Weather Radar Estimations Feeding an Artificial Neural Network Model

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ABSTRACT

The application of ANNs (Artificial Neural Networks) has been studied by many researchers in modelling rainfall runoff processes. However, the work so far has been focused on the rainfall data from traditional raingauges. Weather radar is a modern technology which could provide high resolution rainfall in time and space. In this study, a comparison in rainfall runoff modelling between the raingauge and weather radar has been carried out. The data were collected from Brue catchment in Southwest of England, with 49 raingauges covering 136 km^2 and two C-band weather radars. This raingauge network is extremely dense (for research purposes) and does not represent the usual raingauge density in operational flood forecasting systems. The ANN models were set up with both lumped and spatial rainfall input. The results showed that raingauge data outperformed radar data in all the events tested, regardless of the lumped and spatial input.

RESUMEN

La aplicación de Redes Neuronales Artificiales (RNA) en el modelado de lluvia-flujo ha sido estudiada ampliamente. Sin embargo, hasta ahora se han utilizado datos provenientes de pluviómetros tradicionales. Los radares meteorológicos son una tecnología moderna que puede proveer datos de lluvia de alta resolución en tiempo y espacio. Este es un trabajo de comparación en el modelado lluvia-flujo entre pluviómetros y radares meteorológicos. Los datos provienen de la cuenca del río Brue en el suroeste de Inglaterra, con 49 pluviómetros cubriendo 136 km^2 y dos radares meteorológicos en la banda C. Esta red de pluviómetros es extremadamente densa (para investigación) y no representa la densidad usual en sistemas de predicción de inundaciones. Los modelos de RNA fueron implementados con datos de entrada de lluvia tanto espaciados como no distribuidos. Los resultados muestran que los datos de los pluviómetros fueron mejores que los datos de los radares en todos los eventos probados.

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INTRODUCTION

Weather radar information (Met Office, 2008) is widely and easily available, displayed as rainfall precipitation on national or regional maps (the likes of the Met Office, UK, National Weather Service, US, and Servicio Meteorológico Nacional, Mex.), but, from the UK experience, it is rarely used as input data in flood forecasting models; though there are active efforts in their promotion as presented in Moore *et al.,* (2004). Among the problems arising from the operation of radars are: ground clutter, anomalous propagation, bright, band, Z-R relationship, and radar calibration (Collier, 1996). In spite of these difficulties, the advantages from radar data maintain the radar hydrology community working on overcoming such problems, see for example, (Joss and Waldvogel 1990), (Smith 1990), and (Illingworth *et al.,* 2000). Harrison *et al.,* (2000) examined the steps taken by The Met Office, in the UK, where data used here were generated to address these problems.

The development of Artificial Neural Networks (ANNs) began approximately 50 years ago (McCulloch and Pitts, 1943), trying to emulate neurons in the human brain. Mathematical descriptions can be consulted elsewhere, for example, Haykin, (1998), Fine (1999) and Cichocki and Unbehauen, (1993) present ANNs for general purposes. The ASCE Task committee (Govindara-

Palabras clave:
Red neuronal artificial; Lluvia-flujo; Modelo distribuido; Modelo no distribuido; Radar meteorológico.

Keywords:
Artificial neural network; Rainfall-runoff; Distributed model; Lumped model; Weather radar.

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ju, 2000a and b) published an excellent two-part series introduction to ANNs in hydrologic applications. Dawson and Wilby (1998) present a very descriptive application example.

The ability of ANNs to associate input arguments to target values, independently of differences in dimension and magnitude, generates the expectation to discover the relationship level between radar estimations and runoff measures. To address this issue a comparison exercise was undertaken between raingauge and radar estimations from the "Natural Environment Research Council – HYdrological Radar EXperiment" (NERC HYREX) project. These two data series were used to feed a rainfall-runoff model based on ANNs. The radar data were structured in two arrangements: as a lumped model taking the average value among all the squares overlapping the Brue catchment, and as a distributed model where the spatial (geographical) variations are considered explicitly.

