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Deep learning neural network: A machine learning approach for monthly rainfall forecast, case study in eastern region of Thailand

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Abstract

Accurate monthly rainfall forecasting is essential for efficient watershed management, particularly for the current situation with high variation of rainfall due to global climate change. A variety of researchers attempted to develop more sophisticated models to enhance model capability to capture uncertainty due to high variation in rainfall both in time and space. The objective of this study is to investigate capability of a Deep Learning Neural Network (DNN) in forecasting monthly rainfall. A river basin in eastern region of Thailand, where a high increase in water demand is expected in next 20 years due to the national development plan, is selected as the study area. In this study LAV with different atmospheric layers, such as air temperature, geopotential height, meridonal wind, omega, outgoing longwave radiation, relative humidity, specific humidity, sea level pressure, sea surface temperature, zonal wind, precipitation rate and precipitable water, were selected as inputs to the DNN model. Monthly rainfall at Pluak Deang station from 1991 to 2010 were used for the training process in the DNN model. Monthly rainfall from 2011 to 2016 were used for model validation. Results of forecasting revealed that DNN is able to predict monthly rainfall from one month up to 12 months in the future, however, accuracy of forecasting decreases when the forecast time horizon increases. The most practical time of forecast is one month into the future yielding a forecast where around 70% of the forecasted values are within the range of one standard deviation from the observed values.

Keywords: Rainfall forecast model, Deep learning neural network, Eastern River Basin of Thailand

1. Introduction

Accurate monthly rainfall forecasts are essential for efficient watershed management, particularly for the current situation of high variation of rainfall due to global climate change. A variety of researchers have attempted to develop more sophisticated models to enhance modeling capability to capture uncertainty due to high variation of rainfall both in time and space.

Studies investigating the influence of climate on rainfall over Thailand were conducted in various river basins by Weesakul et al. [1-8]. They reveal that Large Scale Atmospheric Variables (LAV) such as sea level pressure (SLP), sea air temperature (SAT), surface zonal wind (u) and surface meridian wind (v) influence seasonal rainfall. A stochastic modified K-nearest neighbor (Knn) model was developed to forecast seasonal rainfall in two different basins in Thailand [7-8]. The model is able to forecast three months rainfall with a lead time from one month to one year and a reliability of around 60% that forecasted rainfall quite well with historical data.

A black box model, like an Artificial Neural Network (ANN) model, was applied to rainfall forecasting in many countries. For example, an ANN was used to forecast short-term rainfall in Italy by Toth et al. [9]. Comparison between ANN and Autoregressive (ARMA) models in forecasting short term rainfall for real time flood forecasting were conducted in the study. The result of the study revealed that ANN model provided more accurate forecasted rainfall than the ARMA model, particularly for forecasting rainfall with lead time from 1-6 hours.

An ANN model was also applied to rainfall forecasting in Turkey by Terzi et al. [10]. Comparison of forecast rainfall from an ANN model and that from a Multiple Regression Analysis Model with observed data revealed that the ANN model provided more accurate forecasted values.

Chantasut et al. [11] used an ANN model to forecast annual rainfall in the Chao Phraya river basin, located in the central part of Thailand. The result of this simulation showed model capability in forecasting of annual rainfall in this region with excellent accuracy, 96%, with a lead time of one year in the future.

Furthermore, an ANN model was adopted to forecast seasonal rainfall in the Chao Phraya River Basin by Rangsiwanichpong et al. [12]. The ocean indices from the National Oceanic and Atmosphere Administration (NOAA), such as the southern oscillation index (SOI), sea surface temperature in the Pacific Ocean (NINO) and dipole mode index (DMI) were used as predictors in the model. Monthly rainfall values from 31 stations from 1982-2013 were used

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in the study. The correlation coefficient and root mean square error (RMSE) were adopted for analysis of model performance. Results of model evaluation revealed that this ANN was capable of forecasting seasonal rainfall in the central region of Thailand with a lead time of up to 12 months into the future. Better prediction accuracy was found in the dry season from October to February, with coefficient of determination of 0.917 and RMSE of 0.092.

