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ORIGINAL ARTICLE

Optimal time series model for forecasting monthly temperature in the southwestern region of Thailand

Wandee Wanishsakpong[1,3] · **Bright Emmanuel Owusu**[2]

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Abstract

Forecasting and describing the dynamic changes of climatic variables are essential in determining the occurrences of extreme climate events. The understanding of these events will help in taking actions to lessen their related effects. This study compares auto-regressive integrated moving-average (ARIMA) and the auto-regressive integrated moving average with exogenous variables (ARIMAX) models in forecasting temperature in Ranong and Phuket, Thailand. The average monthly temperature observations between 2006 and 2016 were collected from the Thai Meteorological Department for the study. The ARIMA and ARIMAX models were then applied to the average monthly temperature using the relative humidity and rainfall as the explanatory variables. Analysis of the root mean square error and the relative root mean square error (RRMSE) values from the models revealed that the methods fitted the data quite well. However, the optimal ARIMAX model obtained in Ranong was the ARIMAX $(1,0,0)(0,1,0)_{12}$ with RRMSE value of 0.874 did better than the optimal ARIMA model. The relative humidity and rainfall factors were very influential in the models. Also, the ARIMA $(3,0,2)(0,1,0)_{12}$ model with RRMSE value of 1.113 was observed to be the optimal model in the temperature modelling in Phuket. This model fitted better than the optimal ARIMAX model in temperature modelling at Phuket. The fitted models will be beneficial in numerous applications where the observed temperature records are quite short, incomplete, or lack spatial coverage

Keywords Temperature · Forecasting · Optimal · Time series · ARIMA and ARIMAX models

Introduction

The quantitative analysis of the variability of weather and climate variables is essential to governments, industries and communities due to the increasing extreme events as a result of climate change. The southern region of Thailand is on the Malay Peninsula between the east coast of the Gulf of Thailand and the west coast of the Andaman Sea. There is mostly rain and tropical monsoon, with continues rainfall and humidity all year round in these parts of Thailand. The highest recorded temperature (40.5 °C) that has been observed in the south was recorded in Trang and the lowest temperature (13.7 °C) was observed at Ranong. In general, surface temperatures are mild throughout the year in the southern part relative to the upper parts of Thailand. The general low temperatures observed in these regions may be due to the maritime features of this area. The evident high temperatures, which are common to the upper parts of Thailand rarely, take place in the south of Thailand. The observed diurnal and seasonal temperature variations in the south are considerably fewer than those in upper Thailand (TMD 2016). Rainfall, humidity and wind direction are mostly the primary causes of the variability of weather systems as a result of the influence of the southwest and northeast monsoons.

Furthermore, the formation and a lineup of the mountain make it the perfect monsoon. The southwest monsoon approach west coast then collides with the Tanaosri mountain causing heavy rainfall and temperature change, especially in Ranong. The backside of the mountain in Suratthani province is rain shadow that affects tourism and fishery. According to the Ministry of Tourism and Sports

✉ Bright Emmanuel Owusu
bright.owusu@presbyuniversity.edu.gh

1 Department of Statistics, Faculty of Science, Kasetsart University, Bangkok 10900, Thailand

2 Department of Mathematics, Faculty of Science and Technology, Presbyterian University College Ghana, Abetifi, Ghana

3 Centre of Excellence in Mathematics, CHE, Si Ayutthaya RD, Bangkok, Thailand

(2019), tourism is still a dependable driver of Thailand's economic growth. This report is due to the rapidly increasing number of visitors to Thailand, which has grown from 14.1 m in 2009 to 38.3 m in 2018. Tourism, therefore, is a more critical driver of Thailand's Gross Domestic Product (GDP) growth, accounting for 12.3% of GDP in 2018 compared to only 5.3% in 2009. Therefore, temperature forecasting will help in providing adaptive measures in minimising the effects of temperature problems associated with tourism.

Time series modelling has been effectively used in many areas of study to describe, explain, predict and control processes. These areas include economics, geophysics, control engineering and meteorology (Chatfield 1996). Application of time series models in climate modelling includes (Machiwal and Jha 2009) and Bari et al. 2015 in precipitation modelling. There are many methods used in forecasting monthly temperature. One of the arguably widely used statistical methods for forecasting temperature time series is ARIMA by Box-Jenkins (Jenkins et al. 2015). The use of the ARIMA models in forecasting temperature observations may be due to its reliability and accuracy relative to other methods in modelling various time-series observations.

