} - Q_{\mathrm{pred}}\right)^2}{\sum \left(Q_{\mathrm{obs}} - Q_{\mathrm{obs.mean}}\right)^2}, \tag{2.2}$$

$$\eta = \frac{\left|Q_{\mathrm{pred}} - Q_{\mathrm{obs}}\right|}{Q_{\mathrm{obs}}}, \tag{2.3}$$

where, Q_{obs} = observed river flow and $Q_{\mathrm{obs.mean}}$ = mean observed river flow and Q_{pred} = predicted river flow.

3. Results and Discussion

3.1. Downscaling Precipitation

In respect of precipitation prediction, it has been considered as the most difficult variable to be predicted. The precipitation evolution involves a complex process that is not only driven by the dynamic change in atmosphere but also affected by land-surface characteristics. The NWP models, in general, tend to overestimate light rainfall. On the other hand, it seems to severely underestimate intense rainfall, particularly in elevated watersheds. In practice, the longer the forecast lead time is, the most effective flood mitigations can be put in place. Unfortunately, forecast uncertainty is likely to be larger along with the forecast lead time. It is necessary to evaluate to what lead time of the forecast is required for flood mitigation purposes. In the context of this study, forecasting for flood warning was defined. The forecast lead time is supposed to be sufficient, such as for evacuation that is considered within 24 hours, in places like developing countries which have very limited access to proper logistic

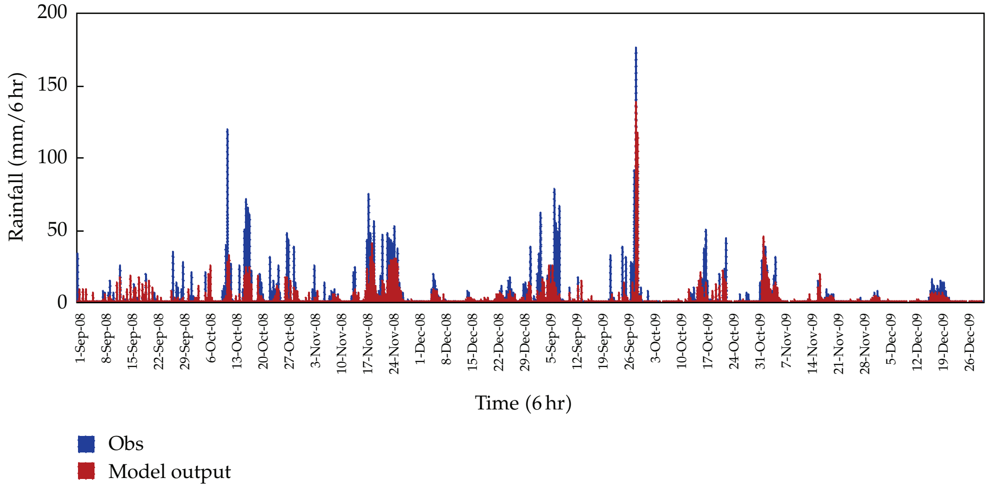

Figure 3: Time series of observed rainfall and those derived from the model outputs for wet seasons, 2008 and 2009.

availability and evacuation routes. As a consequence, analyses are focused on model outputs of 24-hour forecast lead time by updating the exiting forecast lead time (84-hour) on daily basis. In addition to the increased trend of the uncertainty along with the forecast lead time, it has been observed that forecast skill of NWP models is higher as model resolutions are increased.

Preliminary downscaling precipitation was conducted by interpolating the model outputs from the grid point value representation (0.5° or equal to grid cell size of 50×50 km) to subgrid scale then was averaged for catchment scale. The comparison of area-average rainfall derived from rain gages and model outputs for periods Sep–Dec, 2008 and 2009, is presented in Figure 3. These periods are classified as wet seasons when most intense rainfall storms were observed. The wet season usually holds up to 70 percent of the total annual precipitation. As seen in Figure 3, model bias was found for most storm events. The model-output-driven precipitation prediction was much lower than the actual observation. A reason for this discrepancy might be explained by the converse behavior of altitudinal dependence of precipitation between actual observation and that obtained from model outputs, especially in elevated watersheds. The comparison of altitudinal dependence of precipitation between observation and model outputs was conducted for various locations (9 rain gages, as seen in Figure 1) with different heights in the Central Vietnam [17]. Results showed that the increase tendency of relationship between the rainfall observed at 9 rain gages and its elevation was found. Rain gages in low location, in other words, close to the shoreline, were observed to show less rainfall than those located in higher elevations. On the contrary, rainfall prediction, which was preliminarily downscaled from model outputs to individual rain-gage using interpolation method, depicted an opposite trend. It was found to be a considerable declining of forecasted rainfall towards the altitudinal increase. The forecasted precipitation was found closer to the observation in low-elevation locations. This model bias might be interpreted as surface elevation is averaged within a coarse spatial resolution; thus, small-scale effects of topography may not be resolved in the global NWP model.