METHOD

Radar and Raingauge Data

The NERC HYREX project generated rainfall estimates from raingauges and from weather radars. A network of raingauges was installed across the Brue catchment, in Somerset, South-West England. Radar rainfall data were obtained from continuously scanning C-band radars (operating on a 4-8 cm wavelength) at Wardon Hill, 30 km south of the catchment, at Cobbacombe Cross, 70 km to the west, and an experimental Doppler dual-polarisation S-band radar at Chilbolton, see figure 1. The Brue catchment is overlapped by 14 of the 5 km squares which form the radar data grid displayed in figure 2.

This grid of radar data presents spatial and temporal variations. Fig. 3 shows hyetographs for squares D, G, and L (from grid displayed in figure 2) along the same time period: 20:45 UTC (Coordinated Universal Time), 17 January to 0230 24 January 1995. These hyetographs present a general similar patter with variations at some specific points. Rainfall precipitation from the raingauge network and radar grid has been averaged to produce one-dimension rainfall series from each system. Radar rainfall estimations are given in instantaneous values of mm hr^{-1}. Raingauge data series, obtained by the network of 49 raingauges were generated, likewise, every 15 minutes. The accumulated rainfall along those 15 minutes was multiplied by 4 to present it in mm hr^{-1}. Figure 4 compares the two average rainfall series; the period coincides with that of figure 3. The river flow was measured at Lovington, Somerset.

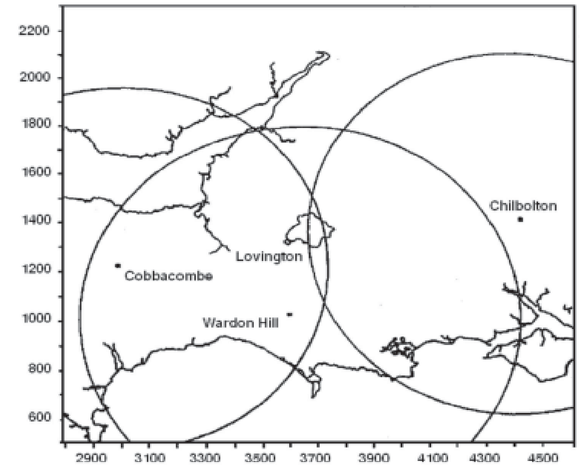

Figure 1. Radars overlapping the Brue catchment. Adapted from Moore *et al.,* (2000)

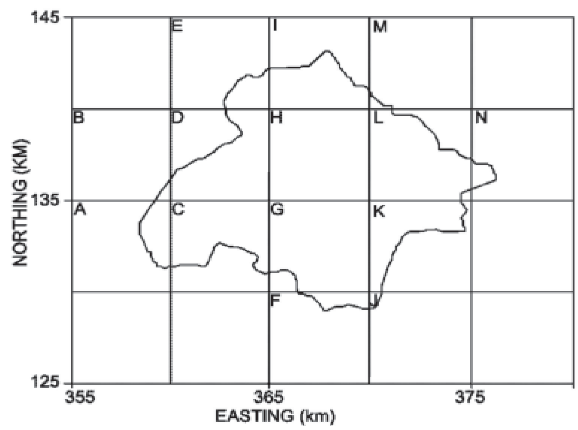

Figure 2. Radar grid overlapping the Brue catchment. Adapted from Moore *et al.,* (2000).

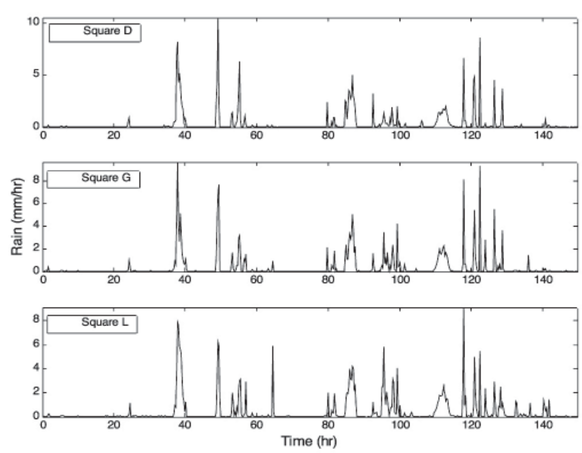

Figure 3. Hyetographs from radar squares.

