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Original Article

Rainfall prediction and meteorological drought analysis in the Sakae Krang River basin of Thailand

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ABSTRACT

Rainfall was predicted and used to analyze the severity levels of meteorological drought in the Sakae Krang River basin. Three forecasting models based on the Time Series Prediction technique, Single Moving Average, Simple Exponential Smoothing and Double Exponential Smoothing (Holt's model) were used to predict rainfall using the data collected from five rain gauge stations between 1970 and 2014. The minimum mean percentage error (MPE) score was used to indicate the accuracy of prediction. A standardized precipitation index (SPI) was used to indicate the drought severity levels in the Sakae Krang River basin between 1970 and 2015. The Simple Exponential Smoothing model produced the most accurate rainfall prediction followed by Double Exponential Smoothing (Holt's model) and the Single Moving Average model with MPE scores of 28%, 31% and 36%, respectively. The drought analysis results indicated that from 1970 to 2014, there was no clear trend in meteorological drought in the Sakae Krang River basin. In 2015, the meteorological drought severity level analysis of the sub-basins of the Sakae Krang River basin was graded as moderate drought for the lower part of Mae Nam Sakae Krang 1 and mild drought for Nam Mae Wong, the lower part of Mae Nam Sakae Krang 2, Khlong Pho and Huai Thap Salao with SPI scores of −1.01, −0.97, −0.91, −0.57 and −0.32, respectively.

Introduction

Thailand is consistently confronted with the recurrent problem of annual drought which seriously impacts both regional and national socioeconomic conditions. For example, in 1989–2013, 29–72 provinces were damaged by drought and during this period, the greatest damage was in 2005 being THB 7565.9 million (approximately USD 220 million) and covering 71 provinces (Department of Disaster Prevention and Mitigation, 2015).

The Sakae Krang River basin is one of the 25 main river basins of Thailand and data from Department of Water Resources (2008) indicates that this basin continually faces severe drought problems having the highest water scarcity levels compared with the other main river basins. For example, in 2005, the Sakae Krang River basin could supply only 62.51% of the demand, while more recently (2011–2015), part of the Sakae Krang River basin was classified as a recurrent drought area as drought is expected to increase both in frequency and severity in the near future (Department of Water Resources, 2008).

The major cause of meteorological drought is a deficit of rainfall. Consequently, an accurate rainfall forecast model is important for drought analysis and drought prediction. A skillful drought analysis method can inform better water resources management decisions, support the optimal allocation of the area's water resources, and mitigate socio-economic losses caused by droughts (Shukla et al., 2015). However, drought analysis and prediction in a specific area face several challenges and the lack of a skillful drought analysis method is one of those major challenges.

This study considered the accuracy of different rainfall forecasting models and predicted data on an annual and monthly basis. The modified data were then used for drought analysis and prediction in the Sakae Krang River basin.

Materials and methods

Research area

The research was conducted in the Sakae Krang River basin located in central region of Thailand. This river basin covers

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5192 km^2 in four provinces—Uthai Thani, Nakhon Sawan, Chai Nat and Kamphaeng Phet. It lies in an east-west direction between 14° 25′ N and 15° 08′ N and between 99° 05′ E and 100° 05′ E. It borders the Ping River basin in the north, the Tha Chin River basin in the south, the Meklong River basin in the west and the Chao Phraya River basin in the east. The Sakae Krang River basin consists of four sub-basins—Nam Mae Wong, Khlong Pho, Huai Thap Salao and the lower part of Mae Nam Sakae Krang, as shown in Fig. 1.

Data collection and application

This study collected and used rainfall data, expanded rainfall data, data from the adequacy test of the number of rain gauge stations and data from the consistency test of rainfall data.

Collection of data of rainfall

Rainfall data between 1970 and 2014 were collected by the rain gauge stations of the Royal Irrigation Department, Thailand. Complete and continuous rainfall data were available only from five rain gauge stations and they were used in this study. In the process of data analysis, rainfall data were used and reported based on calendar year (January—December). The lower part of the Mae Nam Sakae Krang sub-basin was divided into two sections—Mae Nam Sakae Krang 1 and Mae Nam Sakae Krang 2—according to the rain gauge stations of the Royal Irrigation Department in the lower part of the Mae Nam Sakae Krang sub-basin. The location details of rain gauge stations are shown in Fig. 2 and Table 1.

Expansion of rainfall data and adequacy of rain gauge stations

Due to the different numbers of data years collected from each rain gauge station, it was necessary to expand the rainfall data to achieve the same period of data years for all five rain gauge stations. The HEC-4 Monthly Streamflow Simulation program, developed by the Hydrologic Engineering Center (US Army Corps of Engineers–HEC, 1971), was used to expand the rainfall data (Sarango and Velásquez, 2009; Villazón and Willems, 2010; Chuenchooklin et al., 2013; Kangrang et al., 2013) for subsequent analysis.