Besides, the ARIMAX model is an extension of the ARIMA model. It includes other independent variables. When an ARIMA model consists of additional time series variables as input, the model is sometimes known as an ARIMAX model. Pankratz (2012) also referred to ARIMAX models as dynamic regression models. Jalalkamali et al. (2015) compared the predictive ability of several artificial intelligence and ARIMAX models for predicting drought using the Standardized Precipitation Index (SPI). The models of the artificial intelligence included the multilayer perceptron artificial neural network (MLP-ANN), adaptive neuro-fuzzy inference systems (ANFIS) and the support vector machine (SVM) model. Their results indicated that in 9 months, the ARIMAX model gave optimum SPI values and did forecast drought with more accuracy than the SVM, ANFIS, and MLP models.

Peter and Silvia (2012) compared the predictive ability of the ARIMAX and the ARIMA models in the analysis of a microeconomic time series data. They observed that the predictive ability of the ARIMA models was slightly better than that of the ARIMAX models. In contrast, a similar study by Anggraeni et al. (2015) revealed that the predictability of the ARIMAX was superior to that of the ARIMA model. Application of ARIMA models in temperature forecasting includes Nury et al. (2013) and Oraiopoulos (2015). The present study aimed at modelling and forecasting average monthly near-surface temperature in Ranong (in the southeast) and Phuket in the southwest regions of Thailand. By so doing an optimal model capturing the properties of the monthly temperature observations will be determined.

Data and methods

Eleven years average monthly near-surface temperature, rainfall and relative humidity observations were used for this study. The considered data set of Phuket and Ranong ranged from January 2006 to December 2016 and was acquired from the Thai Meteorological Department (Fig. 1). A preliminary analysis of the data was conducted using descriptive statistics to examine the nature of the observations. Besides, boxplots were constructed on the monthly temperature observations to examine the monthly pattern and the distribution of the observations.

The average monthly temperature (response variable) was then modelled using ARIMA and ARIMAX models, while the average monthly rainfall (R) and relative humidity (H) observations were employed as the explanatory variables in the ARIMAX models. The observed seasonal effect in the observations was adjusted by taking the seasonal difference. Stationarity of the monthly temperature observations was then tested with the unit root test using the Augmented Dickey–Fuller test (ADF) (Mushtaq 2011). A major challenge in modelling a time series observation is the dependency of the observations with itself with time (serial correlation). This problem was checked to ascertain whether AR or MA terms are needed in the models to remove any autocorrelation that remains in the differenced series by considering the autocorrelation (ACF) and partial autocorrelation (PACF) plots of the differenced series. The ARIMA model when Y (response variable) is stationary at a difference of 1 (Maindonald 2009) is written as Eq. (1)

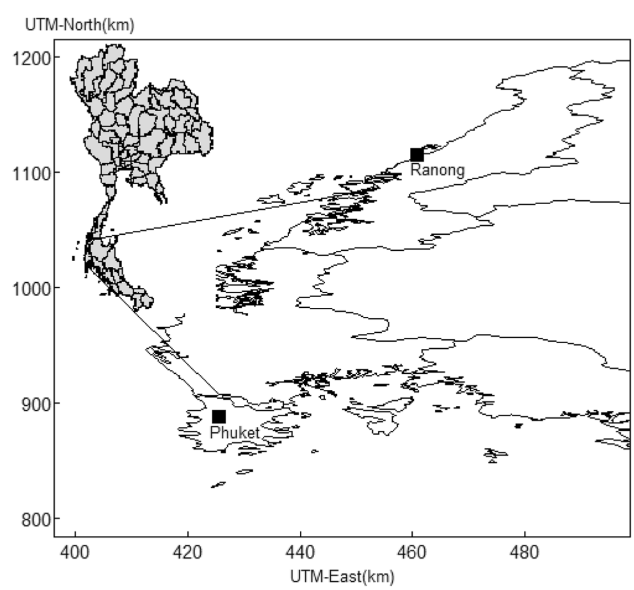

Fig. 1 The map of Thailand showing the locations of the study area

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^{p} \phi_i \Delta Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t, \quad (1)$$

while Hamilton (1994) defined the ARIMAX model as

$$\Delta^D Y_t = \sum_{i=1}^{p} \phi_i \Delta^D Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{m=1}^{m} \beta_m X_{m,t} + \varepsilon_t \quad (2)$$

where X_t is exogenous variables (rainfall and humidity) time series data at a time (t), Y_t is the time series data at time (t) (monthly temperature), α is invariant, Δ^D is differences operator at D, ϕ, θ and β are the regression coefficient, p, q, m are the optimal lag length variables,ε_t is the errors in variables with $\varepsilon_t \sim \mathrm{NID}\left(0, \sigma^2\right)$ and $t = 1,2,\ldots,n$