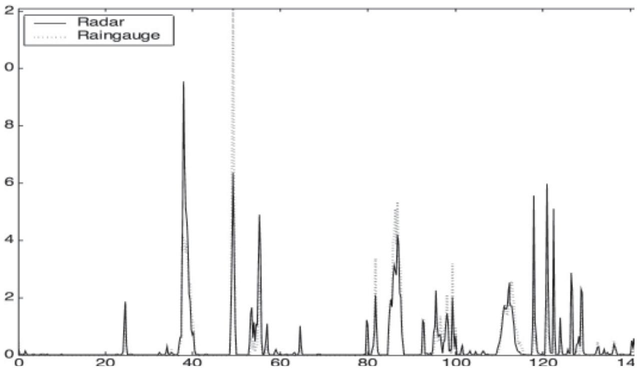

Figure 4. Comparison between raingauge and radar hyetographs.

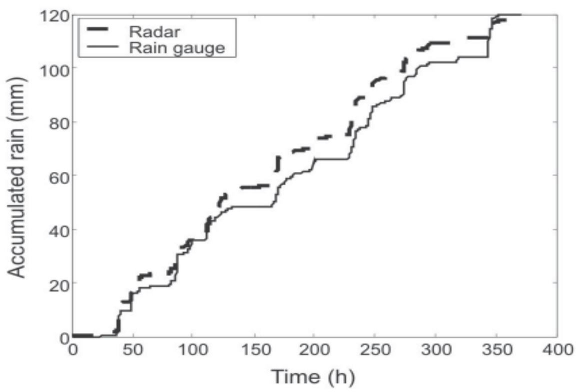

Figure 5. Cumulative hyetographs estimated by rain gauge and radar.

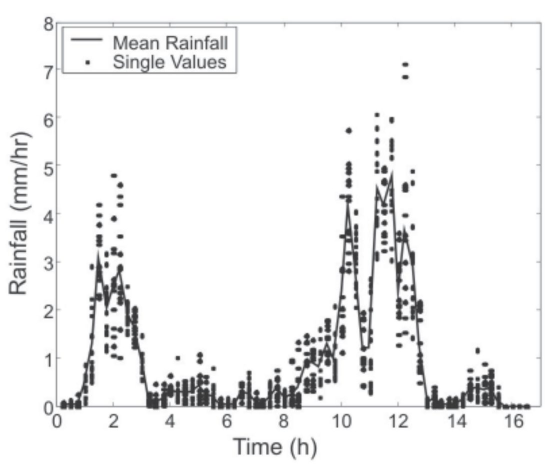

Figure 6. Radar average and single values of rainfall.

The cumulative rainfall from radar and raingauge is shown in figure 5. In this plot the gap between both cumulative series goes up to 28.9 mm at the end of the 150-hr period and it is just 5.1 mm 34 hours before. These discrepancies between both estimation methods, weather radars and raingauges, will be put on test by the same ANN model in order to asses their accuracy in relation to the generated flow. This ANN model generated different network architectures for each one of the two data structures and the two data sources used in this work to get the best flow estimations.

Running the model with average rainfall data made it work like a lumped model, that is, the spatial (geographic) variations of rainfall values were averaged. Figure 6 plots a radar average rainfall series against the single values of each one of the points overlapping the Brue catchment. The display covered the period from 0515 to 2130 UTC on 08 January 1996.

The radar rainfall series available contained many short periods of missing data; this situation limited the number of periods with enough available values to train and test the ANN model. Nevertheless, the tests allowed a proper comparison among the different options employed to run the model.