Adequacy testing of the number of rain gauge stations in this study was based on the World Meteorological Organization (WMO) method using Equation (1) (World Meteorological Organization, 2012):

$$N = \left[\frac{C_v}{\varepsilon}\right]^2 \tag{1}$$

where, N is the optimal number of stations, ε is the allowable degree of error in the estimate of the mean rainfall and a value of 10% was used in this study according to the recommendation in World Meteorological Organization (2012) and C_v is the coefficient of variation of the rainfall value at the existing m stations (as a percentage). If there are m stations in the river basin and each records a

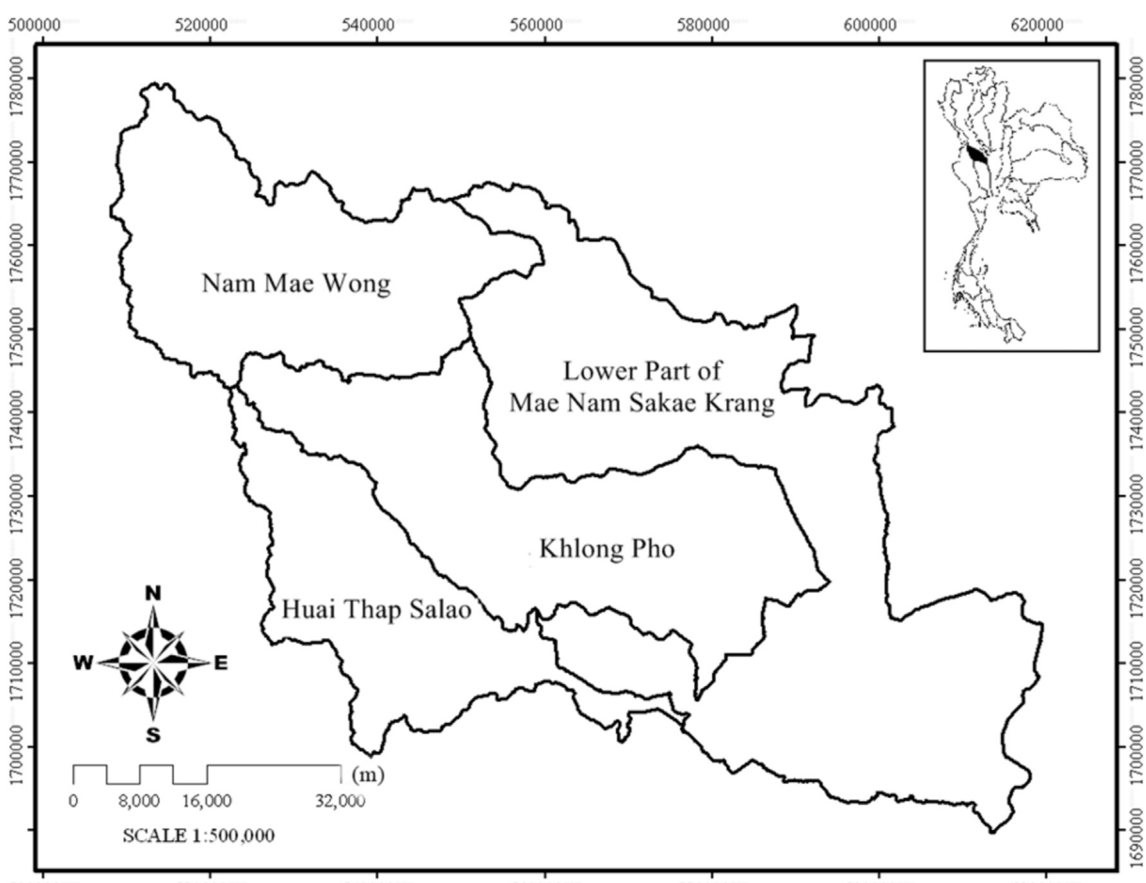

Fig. 1. Sakae Krang River basin and sub-basins.