In the following paragraphs, results for downscaling precipitation are presented, using the feed-forward MLP with error back-propagation training algorithm. The input layer of

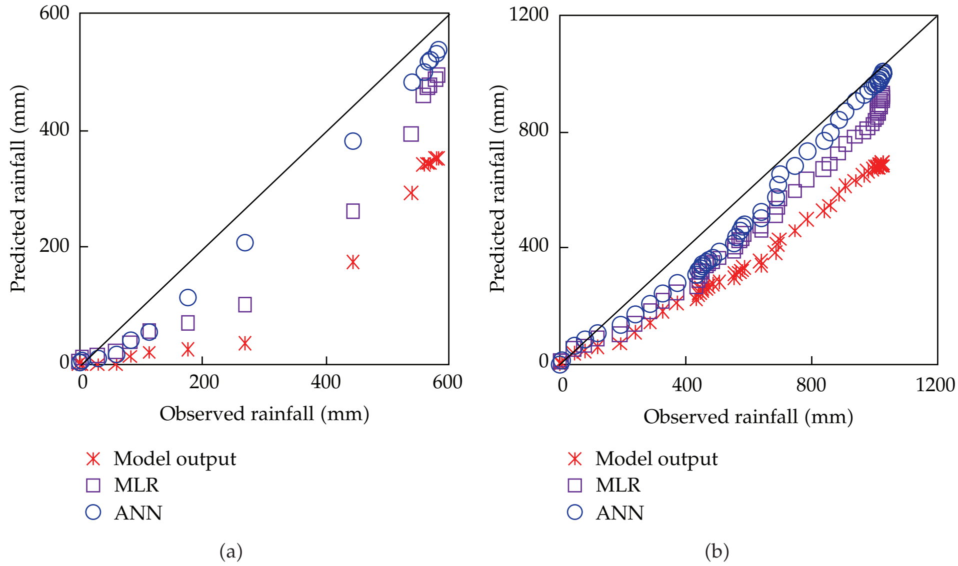

Figure 4: Comparison of accumulative rainfall between observation and prediction obtained from model output and downscale using MLR and ANN for single storm event (a) on Sep. 26–30th, 2009 and continuous storm event (b) on Nov. 17th–27th, 2008.

the feed-forward MLP architecture, as a result of stepwise regression, comprises 3 predictors (3 nodes) that are derived from the model outputs, including vertical changes in atmosphere pressure at (i) the layer 700 hPa, (ii) the layer 850 hPa, and (iii) precipitation prediction on the surface. 6 nodes are selected for the hidden layer. Finally, results from the output layer are the downscaled precipitation. Data of 12 storm events which occurred in wet seasons, 2008 and 2009, was selected for the analysis. The data set was divided into training and validation data, which a majority of studies have used.

The area-average downscaled precipitation and that obtained from model outputs were then compared to the actual area-average observation, known as reference rainfall, on storm event basis. The results showed that there is a low forecast skill of the NWP model at the initial stage of each storm event. The model severely underestimated the actual precipitation. A better forecast skill was found towards the recession limb of the storms. However, the comparison of accumulative precipitation shows that rainfall predicted by the NWP model is much less than the actual observation (Figure 4). These uncertainties can be understood as not only resulting from the averaged surface elevation in a coarse grid cells and the altitudinal bias of the global NWP model but also because of the incompleteness of initial condition assumptions inputted into the NWP models at every initial stage of the storms.

On the other hand, significant improvement of rainfall prediction was observed using the proposed downscaling method. With respect to the comparison of accumulative rainfall between downscale and observation, very good agreements were found. As seen in Figure 4, the downscaled precipitation (circles) shows best fit with the perfect line (solid line). Correlation coefficient for the area-average rainfall increased about 12% and 5% for single storm and continuous storms, respectively. The coefficient of determination (R^2) that