ANN with the Backpropagation Neural Network (BPNN) algorithm was adopted to formulate a monthly rainfall forecast model in East Kalimantan, Indonesia, by Mislan et al. [13]. Monthly rainfall data at Tenggarong station from 1986-2008 was used for training while monthly rainfall data from 2009 to 2014 was used for testing. The mean square error (MSE) was employed to measure the performance of the model. The results of this study showed that BPNN models can be used as a predictive algorithms that provide good accuracy. The prediction results have demonstrated their suitability in the Tenggarong area, which has an equatorial nature with two rainy seasons, in April and November.

An effort to develop monthly a rainfall forecast model for river basins in Thailand was conducted by Thammakul and Kaewprapha [14] using an ANN model. Monthly rainfall as well as monthly temperature at Pluak Daeng station from 1994-2015 were used in the study, where 70% of the data was used for training, 15% were used for validation and another 15% were used for testing. Root mean square error, mean absolute error and mean absolute percentage error were employed for evaluation of model performance. The results of model validation showed that an ANN model could be used to predict monthly rainfall in the eastern region of Thailand, using temperature and data from other rainfall stations in the area as predictors, with a lead time of three months into the future. However, the accuracy of this forecast is still not good enough for use in practice as it has a RMSE of around 75mm.

Previous research results indicate that further development is needed for accurate rainfall forecast models. Recently, powerful computing technique in deep learning have been developed such as the recurrent neural network (RNN), long short-term (LSTM) models [15-23]. Deep learning and convolutional neural networks (CNN) [24] provide some useful insights into improvement of rainfall forecast model accuracy.

In recent years, deep learning and particularly convolutional neural networks (CNNs) have become increasing popular in solving variety of problems, e.g., object recognition, objection localization, cancer detection, face recognition and scene labelling [25-30]. More advanced computation makes traditional neural networks more powerful through the use of a convolutional layer. This layer computes output feature maps by convoluting the feature maps of previous layers with a set of filters. However, a traditional back-propagation algorithm is used during training phase to learn and recognize the pattern to determine a set of filters, which are the only parameters of the convolutional layers.

Recently, a new deep network layer, the so called, "dynamic convolutional layer", was used for the task of short range weather prediction [31]. Comparison the results of short range weather prediction, using a dynamic convolutional layer, with other baselines, including a convolutional neural network that does not employ a dynamic convolution layer revealed that prediction performance was improved.

Recent advances in deep learning, especially recurrent neural networks (RNN) and long short-term memory (LSTM) models provide some useful insights on how to tackle a spatiotemporal sequence forecasting problem. Fully connected LSTM (FC-LSTM), have convolutional structures in both the input-to-state and state-to-state transitions, was applied for a precipitation nowcasting model [32]. The objective of the study is to predict the future rainfall intensity in a local region over a relatively short period of time. Precipitation nowcasting was formulated as a spatiotemporal sequence forecasting problem in which both the input and the prediction target are spatiotemporal sequences. A convolution LSTM (ConvLSTM) was proposed to build an end-to-end trainable model for a precipitation nowcasting problem. The results of the study showed that the ConvLSTM network captures spatiotemporal correlations better while consistently outperforming FC-LSTM and the state-of-the-art operational Real-time Optical flow by Variational methods for Echoes of Radar (ROVER) algorithm for precipitation nowcasting.

Another technique in artificial intelligence is random forests which recently has been widely used for forecast process. A comparative study of three artificial intelligence techniques for the rain domain in precipitation forecasting was conducted [33]. The study showed the advantage of a random forest in a random collection tree process which offers a better method from one plant supply. This technique helps to display variable trees in more detail so that no variable in the domain will be exempted from analysis. However, this random forest technique arranges specifications until it is difficult to analyze.

The random forests model was first applied and compared with artificial neural networks, support vector regression and a linear model for prediction of daily lake water levels of Poyang Lake in China [34]. The results indicated that the random forest model exhibited the best performance for daily forecasting.

The random forests model was also used to forecast an annual temperature time series [35]. The outcome of the study revealed that the highest predictive performance of the random forest was observed when using a low number of recently lagged predictor variables.