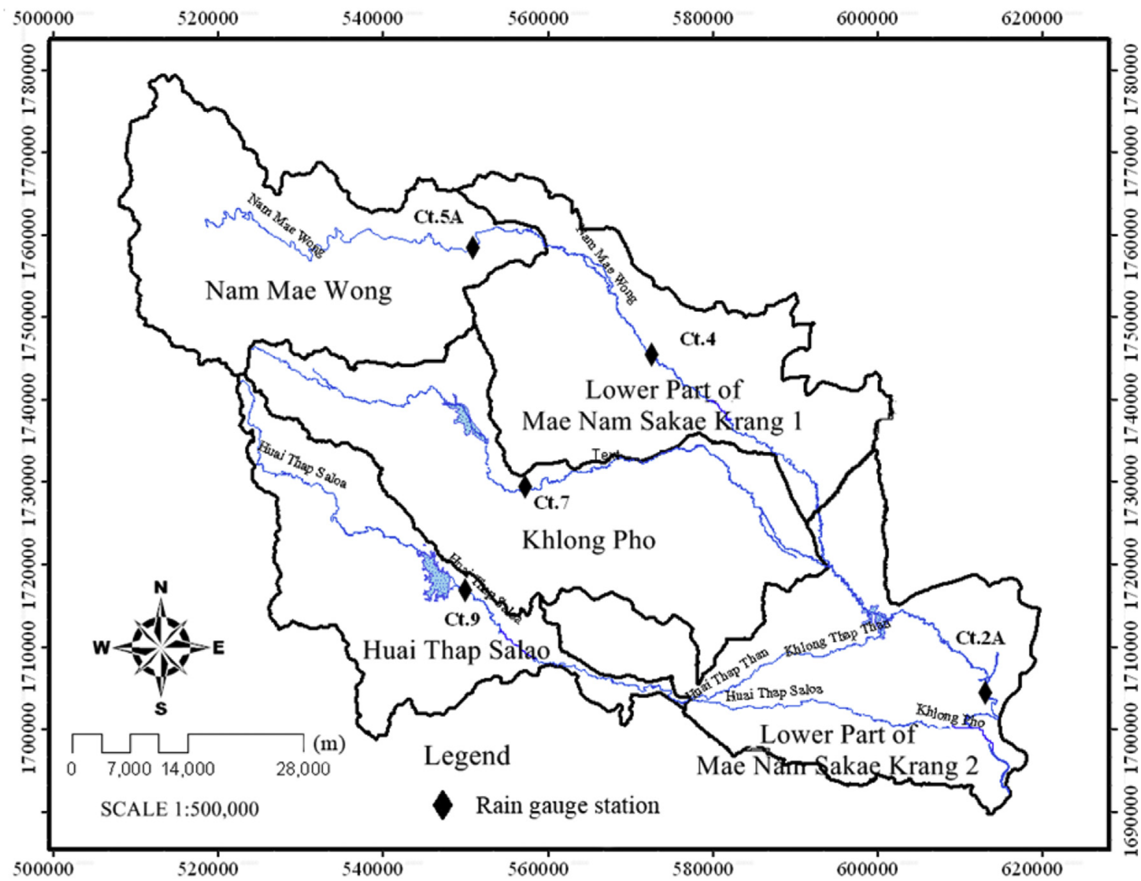

Fig. 2. Location of five rain gauge stations in the Sakae Krang River basin used in this study.

Table 1
Details of five rain gauge stations in the Sakae Krang River basin used in this study.

Station	Sub-basin	Station coordinates		Statistical period of data years	Number of data years
Ct.5A	Nam Mae Wong	N 15-55-33	E 99-30-22	1970–2014	45
Ct.7	Khlong Pho	N 15-38-24	E 99-32-24	1975–2014	40
Ct.9	Huai Thap Salao	N 15-31-35	E 99-28-10	1977–2014	38
Ct.4	Lower part of Mae Nam Sakae Krang 1	N 15-46-58	E 99-40-57	1975–2014	40
Ct.2A	Lower part of Mae Nam Sakae Krang 2	N 15-24-39	E100-03-29	2002–2014	13

rainfall value P_1, P_2 …, P_i … P_m in a known time, the coefficient of variation C_v is calculated using Equation (2):

$$C_v = \frac{100\sigma_{m-1}}{\overline{P}} \quad (2)$$

where the standard deviation is given by Equation (3):

$$\sigma_{m-1} = \sqrt{\frac{\sum_1^m [p_i - \overline{p}]^2}{m-1}} \quad (3)$$

and P_i is the rainfall magnitude in the ith station and the average rainfall is given by Equation (4) (Subramanya, 2008):

$$\overline{P} = \frac{1}{m}\left[\sum_1^m P_i\right] \quad (4)$$

Consistency testing of rainfall data

Errors in data may arise from instrumentation, station condition, observation and recording, transmission, coding and transcription. Therefore, it is necessary to conduct consistency testing and rainfall data adjustment. According to Searcy and Hardison (1960), Sulam (1979) and Gao et al. (2011), the Double Mass Curve Method was used for consistency testing in this study.

Data analysis

Rainfall forecast

Three forecasting models were used to predict the monthly rainfall in each year for each rain gauge station.

Single Moving Average model

This model is useful where the item being forecasted stays fairly steady over time and has been used for forecasting rainfall in

Table 2
Classification of drought severity level based on standardized precipitation index (SPI) scores.

SPI score	Level of drought severity
>2.00	Extremely wet
1.50–1.99	Very wet
1.00–1.49	Moderately wet
0.01–0.99	Mildly wet
−0.99–0.00	Mild drought
−1.00–−1.49	Moderate drought
−1.50–−1.99	Severe drought
<−2.00	Extreme drought

Adapted from McKee et al. (1993) and World Meteorological Organization (2012).

Southeast Asia (Mohamed et al., 2014). The monthly rainfall in each year was equally weighted and used to predict the monthly rainfall in each year from Equation (5):

$$F_{t+1} = \frac{X_t + X_{t-1} + \ldots + X_{t-n+1}}{n} \quad (5)$$

where F_t is the predicted rainfall in time t, X_t is the actual rainfall in time t and n is the number of times used to calculate the average rainfall.

Simple Exponential Smoothing model

This model has been used by numerous researchers for smoothing out sudden fluctuations in the demand pattern in order to provide stable estimates (Pagourtzi et al., 2003; Mohamed et al., 2014; Sopipan, 2014). It is used to calculate a weighted average as the significance or weight is given to the available data. For this model, the predicted rainfall was calculated using Equation (6):

$$F_{t+1} = F_t + \alpha(X_t - F_t) \quad (6)$$

where F_t is the predicted rainfall in time t, X_t is the actual rainfall in time t and α is the constant smoothing parameter and significance or weight given to the data in time t, while α ranges from 0 to 1. If α is low, more weight will be given to data in the past. If α is high, more weight will be given to recent data.