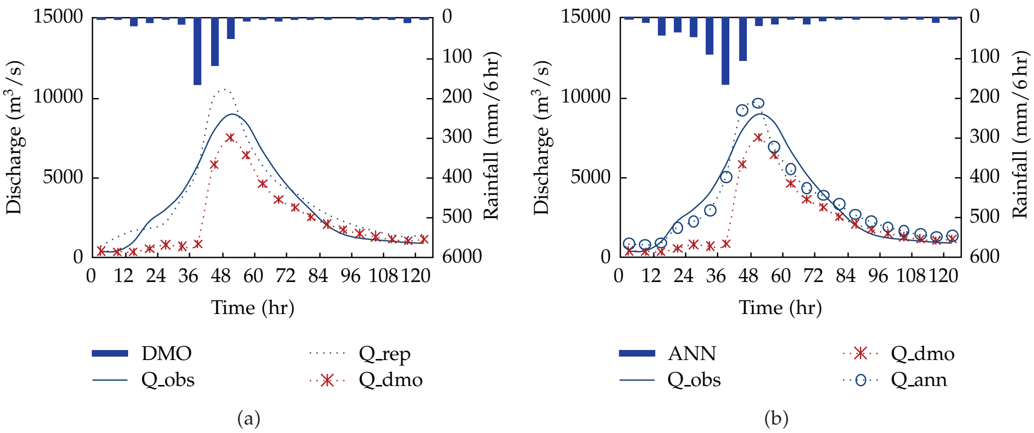

Figure 5: Time series of observed hydrograph (Q_obs) and those based on different precipitation estimation: (a) observed by rain gages (Q_rep) and derived from direct model outputs (Q_dmo), and (b) downscaled using ANN (Q_ann) for the flood event on Sep. 26th–30th, 2009.

measures the fitness of the regression model was found rising from 0.55 for the direct model outputs to 0.96 for the downscaled rainfall using ANN technique for the single storm event. Similarly, values of 0.39 and 0.56 were obtained for the continuous storm event. Meanwhile, skill scores of precipitation forecast based on ANN outperformed those based on DMO, approximately 45% increase. This implies that the present downscaling method attributed with some physical-based features is appropriate, universally applicable across the requirement of a long historical record for the calibration processes. Another regression technique that was presented in [2], the stepwise multiple linear regression (MLR), as expressed in (3.1), is also addressed here for the intercomparison. It was observed that downscaled precipitation using MLR technique showed lower forecast skill score than ANN approach, of about 30%. The R^2 for the downscaled rainfall using MLR technique was found to be 0.68 and 0.46 for the single and continuous events, respectively

$$P_{\mathrm{mlr}} = a_0 + a_1 P_{\mathrm{dmo}} + a_2 X_2 + \cdots + a_n X_n, \tag{3.1}$$

where P_{mlr} is downscaled precipitation using MLR, P_{dmo} is direct model output precipitation forecast, $X_{2,n}$ is independent model output variables, a_o is regression constant, $a_{1,n}$ is regression coefficients, and n is number of independent variables.

3.2. Flood Forecast Based on Downscaled Precipitation

Though the super tank is nearly calibration-free requirement, it is essential to validate parameters of the super tank model through the reproduction of runoff using rainfall information obtained from rain gages. Detailed runoff model setup and validated parameters were presented in [2]. The hydrograph simulated by the super tank model at the outlet of the catchment using input precipitation derived from rain gages, or the so-called reproduction of flood runoff (Q_rep), for the flood event on September 27–30th, 2009, is plotted in Figure 5(a). It showed a very good agreement with the observed hydrograph (Q_obs). Model performance was evaluated by NSI, showing a very high efficiency, approximately 0.93. Meanwhile, relative error of 16% was observed for the peak discharge.

In next steps, different rainfall estimations from direct model outputs and downscaled results, hereinafter referred to as DMO and ANN, respectively, were then used as inputs to the super tank model to predict flood runoff. Forecasted flood runoff was compared to the observed discharge and also the reproduced flood runoff, as illustrated in Figures 5(a) and 5(b). Considerable uncertainties were observed on the rising limb of the hydrograph that was driven by DMO (Q_dmo). On the other hand, a better forecast towards the recession limb was found. It is evident that the underestimate of precipitation is a main cause for a low hydrograph. It underestimated about 16% lower than the actual peak, but time to peak agreed well with that observed. Overall model performance was indicated by NSI, of about 0.74.

Given the downscaled precipitation was observed for higher forecast skill to the direct model outputs, for that reason, ANN has increased flood forecast skill, as seen in Figure 5(b). The predicted hydrograph (Q_ann) was comparable to that obtained using rain gages (Q_rep), as mentioned in the previous paragraphs. Improved model performance was found, and the model efficiency increased to 0.92; meanwhile, relative error of the peak discharge decreased to 3.8%.

3.3. Model Validation

To evaluate the skill of ANN models, the data set should be ideally divided into three sub-sets, respectively, for learning phase, testing phase, and validating phase [4]. In fact, regarding the limited data availability, only the learning phase and validating phase were conducted. In present study, the storm event on November 1st–7th, 2009 was selected for model validation. Downscaled precipitation was accumulated, and was then compared to that obtained from model outputs as well as actual observation. It was noticed that model-output-driven precipitation remained underestimated, while the downscaled rainfall showed a very good agreement with the actual observation, except a slight overestimate at the end of the storm. These are clearly illustrated in Figure 6. It means that a considerable precipitation prediction skill of ANN model was demonstrated.