Artificial Neural Network Model

The model used in this work is described in detail in (Cerda-Villafaña, 2005, pp. 51-58); hence, following is a brief description.

The model is based in a feedforward ANN, trained by the backpropagation algorithm, which convergence properties are clearly presented in (Bertsekas and Tsitsiklis, 1996). The selection of the best suited architecture was performed by a Genetic Algorithm. Besides the pre-processed data series an extra element is added to the input: the values of moving average windows A_1. The window extension or number of average data is represented by N_a. Table 1 describes the range of parameter values for the ANN for two different data structures presented in the next section. The final ANN architecture for each data structure and data source is described in Table 2. Matlab was the software package used in this project.

Proposed Data Structures

The rainfall data has been structured as a matrix of 14 columns (one for each 5-km-square overlapping the Brue catchment) by n rows, where n is the number of data units in the selected period of time (every 15-minutes). These data series have been used by the ANN model through two different implementations:

Table 1.
Range of the ANN model's parameters for the Brue catchment using matrix and average values.

Parameter	Range Average values	Range Matrix and average values
Number of layers N_l	3-5	3-5
Number of neurons on each layer N_n	20 in first layer 1 in last layer 4-26 (in increments of 2) in hidden layers	71 in first layer 1 in last layer 44-76 (in increments of 2) in hidden layers
Previous average-rainfall inputs A_l	0-2	0-2
Number of average data N_a	20-100 (in increments of 20)	20-100 (in increments of 20)
Learning rate	Variable: 0,2 – 0,001	Variable: 0,2 – 0,001

Table 2.
Best set of the ANN model's parameters for the Brue catchment using matrix and average values

Arquitecture	Data from weather radars	Data from raingauges
For average values	3 layers 20 – 16 – 1	3 layers 20 – 22 – 1
For matrix and average values	3 layers 20 – 18 – 1	3 layers 20 – 16 – 1
Previous average-rainfall inputs A_l	1	1
Number of average data N_a	80	80

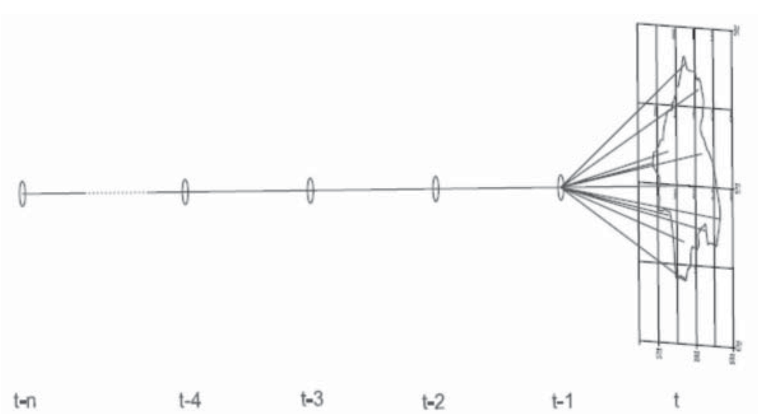

Figure 7. Matrix and average values graphical description.

1. *Average values.* One-dimension rainfall series. Every value in this series is a row-average or average of the 14 columns, coming from the radar grid, aligned on time. This implementation is similar to the raingauge series. The signal pre-processing is identical to the implementation applied in the case of the raingauge data. It included the IIR filtering with 18 coefficients, mean removal and resizing of the data series. An average of 80 previous values was added as one of the inputs to the ANN model.

2. *Matrix and average values.* A matrix of distributed values at time *t* plus row-average values at times *t* - 1, *t* - 2, ... and *t* - 6. Figure 7 shows a graphical description of this implementation. The matrix displayed in figure 2, presented here at time *t* represents the 14 distributed values of rainfall estimation overlapping the Brue catchment. This grid represents the values from the weather radars and was taken straight from the squares A to N, as they are shown in figure 2. Those from the raingauges were combined among the raingauges deployed on the same squares as the weather radar data grid. All these values were filtered along time with the previous values corresponding to the same spatial position, making the filtering work on data series like the three series presented in figure 3. The average of 80 previous average values was equally added to the model.