Double Exponential Smoothing (Holt's model)

This model is one of the time series forecasting models that is usually used to predict rainfall (Jahani et al., 2013). It gives more weight to recent rainfall and the weight slightly decreases for data in the past. For this model, the predicted rainfall was calculated using Equation (7):

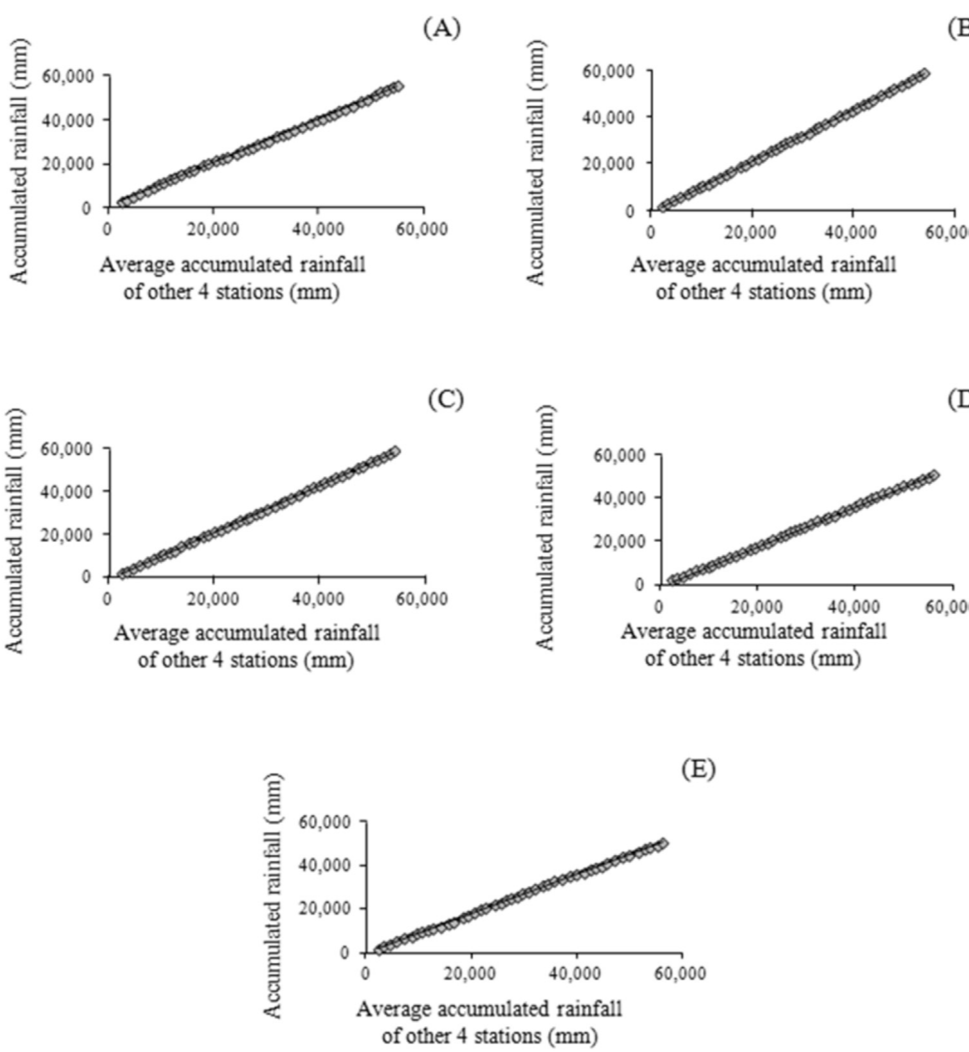

Fig. 3. Consistency testing of rainfall data for each station relative to the other four rain gauge stations: (A) Station Ct.5A; (B) Station Ct.7; (C) Station Ct.9; (D) Station Ct.4; (E) Station Ct.2A.

$$F_{t+m} = S_t + b_t m \quad (7)$$

where F_{t+m} is the predicted rainfall in time $t+m$ in which both t and m are in the same unit of time and m is equal to 1. S_t and b_t can be calculated from Equations (8) and (9):

$$S_t = \alpha X_t + (1-\alpha)(S_{t-1} + b_{t-1}) \quad (8)$$

$$b_t = \delta(S_t - S_{t-1}) + (1-\delta)b_{t-1} \quad (9)$$

where α is the smoothing constant for the actual data and the predicted values, X_t is the actual rainfall in time t and δ is the smoothing constant for the actual and estimated trend.

Measurement of the accuracy of rainfall forecast

The mean percentage error (MPE) of predicted rainfall from each forecasting model was used to indicate the accuracy (Cecílio et al., 2009; Xavier et al., 2014). Lower absolute values of the MPE indicate a more accurate prediction. A negative (−) MPE value indicates the predicted rainfall is higher than the actual rainfall, while a positive (+) MPE value indicates the predicted rainfall is lower than the actual rainfall. Equation (10) was used for MPE calculation:

$$MPE(\%) = \frac{\sum\left[\frac{X_t - F_t}{X_t}\right] \times 100}{n} \quad (10)$$

where X_t is the actual rainfall, F_t is the predicted rainfall and n is the number of time data series.