In fitting the ARIMA and ARIMAX models, the data was divided into two parts. The training data set (2006–2014) and the test data set (2015). The precision of the two models was evaluated, and the optimal model was then selected.

Evaluation of the models

The root mean square error approximation (Steiger and Lind 1980; Willmott and Matsuura 2005) is arguably one of the most used goodness-of-fit indices in most modelling applications (Eq. 3). The root mean square error of approximation (RMSE) is generally not affected by the sample size and permits detecting circumstances of poor model fit. Low RMSE values signify a well-fitting model in terms of its absolute deviation. This method is affected by extremely low or high values of the observations. The relative root mean square error (RRMSE) is an index calculated by dividing RMSE with the average value of the measured data, Eq. (4) and expressed as a percentage (Despotovic 2016). Li et al. (2013) revealed that the model precision is considered excellent when the RRMSE is less than 10%, good if it is between 10 and 20%, fair when it falls within 20 and 30% and weak if it is above 30%. The RMSE and the RRMSE index were used to ascertain the goodness of fit of the models in this study.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (Y_t - \hat{y}_t)^2}, \quad (3)$$

$$\mathrm{RRMSE} = \frac{\sqrt{\frac{1}{n} \sum_{t=1}^{n} (Y_t - \hat{y}_t)^2}}{\frac{1}{n} \sum_{t=1}^{n} Y_t} \times 100, \quad (4)$$

where Y_t, is the actual meant monthly temperature at the time (t), $\hat{y}_t$ is forecast temperature value at the time (t) from the ARIMAX and ARIMA models and n is the number of observations. The models were also assessed and selected using the Information Criterion Akaike (1973), and now the Akaike information criterion (AIC). Lower AIC values of a fitted model, reveals a good fit of the model. All data analyses were done in Minitab 17 and graphical displays were done using the R (R Development Core Team 2017).

Results and discussion

Preliminary results

The results of the preliminary analysis of the data revealed that temperature ranges from 26.7 to 29.3 °C with a mean of 28.2 °C in Phuket while it ranges from 26.4 to 29.0 °C with a mean of 27.9 °C in Ranong. Phuket and Ranong have approximately the same mean monthly temperature of 28 °C. However, the monthly mean temperature is more consistent in Phuket (coefficient of variation of 2.6%) than in Ranong (coefficient of variation of 3.3%). Analysis of the coefficients of variations from the monthly temperature observations revealed that, generally, the temperature was quite stable in both areas during 2006–2016.

The distribution patterns of the monthly average temperature from Phuket and Ranong have been shown on the boxplot (Fig. 2). The horizontal dark lines on Fig. 2 indicate median temperature while the boxes indicate the first and third quartiles of the distribution. The lines extending from the boxes extend to 1.5 times the interquartile range and the circle indicates extreme monthly temperature observation. Analysis of Fig. 2 revealed that monthly temperature increases gradually from January to February in Phuket. It then reduces steadily from February to April and increases again until September where it observes a sharp fall to October and rises again for the remaining months. However, the mean monthly temperature is quite stable between July and September.

In Ranong, the mean monthly temperature reduces steadily from January to February. It then rises sharply to March where it reduces again until April. The temperature rises gradually between May and July where it reduces again until August. It then rises again from August to November where it reduces again for the remaining part of the year. Temperatures between May and July are quite stable in Ranong.