RESULTS

The figures 8, 9 and 10 present the results showing the measured values as "observed" and the values obtained by the model as "simulated". The first data set to train and test the ANN model was from the winter months: February 1995 for training the model and January

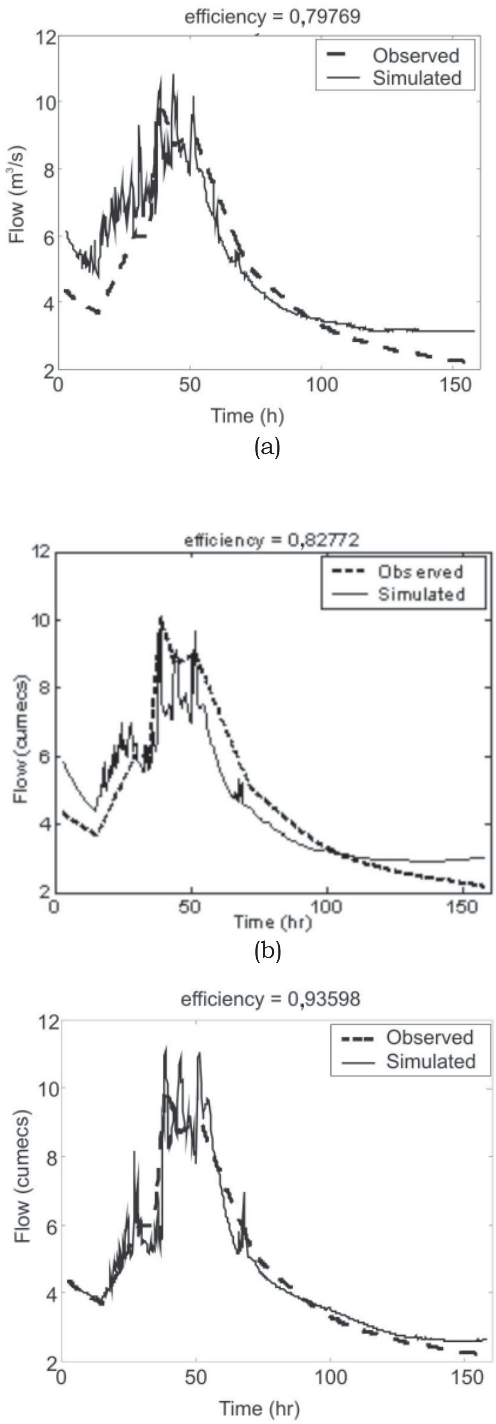

Figure 8. Results for the period described in Table 3: (a) matrix and average-values radar, (b) average radar, and (c) raingauge.