The rainfall information was subsequently used to predict the flood runoff. Forecasted hydrographs based on rainfall derived from DMO and downscale using ANN are illustrated in Figure 7. Again, it was found that the DMO-driven hydrograph has severely underestimated the peak discharges. Model efficiency was very low, with NSI of about 0.25 and relative error of the peak of 38%. On the other hand, the downscaled precipitation using ANN-driven flood forecast, in case of this model validation, showed a substantial improvement, approximately 75%, in terms of the model efficiency NSI is up to 0.81. Flood propagation behavior showed very good agreement with the actual observation, especially the time to peak. The model was found to slightly underestimate peak discharges, approximately 25% lower than the actual peaks. However, comparison of total volume showed a very close estimate to the observed volume, just approximately 14% lower than the true volume. In this case, the reliable estimation in the volume of imminent floods will be very useful information that enables the implementation of flood-control measures, for instance, through proper reservoir operation system.

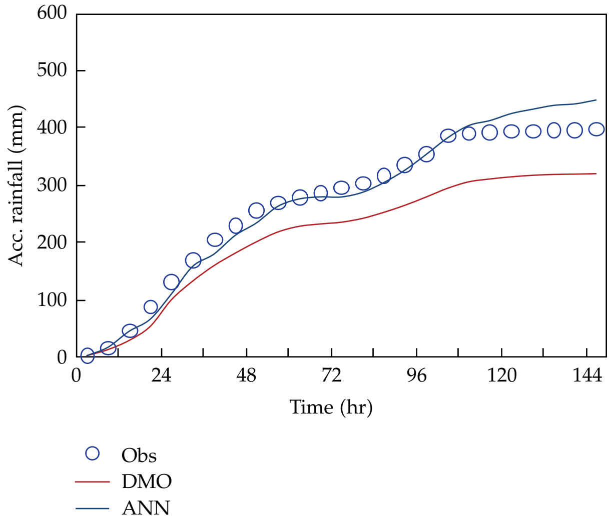

Figure 6: Time series of observed and forecasted hyetographs for the validated storm event on Nov. 1st–7th, 2009.

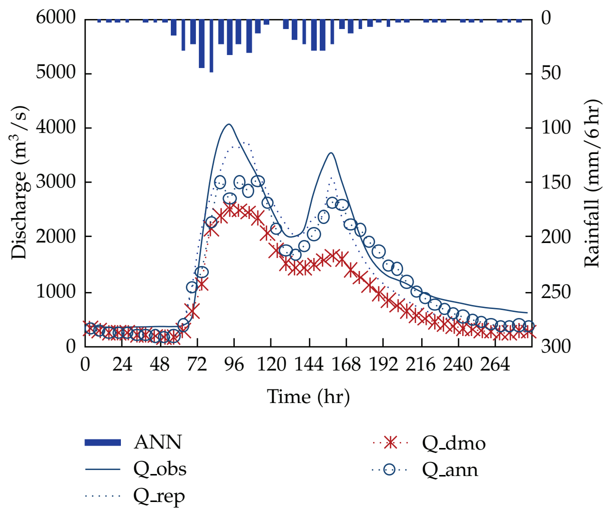

Figure 7: Time series of observed and forecasted hydrographs for the validated flood event on Nov. 1st–7th, 2009.

4. Conclusion

This paper has presented an efficient empirical-statistical approach, using the most favorite ANN architecture, the MLP, with error training back-propagation method, to downscale the precipitation from global NWP outputs to a basin-average scale, subsequently, was used for flood-runoff forecast. The downscaling model has taken into account the physical bases of the precipitation evolution induced by meteorological and land surface characteristics in the study area. As a result, the present model has exhibited cost-effective, simple to implement, and universal application.

The study results indicated considerable uncertainties in precipitation predicted by the global NWP model due to the coarse spatiotemporal resolution and inherent system bias. Accordingly, the flood forecast based on DMO was not what had been expected. It severely underestimated the true hydrograph. By using downscaling approach, however, significant increase of forecast skill was observed for flood prediction based on the downscaled precipitation. The ANN has showed a better learning ability than those using the MLR method.

The presented model has demonstrated the provision of reliable information of the coming flood in a very early stage (24 hr lead time), as considered outperforming other conventional forecasting methods, so that vulnerable communities and flood-control bodies are more active in coping with potential threat and damage in order to insure that flood mitigations are effectively put in place. In addition, it should be stressed that using simple, reliable, and widely applied approaches is the benefit of the study. The prediction model is therefore considered as universally applicable, especially in the developing countries where weather observation is scarce and access to high-resolution weather prediction models is limited.

Acknowledgments

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