Also, the annual average monthly rainfall for Ranong and Phuket was computed, and the results are shown in Fig. 3. The patterns of the annual monthly average temperature revealed a slightly decreasing trend between 2006 and 2007 in Ranong. It then increased sharply between 2007 and 2011 until it attained the maximum in 2011. Since 2011, the annual average monthly temperature in Ranong has been decreasing steadily. On the other hand, an increase in annual monthly temperature was observed in Phuket between 2006 and 2011 where it attained its

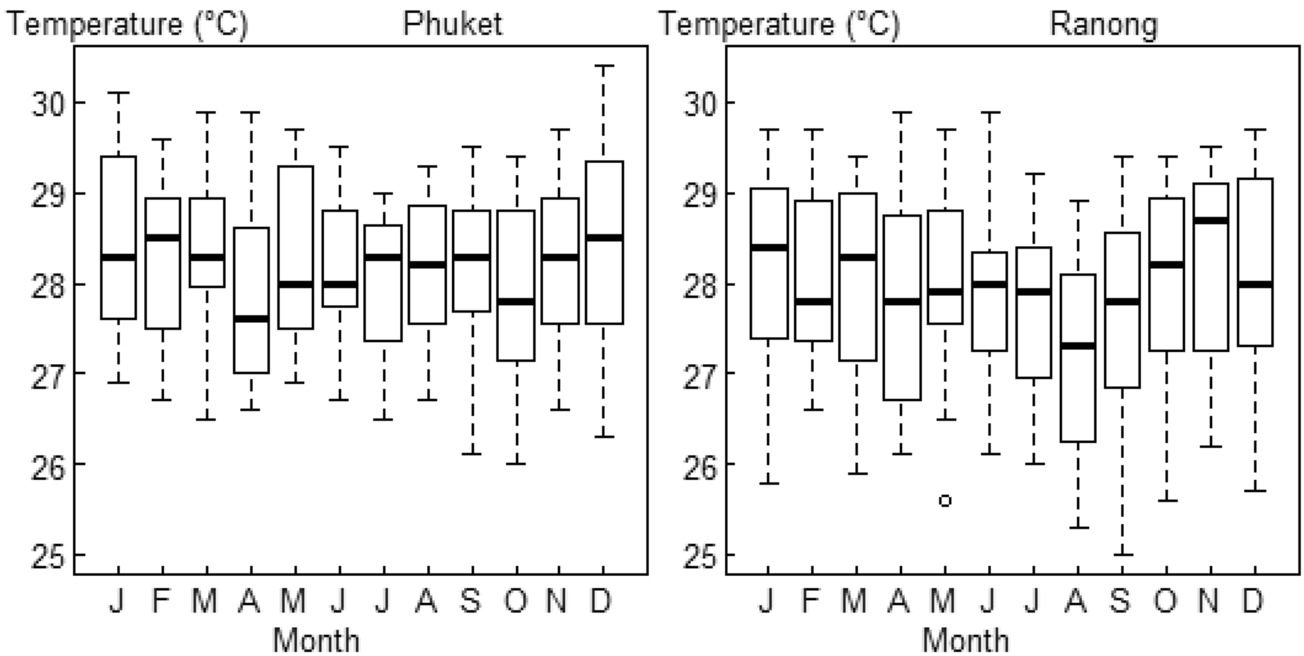

Fig. 2 Boxplots of the monthly average rainfall distributions at Phuket and Ranong during 2006–2016