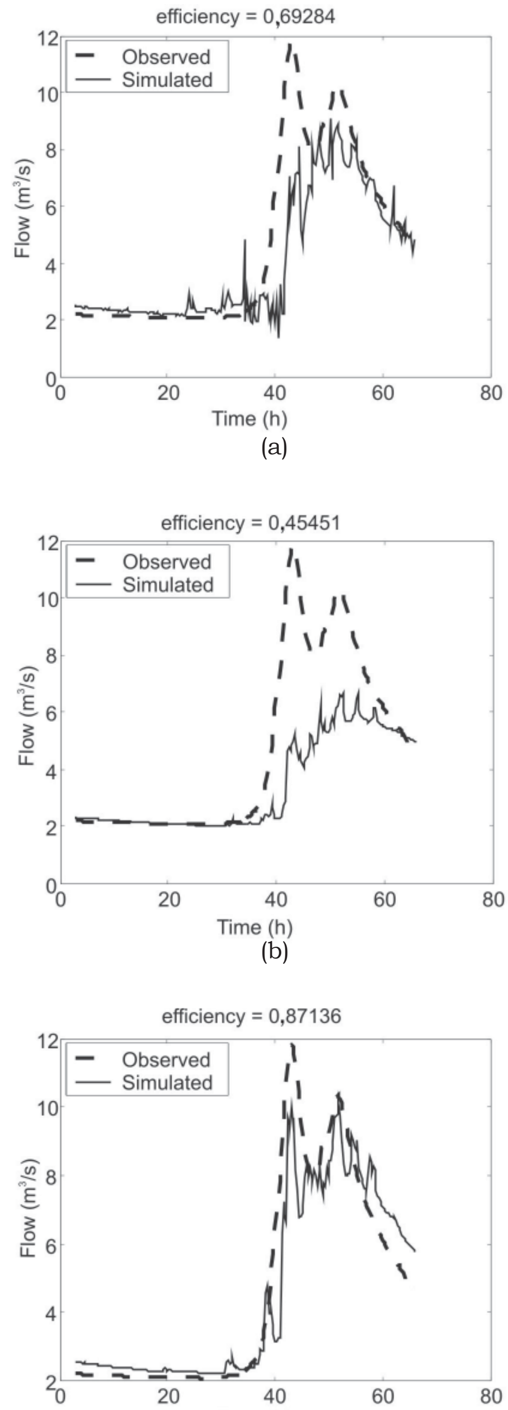

Figure 9. Results for the period described in Table 4: (a) matrix and average-values radar, (b) average radar, and (c) raingauge.

1996 for testing it. Table 3 presents the exact dates and times applied to the model.

The results using these data series are displayed in figure 8. The efficiency R^2 went from 0.936 in the case of the raingauge data structure, to 0.798 for matrices and average values, or structure 2. From the two radar data, average values had the best performance (R^2 = 0.828). It is, nevertheless, lower than that obtained by the model running raingauge data.

The second data used to run the ANN model was from winter months too: all from January, but from year 1996 for training the model and from 1998 for testing it. Table 4 presents the precise dates and times applied to the model. The results from these data series are shown in figure 9. In this case, the efficiency R^2 was lower compared to the previous test. The highest value was likewise from the raingauge data model with an R^2 = 0.871. The efficiency for the radar data structures went from 0.693 in the case of the matrix and average values or structure 2 to R^2 = 0.454 for the average values. The performance for the radar data was, as for the previous test, lower than that obtained by the model running raingauge data.

The last data set to be tested came from a summer month: August. This season is characterised by low flow, being the opposite of winter. The time period is presented in Table 5.

Running low flow the efficiency decreased dramatically; hence, to get a better assessment of the model performance, the Root Mean Square Error (RMSE) was employed as a second performance indicator. Figure 10 displays the four results from the different data. Raingauge data generated the highest efficiency, R^2 = 0.195, and though this value is low compared to the two previous tests, the RMSE = 0:0248 demonstrates that the model generated a flow with a small deviation from the observed flow. When testing the model with radar data, in this occasion it was the matrices and average values the structure with the lowest RMSE = 0:944. (WMO, 1992) indicates that, in global terms, the estimation could be considered acceptable.

In each one of the three tests presented in this section the performance was always better for the model running raingauge data.

DISCUSSION

ANN models have been widely used in rainfall runoff modelling with raingauges as their rainfall input. The novelty of this study is in the application of ANN with lumped and spatial rainfall information by weather