Another novel stochastic gradient boosting method was tested to forecast daily river flow of the Ohinemuri catchment in New Zealand [36]. In the study, four models were selected for comparison of results. They were linear perturbation, linear varying gain factor, soil moisture accounting and routing and Nedbor-Afrstromnings models. The overall results of this study showed that the use of a combination of techniques can improve the simulated river flows. The results also indicated that the novel stochastic gradient boosting combination method is capable of developing a multi-model combination system.

Gradient boosting decision tree models and a deep neural network were used to forecast three hours of precipitation [37]. Models of short-term precipitation forecasting were trained on a large amount of spatiotemporal meteorological data, using an algorithm platform built upon Alibaba Cloud (PAI). Extensive experiments showed that the capability of complex relationships among meteorological features can be described by non-linear models better than basic linear models.

Very few previous studies have examined the crucial and challenging weather forecasting problem from a machine learning perspective. It is therefore interesting to tackle such problem by using these new advanced machine learning

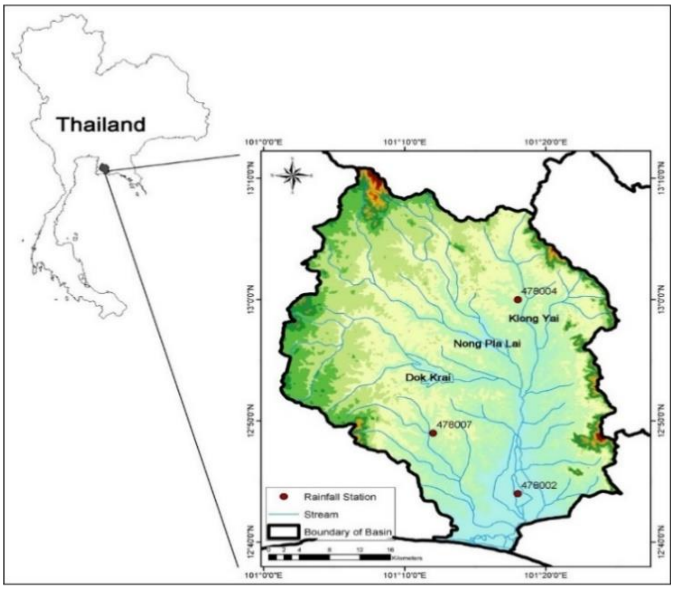

Figure 1 Khlong Yai River Basin and the locations of rainfall stations

approaches. This study aimed to investigate whether the DNN technique is applicable to monthly rainfall forecasting. The eastern region of Thailand, where accurate monthly rainfall forecasting is essential for regional development and planning, was adopted as the study area.

2. Study area and data collection

Based on Thailand's National Development Plan, the eastern region of the country will be included in an Eastern Economic Corridor (EEC). Water security in the future is a critical issue in this region. Therefore, it is necessary to have a rainfall forecasting model with sufficient accuracy for water management and allocation in the area. The Klong Yai River Basin, located in the eastern region of Thailand, was selected as study area, as shown in Figure 1. The river basin has a total drainage area of about 1,804 km^2.

Rainfall in the area is influenced by tropical monsoons with some tropical depressions during the rainy season, beginning in May and ending in October. The average annual rainfall is about 1200 mm. There are quite few rainfall stations in the area, as shown in Figure 1. Based on rainfall data availability and reliability, Pluak Daeng [478004] rainfall station was selected as a representative in the study area. Monthly rainfall data from Pluak Daeng station from 1991 to 2016 was used for analysis in this study.

LAV are correlated with seasonal rainfall in Thailand. Therefore, they were used in formulation of the monthly rainfall forecast models developed in this study. Table 1 shows list of LAV used in the analysis of their correlations with monthly rainfall in the study area. LAV data were downloaded from the Earth System Research Laboratory (ESRL), which provides monthly LAV data with a grid cell of 2.5^o latitude x 2.5^o longitude covering the area between longitude 60^o E to 160^o E and latitude 20^o N to 20^o S. Each LAV is comprised of various atmospheric layers at different heights from the ground. The location of the LAV used in the current study are shown in Table 1.