Drought analysis

Since drought analysis in this study mainly focused on meteorological drought, the standardized precipitation index (SPI) was used to assess drought severity levels. SPI has been used by numerous researchers (Lloyd-Hughes and Saunders, 2002; Paulo et al., 2012; Alam et al., 2013; Elagib, 2013) and organizations worldwide including the World Meteorological Organization, the Colorado Climate Center, the National Drought Mitigation Center, Thailand and the Thai Meteorological Department.

The SPI is an index for drought severity level analysis based on rainfall data at various periods of 1 month, 3 month, 6 month, 9 month, 12 month and 24 month. In this study, the drought severity level was analyzed at periods of 1 month and 12 month (on a

Table 4
Averaged mean percentage error of each model.

Model	Average mean percentage error (%)[a]
1. Single Moving Average	−36
2. Simple Exponential Smoothing	−28
3. Double Exponential Smoothing (Holt's model)	−31

[a] Negative (−) MPE score = the predicted rainfall is higher than the actual rainfall.

Table 5
Predicted rainfall (millimeters) in 2015 for each rain gauge station.

Month	Rain gauge station				
	Ct.5A	Ct.7	Ct.9	Ct.4	Ct.2A
January	5	5	2	1	3
February	1	2	3	0	0
March	41	98	82	28	18
April	31	58	86	61	29
May	56	86	121	123	135
June	54	149	95	84	184
July	227	97	96	174	94
August	221	255	200	92	127
September	172	202	194	128	167
October	63	138	231	160	126
November	38	23	64	3	6
December	5	2	3	3	0

Table 3
Actual rainfall, predicted rainfall and mean percentage error (MPE) of each model.

Station.	Actual rainfall/ Predicted rainfall (Model[a])	2014												MPE (%)[b]
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	
Ct.5A	Actual rainfall (mm)	0	0	40	29	46	47	230	210	152	58	41	6	–
	Predicted rainfall (mm)													
	(Model 1)	31	47	77	49	212	97	161	219	331	122	7	0	−54.02
	(Model 2)	47	5	50	47	148	121	200	318	355	112	10	0	−46.31
	(Model 3)	25	0	54	46	186	118	147	247	290	108	32	5	−55.75
Ct.7	Actual rainfall (mm)	0	0	106	61	74	135	97	267	181	137	24	2	–
	Predicted rainfall (mm)													
	(Model 1)	38	33	66	70	199	147	150	157	319	132	20	2	−18.68
	(Model 2)	48	19	24	26	191	272	101	150	394	150	13	1	−9.71
	(Model 3)	37	23	51	61	19	151	123	146	318	203	9	5	−26.36
Ct.9	Actual rainfall (mm)	0	0	87	94	117	82	96	198	177	235	69	3	–
	Predicted rainfall (mm)													
	(Model 1)	18	22	83	41	161	155	115	175	331	180	31	1	−1.31
	(Model 2)	15	35	41	10	152	210	97	217	343	199	22	0	2.94
	(Model 3)	14	22	55	26	148	164	111	164	329	205	15	0	7.44
Ct.4	Actual rainfall (mm)	0	0	31	64	113	77	180	81	99	162	2	3	–
	Predicted rainfall (mm)													
	(Model 1)	3	1	21	41	162	102	109	134	280	122	16	0	−65.98
	(Model 2)	9	0	1	32	214	149	120	190	388	139	9	0	−55.42
	(Model 3)	6	5	46	170	136	106	137	286	137	5	0	−22.21	
Ct.2A	Actual rainfall (mm)	0	0	13	31	143	172	87	133	143	133	6	0	–
	Predicted rainfall (mm)													
	(Model 1)	10	0	56	27	185	185	151	110	313	71	5	4	−38.89
	(Model 2)	26	0	60	16	63	288	153	78	384	62	1	1	−32.58
	(Model 3)	7	8	32	34	111	174	159	110	284	104	32	0	−59.18

[a] Model 1 = Single Moving Average; Model 2 = Simple Exponential Smoothing; Model 3 = Double Exponential Smoothing (Holt's model).
[b] Negative (−) MPE score = the predicted rainfall is higher than the actual rainfall.

Table 6
Standardized precipitation index (SPI) scores, ranking scores and levels of drought severity.

SPI score	Ranking score	Levels of drought severity
>2.00	1	Extremely wet
1.50–1.99	2	Very wet
1.00–1.49	3	Moderately wet
0.01–0.99	4	Mildly wet
−0.99–0.00	5	Mild drought
−1.00–−1.49	6	Moderate drought
−1.50–−1.99	7	Severe drought
<−2.00	8	Extreme drought

monthly and yearly basis). The SPI_SL_6 program, which was developed and disseminated by the National Drought Mitigation Center (Chomtha, 2007), was used to classify the levels of drought severity as depicted in Table 2. The SPI was calculated based on Equation (11):

$$SPI = \frac{X_{ij} - X_{im}}{\sigma} \qquad (11)$$

where X_{ij} is the average monthly rainfall of the focus station, X_{im} is the average monthly rainfall of all study stations and σ is the standard deviation.