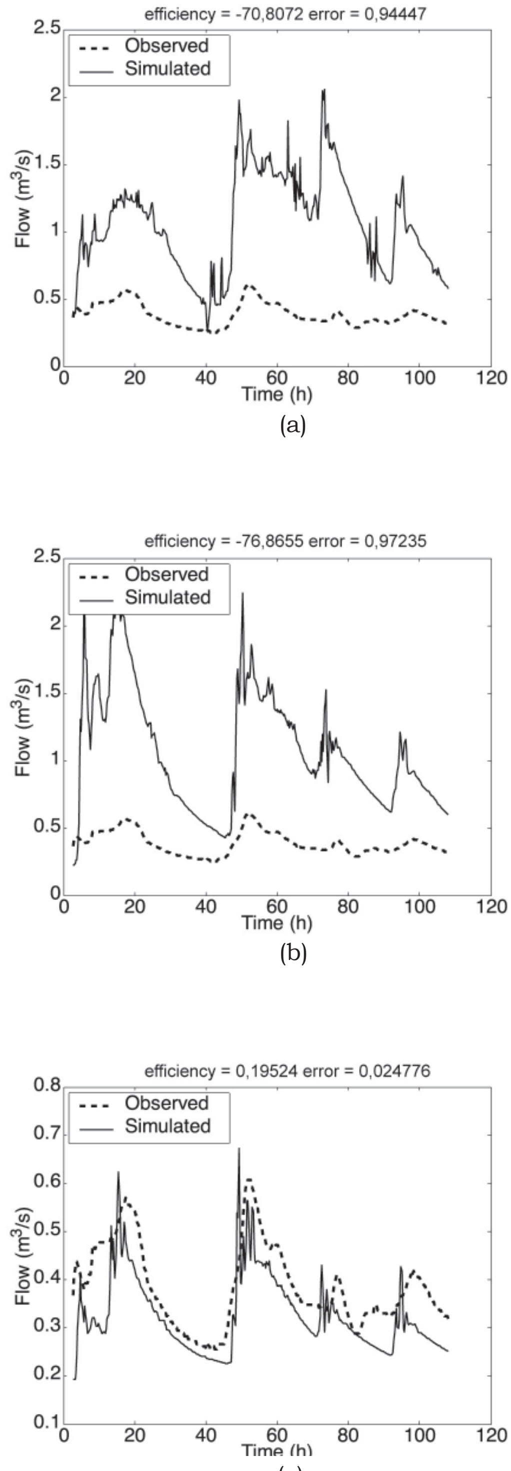

Figure 10. Results for the period described in Table 5: (a) matrix and average-values radar, (b) average radar, and (c) raingauge.

Table 3.
Data sets for test 1.

Set	Time (h)	Start time	End time
Training	355.75	13 h 30 02 Feb 95	09 h 15 17 Feb 95
Validation	168	14 h 15 03 Jan 96	14 h 15 10 Jan 96
Test	166.30	14 h 30 10 Jan 96	13 h 00 17 Jan 96

Table 4.
Data sets for test 2.

Set	Time (h)	Start time	End time
Training	334.25	14 h 45 03 Jan 96	13 h 00 17 Jan 96
Validation	85.75	11 h 30 12 Jan 98	01 h 15 16 Jan 98
Test	85	01 h 30 16 Jan 98	14 h 30 19 Jan 98

Table 5.
Data sets for test 3.

Set	Time (h)	Start time	End time
Training	299.75	16 h 15 28 Aug 95	04 h 00 10 Sep 95
Validation	127.15	18 h 00 16 Aug 96	01 h 15 22 Aug 96
Test	127.15	01 h 30 22 Aug 96	08 h 45 27 Aug 96

radar. It can be found that despite the decades of research in improving weather radar data quality, a dense raingauge network can still easily outperform its modern counterpart as an input for hydrological modelling. It is also interesting to note that the spatial rainfall provided by the weather radar produced poorer modelling results than the lumped ones, indicating that ANN is not suitable for accepting spatial rainfall information due to the multiple increasing in its node number which could prevent effective training of the model. It should be pointed out that the raingauge network in this study is extremely dense (49 tipping bucket gauges over a small catchment of 136 km^2) and does not represent the usual raingauge density in an operational flood forecasting system. Further work is needed to compare an operational raingauge network (with sparse raingauge density) to the weather radar network data.

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