3. Model formulation

The results of many studies revealed that seasonal rainfall in Thailand is influenced by LAV [1-8]. However, they show that there is variation of the LAV by region and season. It has also been found that seasonal rainfall in most of regions in Thailand is influenced by SAT, SLP, u and v [1-4].

In this study, investigation of the more influential predictors was conducted. The LAV in of various atmospheric layers used in the analysis for model formulation are shown in Table 1. The model developed in this study was formulated for forecasting monthly rainfall, which has a higher variation in both time and space than seasonal rainfall [7-8]. Very few studies provided accurate monthly rainfall forecasts in Thailand, especially in recent years with climate change.

Recently, ANN was used to forecast monthly rainfall in the study area [14]. However, the accuracy of forecast was not great enough for practical use in managing a reservoir. With advances in calculation techniques, especially in the development of AI techniques [15-23, 31-32], this study tried to use a DNN technique as a tool to predict monthly rainfall using variety of LAV as predictors.

4. Machine learning approach

Deep neural networks are multiple-layer ANN models. Even though the community recognizes this type of network, implementing and training such networks are computationally intensive. For example, a DNN with 10 layers may need weeks for training. Additionally, the use of graphic computing units (GPU), which is specialized hardware for graphics processing, can accelerate the training speed by 100 fold over a conventional central processing unit (CPU). DNN recently outperformed conventional ANN in several areas such as in computer vision, speech recognition, and self-driving cars. One of the important properties of DNN is that when a data set is large enough, the network can process data directly and perform feature extracting automatically, where ANN may require handcrafted feature selection and preprocessing. In the current study, DNN enabled elimination of manual LAV selection steps, which is rather time consuming.

Table 1 Large Atmospheric Variables used in the DNN model

Variable abbreviation	Variable Name	Height Based on atmospheric pressure (millibar)	Location	
			Latitude	Longitude
AT1	Air Temperature	400	25º to 30º N	175º to 180º E
AT2	Air Temperature	400	0º to 5º S	210º to 218º E
AT3	Air Temperature	850	12º 30’ to 17º 30’ N	157º 30’ to 167º 30’ E
AT4	Air Temperature	2000	3º S to 3º N	250º to 260º E
AT5	Air Temperature	50	9º to 14º N	110º to 120º E
GH1	Geopotential Height	250	7º to 12º N	180º to 185º E
GH2	Geopotential Height	600	0º to 5º N	135º to 140º E
GH3	Geopotential Height	850	0º to 5º N	240º to 250º E
MW1	Meridonal Wind	10	12º to 20º N	180º to 190º E
MW2	Meridonal Wind	150	10º to 15º N	207º 30’ to 212º 30’ E
MW3	Meridonal Wind	200	0º to 5º S	155º to 160º E
O1	Omega	500	11º to 16º N	207º 30’ to 212º 30’ E
O2	Omega	925	5º to 10º N	155º to 160º E
OLR1	Outgoing Longwave Radiation	2000	0º to 5º S	255º to 260º E
P1	Air Pressure	2000	0º to 5º S	220º to 225º E
PR1	Precipitation Rate	2000	2º S to 3º N	255º to 260º E
PR2	Precipitation Rate	2000	0º to 5º N	202º to 207º E
PW1	Precipitable Water	2000	5º to 10º S	180º to 190º E
PW2	Precipitable Water	2000	7º 30’ S to 2º 30’ N	105º to 115º E
RH1	Relative Humidity 28up to 300mb only	925	2º to 7º N	135º to 140º E
RH2	Relative Humidity 28up to 300mb only	400	5º to 10º N	202º to 207º E
SH1	Specific Humidity 28up to 300mb only	500	12º 30’ to 17º 30’ N	205º to 210º E
SH2	Specific Humidity 28up to 300mb only	500	0º to 5º N	180º to 185º E
SH3	Specific Humidity 28up to 300mb only	400	7º to 15º N	120º to 130º E
SH4	Specific Humidity 28up to 300mb only	400	0º to 5º S	110º to 120º E
SH5	Specific Humidity 28up to 300mb only	400	0º to 5º N	110º to 115º E
SH6	Specific Humidity 28up to 300mb only	600	2º 30’ S to 2º 30’ N	217º 30’ to 222º 30’ E
SLP1	Sea Level Pressure	2000	2º to 7º S	255º to 260º E
SLP2	Sea Level Pressure	2000	0º to 5º S	207º 30’ to 212º 30’ E
SST1	Sea Surface Temperature	2000	0º to 5º S	255º to 260º E
ZW1	Zonal Wind	30	10º to 16º N	85º to 95º E
irf	Monthly rainfall Pluak Daeng station (mm)		13º N	101º 18’ E