Results and discussion

Adequacy of number of rain gauge stations

Adequacy testing of the number of rain gauge stations in this study was based on Equation (1) where the calculated C_v was 9.50 and ε was given a value of 10 based on the World Meteorological Organization (2012). The calculation of N is shown as below.

$$N = \left[\frac{9.50}{10}\right]^2 = 0.9(1\ \text{station})$$

The calculation showed that only one rain gauge station was required. Therefore, in this study, five rain gauge stations was considered adequate.

Expansion and consistency testing of rainfall data

To uniformly expand the period of rainfall data for all five rain gauge stations covering 1970–2014, the HEC-4 program was used.

The accumulated rainfall at each rain gauge station was tested for consistency with the average accumulated rainfall of the other four rain gauge stations using the Double Mass Curve method. The results illustrated a single straight sloped line for the five rain gauge stations (Fig. 3) which indicated the rainfall data were consistent. Therefore, there was no need to adjust the data as reported by Sulam (1979).

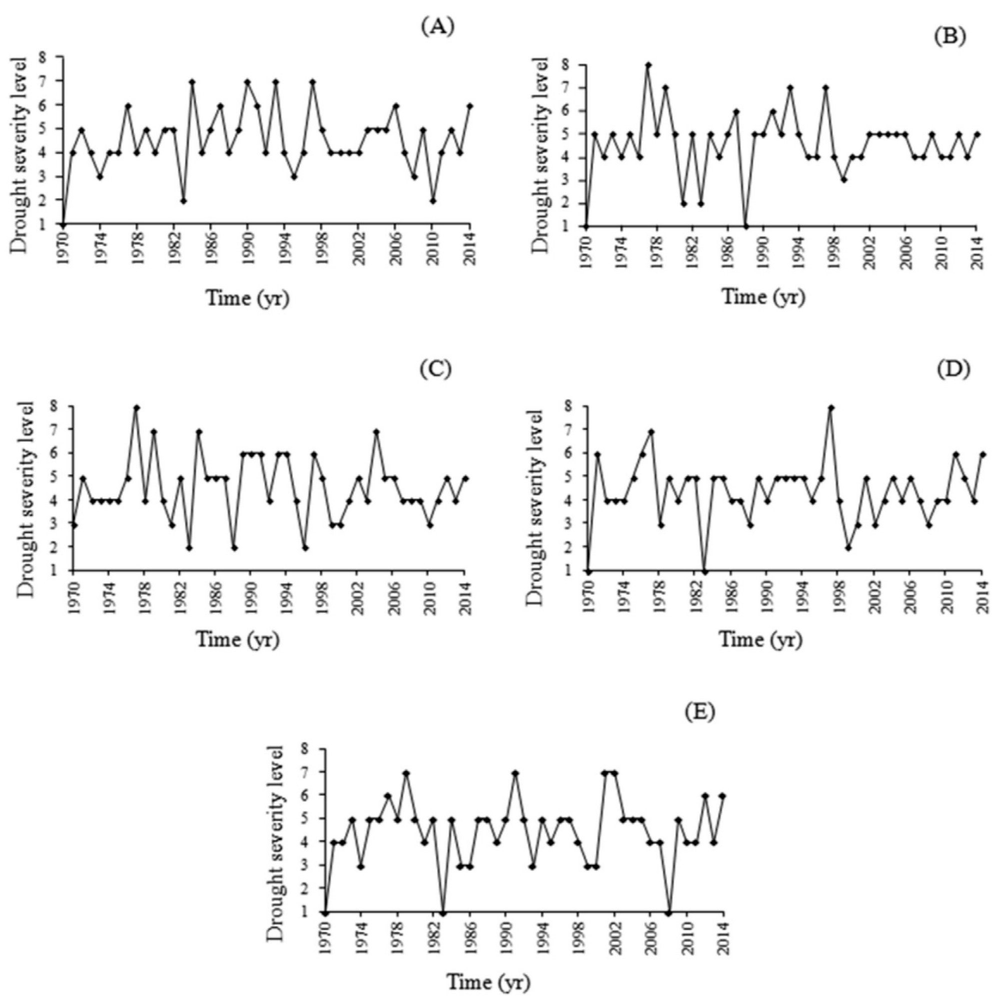

Fig. 4. Annual drought severity levels for each sub-basin in the Sakae Krang River basin for 1970–2014: (A) Nam Mae Wong; (B) Khlong Pho; (C) Huai Thap Salao; (D) lower part of Mae Nam Sakae Krang 1; (E) lower part of Mae Nam Sakae Krang 2.

Rainfall forecast

Three forecasting models—Single Moving Average, Simple Exponential Smoothing and Double Exponential Smoothing (Holt's model)—were used to predict the rainfall at the five rain gauge stations. The rainfall data 1970–2013 at each rain gauge station were used to predict the rainfall in 2014. Thereafter, the predicted rainfall data of each rain gauge station calculated by each model were compared with the actual rainfall data in 2014. These data were then tested for their MPE value prior to being applied to predict the rainfall in 2015. The details of predicted rainfall and MPE values are displayed in Table 3.