4.1 Development and theoretical consideration of DNN

A neural network generally consists of three types of layers, input, hidden and output layers. Input layers are fed external data and the output layer feeds data to an external destination. The difference between an artificial neural network and a deep neural network is that ANN has single hidden layer whereas DNN has multiple (much deeper) hidden layers. For example, the Inception version 3 model used in machine vision is comprised of 23 layers. Two major calculations in a neuron network were used to develop a DNN model. The first is feed-forward propagation [38].

Each node is multiplied by the input with some random individual weight, the results are all combined and applied as an activation function. The mathematical formulation is shown in equation (1). An activation function, for example, a sigmoid function in equation (2) is used to transform a linear combination of inputs through its non-linear characteristics. The computation continues through each node from the input layer is mapped to the output layer. On the output layer, a loss function is applied to calculate the error between observed output and predicted output. The quadratic cost function that was used is given by equation (3).

$$h_j = \sigma(net_j) = \sigma(b_j + \sum_{i=1}^{n} x_{ij} w_{ij}) \quad (1)$$

x_{ij} is input at i value hidden node j
w_{ij} is weight i value hidden node j
b_j is bias on hidden node j
h_j is output on hidden node j
σ is an activation function
net_j is network node input of sigmoid function on hidden node j

$$\sigma(net_j) = \frac{1}{1+e^{-net_j}} \quad (2)$$

$\sigma(net_j)$ is output of sigmoid function on hidden node j

$$E = \frac{1}{2}(O - P)^2 \quad (3)$$

E is the error
O is observed output
P is predicted output

The second calculation is called back-propagation [38]. The back-propagation method uses partial derivatives and a chain rule as presented in equation (4). This technique will find the best weights at each node to which is used to minimize error. The formula for updating the weight can be expressed as equation (5).

$$\delta w_{ij} = \frac{\partial E}{\partial w_{ij}} = (O - P)\, h'_j = (O - P) net_j (1 - net_j) net'_j \quad (4)$$

δw_{ij} is weight change of weights i at hidden node j
h'_j is a derivative activation function at hidden node j
net_j is network node input of sigmoid function at hidden node j
$net_j{}'$ is a derivative of network at node j

$$wnew_{ij} = wold_{ij} + \delta w_{ij} \quad (5)$$

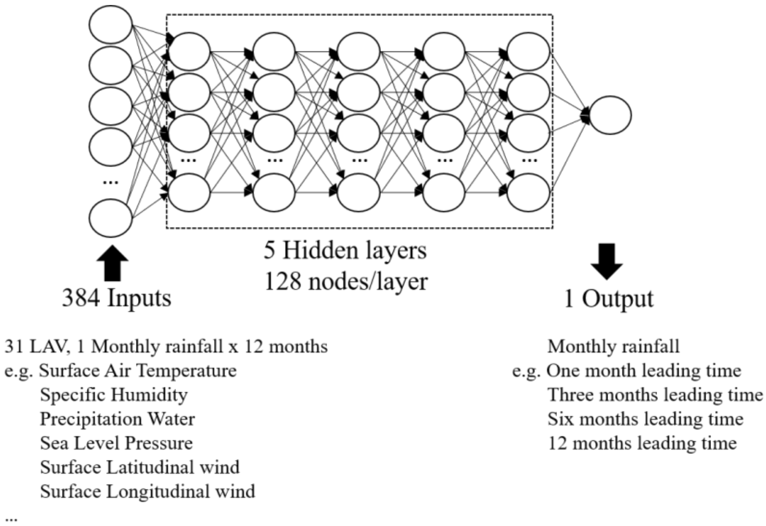

Figure 2 Architecture of the DNN model developed with 384 inputs to predict monthly rainfall

$wnew_{ij}$ is a new weight of i value at hidden node j
$wold_{ij}$ is an old weight of i value at hidden node j

4.2 Design structure of model

Deciding the number of hidden nodes and hidden layers is a very important part of DNN model architecture. Panchal et al. [39], used a rule-of-thumb to determine the suitable number of hidden nodes as follows. The number of hidden neurons should be between the size of the input layer and the size of the output layer. The number of hidden neurons should be 2/3 the size of the input layer, plus the size of the output layer. The number of hidden neurons should be less than twice the size of the input layer. These three rules provide a starting point for a DNN model. Hinton et al. [40] were the first to successfully train a DNN model with many hidden layers and complex datasets. The following summarizes the capabilities of several hidden layer architectures. If there are no hidden layers, the model is only capable of representing linear separable functions. If it has one hidden layer, it can approximate a function that contains a continuous mapping from one finite space to another. With two hidden layers, it can represent an arbitrary decision boundary to arbitrary accuracy with rational activation functions and can approximate any smooth mapping to any accuracy. More than two hidden layers, additional layers can learn complex representations. To decide the model with our dataset we had used trial and error method to find the architecture that had best result for our dataset. There were 31 LAV variables and one monthly rainfall variable with a lead time 12 months. Therefore we had 32x12 = 384 input variables to predict one output, monthly rainfall. Several hidden nodes such as 19, 128, 192 and 256 from two hidden layers to five hidden layers have been tried. The results reveal that 5 hidden layers with 128 nodes each provided better accuracy than other model as depicted in Figure 2. The TensorFlow-Regressor Application Programming Interface (API) from Google was used to develop the DNN model [41]. TensorFlow is an open-source machine learning library created for intensive computational tasks. It takes tensor inputs and yields tensor outputs. Tensor is data represented as dimensional arrays. A tensor can be 1D, 2D, 3D,…, ND. Hardware with CPU: Intel i3-4150 3.50 GHz (4 processors), RAM: 8 GB, HDD: 1 TB, GPU: NVIDIA GEFORCE GTX 950 was used in training and testing.

5. Monthly rainfall forecast model

Monthly rainfall data in the study area were divided into two parts. The first part contained data from January 1991 to December 2010 or 240 months of data (around 77 % of the data). The second part began in January 2011 to December 2016 or 72 months data (around 23 % of data). The first part of the data was used for training or learning while the second was used for model validation.

DNN was applied to forecast monthly rainfall in the study area with LAV as predictors. Various simulations were conducted to find the most accurate lead time of forecast, i.e. 1 month, 3 months, 6 months and 12 months into the future. Various LAV in different atmospheric layers were also analyzed to identify the best predictors of the model.

The model structure proposed in Section 4.2 was used to first learning and training using data from the period of 1991 – 2010. Then the monthly rainfall at Pluak Daeng station was simulated for the six year period from January 2011 to December 2016. To evaluate accuracy of the forecast, a stochastic efficiency of forecast (SEF) was defined as:

$$\text{SEF} = \frac{O}{N} \text{ x } 100\% \qquad (6)$$

where O is number of forecasted monthly rainfalls that were within one standard deviation of observed values for that month, as:

$$ROM_i - \sigma_i \leq RP_{i,j} \leq ROM_i + \sigma_i \qquad (7)$$

Where $RP_{i,j}$ is forecasted monthly rainfall of month i, year j
ROM_i is observed mean monthly rainfall of month i during the year 1991-2010, i = 1..12
σ_i is the standard deviation of observed monthly rainfall in month i during the years 1990-2010, i = 1.. 12
N is total number of forecasted monthly rainfalls during the years 2011-2016, i.e., 72 months