Validation of rainfall forecasting model

To validate the rainfall forecasting model, the average MPE scores of each model were compared. The results showed that the Simple Exponential Smoothing (model 2) gave the highest accuracy with the lowest MPE score of −28% as shown in Table 4.

Rainfall prediction for 2015

The Simple Exponential Smoothing model was used to predict the rainfall in 2015 for each rain gauge station. The rainfall prediction results for each rain gauge station showed the same pattern that was related to seasonal variation with high rainfall in the wet season and low rainfall in the dry season (Table 5).

Drought analysis

The SPI was used to assess the levels of drought severity in each sub-basin of the Sakae Krang River basin from 1970 to 2014 on a yearly basis. The results ranged from scores of >2.00 to < −2.00, indicating drought severity levels of extremely wet to extreme drought for the sub-basins. The drought severity level was determined using a ranking score (1–8) based on the SPI scores as depicted in Table 6. In term of ranking scores, drought severity

Table 7
Details of drought severity level, standardized precipitation index (SPI) and ranking score of sub-basins of the Sakae Krang River basin in 2015.

Sub-basin of Sakae Krang River basin	Level of drought severity	SPI score	Ranking score
Nam Mae Wong	Mild	−0.97	5
Khlong Pho	Mild	−0.57	5
Huai Thap Salao	Mild	−0.32	5
Lower part of Mae Nam Sakae Krang 1	Moderate	−1.01	6
Lower part of Mae Nam Sakae Krang 2	Mild	−0.91	5

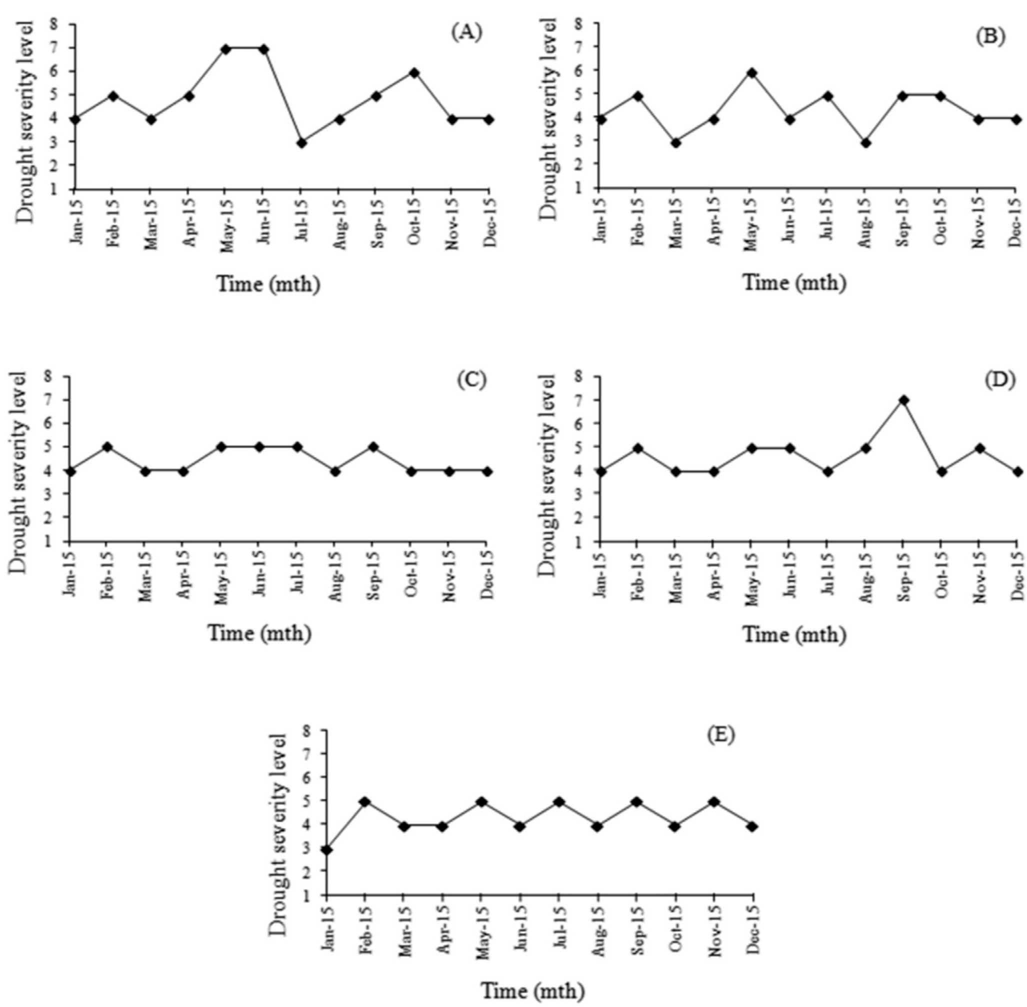

Fig. 5. Monthly drought severity level for each sub-basin in the Sakae Krang River basin for 2015: (A) Nam Mae Wong; (B) Khlong Pho; (C) Huai Thap Salao; (D) lower part of Mae Nam Sakae Krang 1; (E) lower part of Mae Nam Sakae Krang 2.