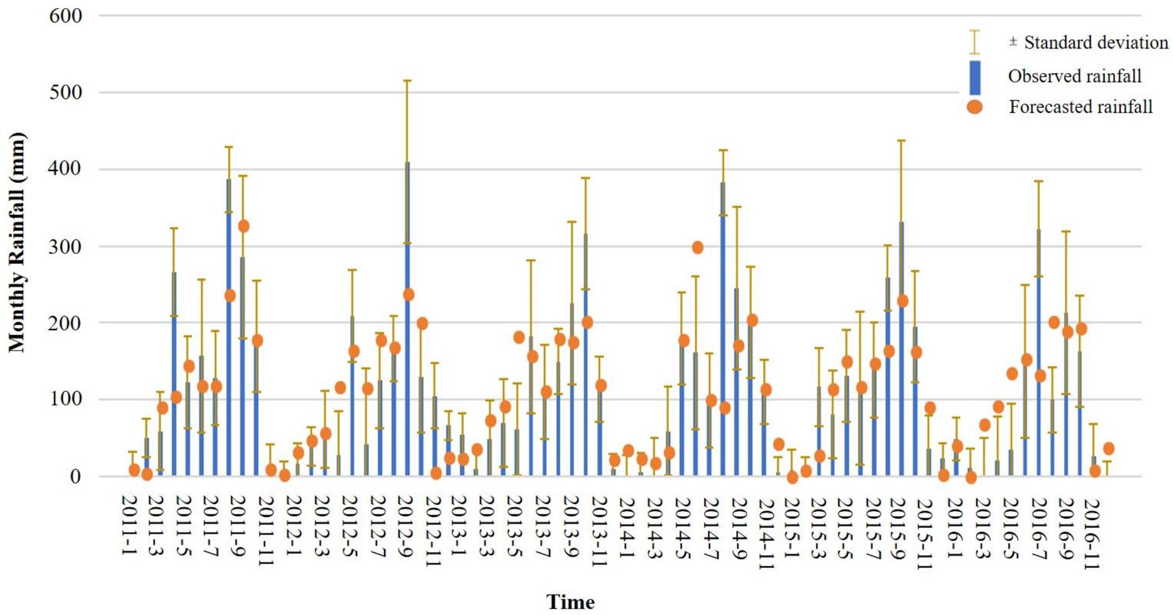

Figure 3 Monthly rainfall forecasted for one month lead time using DNN model at Pluak Daeng station for model validation

Table 2 shows the stochastic efficiency of forecast for various simulation scenarios, i.e., for one month lead time, three months lead time, and six months lead time of the forecast. The results indicate that error of forecast increases with the lead time of the forecast. Comparison of stochastic efficiency of forecast for monthly rainfall from simulation, as shown in Table 2, reveals that the most appropriate lead time of forecast is one month into the future, providing the highest value of efficiency of forecast, 65%. This is because there exists higher correlation between recent monthly rainfalls than rainfall occurring far into the future. Longer lead times lead to more forecast uncertainty.

Figure 3 presents model performance in forecasting monthly rainfall one month into the future at Pluak Daeng station during the validation period, i.e., from January 2011 to December 2016. Stochastic efficiency of forecast was around 65% for this six year simulation.

Table 2 Stochastic Efficiency of Forecast for models varying the lead times

Number of months lead time of forecast			
1 Month	**3 Months**	**6 Months**	**12 Months**
65.3**	59.8	51.4	57

(** in percent)

Table 3 Classification of level of annual rainfall using percentile range and rainfall data for 1991-2010

Percentile	Amount of annual rainfall (mm)	Level of rainfall
1	311	VERY DRY
10	1008	
11	1012	DRY
30	1051	
31	1057	NORMAL
70	1270	
71	1282	WET
90	1496	
91	1506	VERY WET
100	1608	

Annual rainfall was classified into five categories, i.e., very dry, dry, normal, wet and very wet years to better evaluate model performance. Rainfall data for 1991 to 2010 were used as well as a percentile method to characterize rainfall, as shown in Table 3.

Table 4 presents the performance of the model in forecasting monthly rainfall with one month of lead time from 2011 to 2016. The model could forecast quite well in wet and very wet years, with a stochastic efficiency of forecast from 67% to 75%. Better prediction performance is obtained in wetter years than in dry and normal years. Figure 3 reveals that forecasted monthly rainfall can be both overestimated and underestimated. Half of the forecasted rainfall was over the acceptable range and the other half was under.