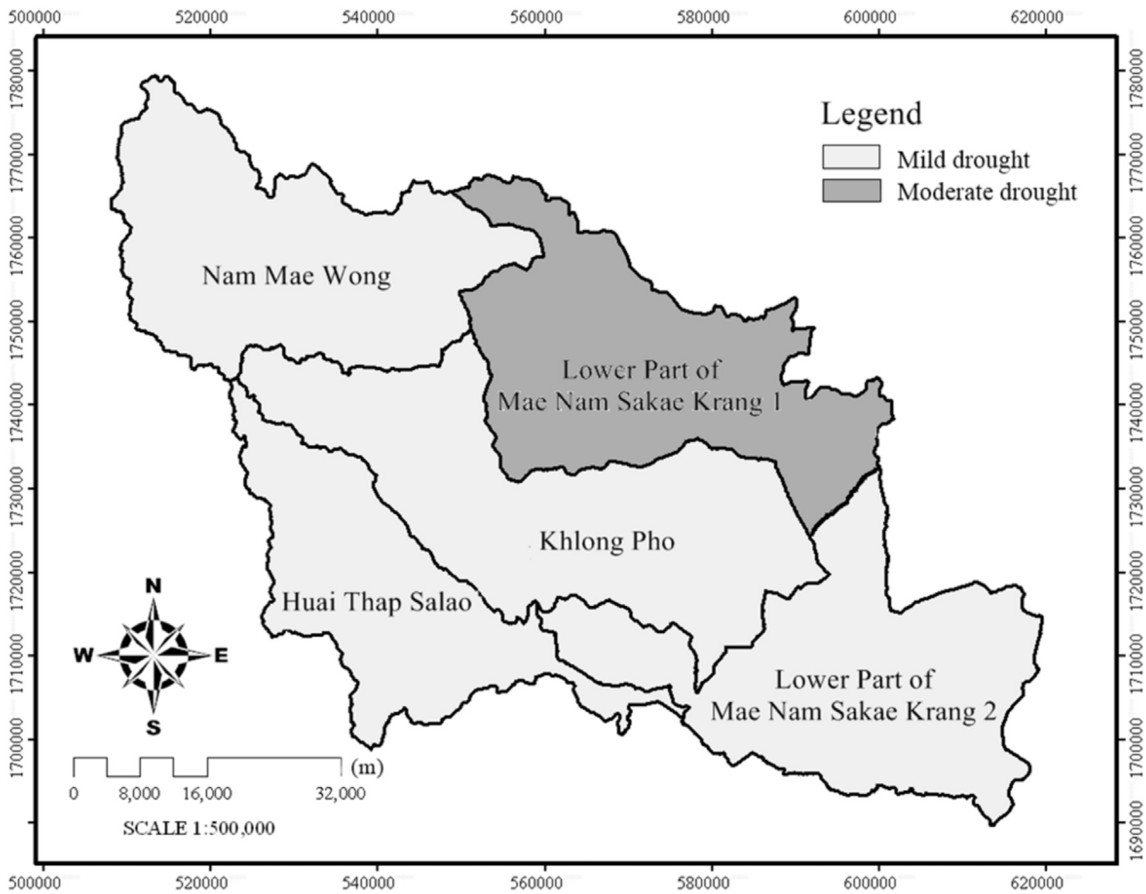

Fig. 6. Map of drought severity levels of sub-basin of the Sakae Krang River basin in 2015.

levels were 1–8 for the Khlong Pho and the lower part of Mae Nam Sakae Krang 1, 1–7 for the Nam Mae Wong and the lower part of Mae Nam Sakae Krang 2 and 2–8 for the Huai Thap Salao, indicating that drought severity levels varied from extremely wet to extreme drought, extremely wet to severe drought and very wet to extreme drought, respectively, as shown in Fig. 4.

The predicted rainfall data for each sub-basin of the Sakae Krang River basin in 2015 are displayed in Table 5. They were used to calculate the SPI scores indicating drought severity levels for each sub-basin of the Sakae Krang River basin in 2015 on a monthly basis, which had ranking scores varying from 3 to 7, indicating drought severity levels of moderately wet to severe drought. The details of the drought severity levels for each sub-basin of the Sakae Krang River basin are illustrated in Fig. 5.

On a yearly basis, the drought severity level SPI scores of each sub-basin of the Sakae Krang River basin in 2015 ranged from −1.01 to −0.32 or from 5 to 6 based on the ranking scores, indicating the drought severity ranged from mild drought to moderate drought (Table 7). The drought severity levels are displayed in map form in Fig. 6.

Among the models appraised, the Simple Exponential Smoothing model provided the greatest accuracy for rainfall prediction with an MPE score of 28% compared to the MPE scores for Double Exponential Smoothing (Holt's model) and the Single Moving Average model of 31% and 36%, respectively. The meteorological drought analysis results for each sub-basin of the Sakae Krang River basin during 1970–2014 did not show any clear trends. Drought forecasting in 2015 for the Sakae Krang River basin, indicated moderate drought was expected in the lower part of Mae Nam Sakae Krang 1 with an SPI score of −1.01 while mild drought was expected in the sub-basins of Nam Mae Wong, the lower part of Mae Nam Sakae Krang 2, Khlong Pho and Huai Thap Salao with the SPI scores of −0.97, −0.91, −0.57 and −0.32, respectively.

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