The forecast monthly rainfall during the period of model validation was compared with observed monthly rainfalls and their correlation determined, as shown in Figure 4. The correlation coefficient was acceptable with an R value of 0.73. It is also notable from Figure 4 that for monthly rainfall in the dry season, the model often provides overestimated values. For monthly rainfall in the wet season, it always provides underestimated values. The performance of model is unstable for dry years and often provides overestimated values.

Table 4 Stochastic Efficiency of Forecast of DNN Model during model validation

Year	Annual Rainfall (mm)	Level of Rainfall	Stochastic Efficiency of Forecast (%)
2011	1642	VERY WET	75
2012	1394	WET	67
2013	1350	WET	67
2014	1449	WET	67
2015	1435	WET	67
2016	1087	NORMAL	50
Average			65

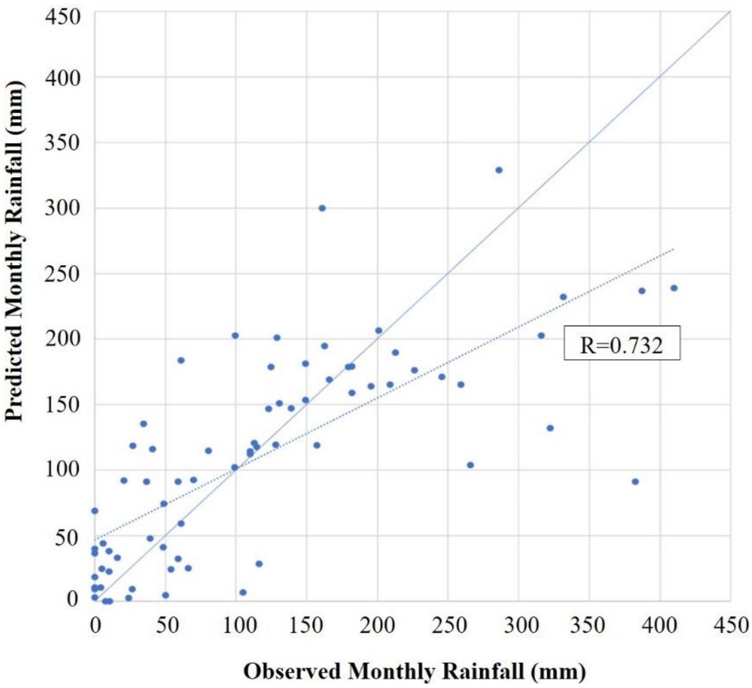

Figure 4 Comparison and Correlation of Forecast and observed monthly rainfall at Pluak Daeng station during 2011-2016 by a DNN model

6. Conclusions

A Deep Learning Neural Network (DNN) was developed in the study for forecasting monthly rainfall necessary for optimum reservoir operation and water resources management. A river basin in the eastern region of Thailand, where water demand for future national development is increasing, was selected as a study area. Large Atmospheric Variables (LAV) in different atmospheric layers were adopted as predictors in the model. Monthly rainfall data at Pluak Daeng station from 1991 to 2010 was used for DNN model training, while monthly rainfall for 2011 to 2016 were used for model validation. Stochastic efficiency of forecast (SEF) was defined and used to evaluate model performance. The results of various scenarios revealed that the DNN model was appropriate for forecasting monthly rainfall with a one month lead time. Its Stochastic Efficiency of Forecast decreased when lead time of forecast increased. The model is able to forecast monthly rainfall quite well for wet to very wet years. Quite few monthly rainfall forecast models provide accurate forecasted values in Thailand. The DNN model developed in this study provides acceptable accuracy of forecast for engineering practices. However, further study and development of the model in terms of computational techniques, as well as more appropriate predictors, should be done. Further study of techniques of downscaling of rainfall into daily rainfall is also necessary for optimum reservoir operation and more efficient water resources management. More investigation to determine other influential predictors should be conducted to obtain longer forecast lead times with more accurate rainfall predictions for better water resource management.

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