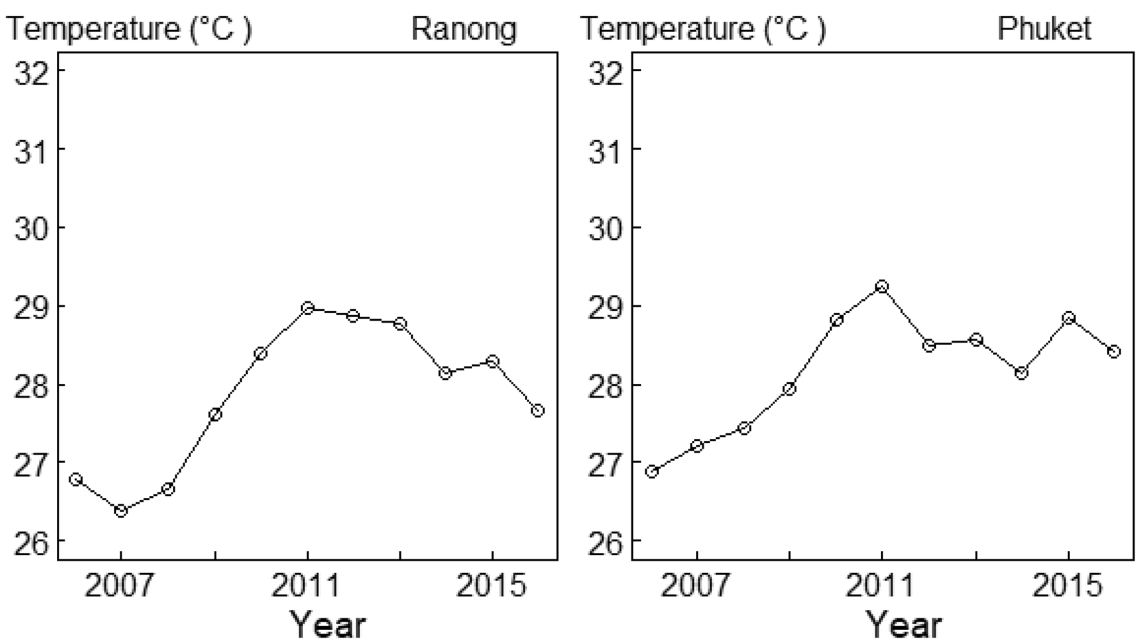

Fig. 3 Time series plot of the annual average monthly rainfall. Panel 1 of Fig. 3 gives the annual monthly average temperature in Ranong while the second panel gives the annual monthly average temperature in Phuket

maximum in 2011. Sharp decreasing patterns of the annual monthly temperature were observed between 2011 and 2014 in Phuket. Interestingly, a notable distinct temperature pattern at the study area is the maximum annual average monthly temperature which occurred at the same year at both Ranong and Phuket.

Modelling results

Modelling mean monthly temperature at Ranong

In testing the stationary of the data using the ADF method revealed *t*-values of − 6.50, − 1.88 and − 10.12, respectively, for the temperature, humidity and rainfall with corresponding p-values of less than 0.001, 0.34 and less than 0.001. These results depict that the monthly temperature and rainfall data were stationary at a 5% level of significance. These results revealed a p value of less than 0.05, but the monthly observations of humidity were non-stationary. Therefore, the humidity observations were adjusted for stationarity using the difference method. The result of the stationarity testing gave t and p values of -9.239 and less than 0.001, respectively, which shows that the humidity observations were non-stationary at a 5% level of significance.

The estimated parameters of the fitted ARIMA$(1,0,0)(0,1,0)_{12}$ and ARIMAX$(1,0,0)(0,1,0)_{12}$ are given in Table 1. Analysis of Table 1 revealed that the coefficients from ARIMA and ARIMAX were influential in the model. The observed low p-values (p-values < 0.05), AIC and SSE values from the models revealed that the parameters estimated from the models were all significant in the models. These low ***p***-values, AIC and SSE values also indicate that the models fit the data quite well. Therefore, the forecast temperature equations of both the ARIMA and ARIMAX models are given by Eq. 5 and 6, respectively, where R and H are the rainfall and humidity observations, respectively.

$$\hat{Y}_t = Y_{t-12} + 0.5217(Y_{t-1} - Y_{t-13}) \tag{5}$$

$$\begin{aligned}\hat{Y}_t = Y_{t-12} + 0.617(Y_{t-1} - Y_{t-13}) - 0.031(R_t - R_{t-12}) \\ - 0.035(H_t - H_{t-1} - H_{t-12} + H_{t-13}) + \varepsilon_t.\end{aligned} \tag{6}$$

Moreover, the fitted models were used to forecast monthly temperature in the year 2016 at Ranong. Figure 4 reveals the estimated monthly temperature for 2016 using the ARIMA$(1,0,0)(0,1,0)_{12}$ (second panel of Fig. 4) and ARIMAX$(1,0,0)(0,1,0)_{12}$ (third panel of Fig. 4) and the observed temperature at Ranong (panel one of Fig. 4). Analysis of Fig. 4 shows that the models fitted the data fairly well. Both models revealed the monthly temperature patterns quite well. However, the extreme observations were poorly modelled by both models. Even though the maximum observed monthly temperature was poorly modelled by the models, the ARIMAX model revealed this value better than the ARIMA model in Ranong. The poorly modelled extreme temperature values may be due to the inability of the models to handle extremely low or high observational values. The decreasing monthly mean temperature and the low mean monthly temperature observed between April and October in Ranong may be due to the onset of the rainy season. The southeast of Thailand where Ranong is located has about 5 months of the rainy period. The rainy period is most active between September and January (Eso 2015).

Furthermore, the reliability of the two models in the mean temperature forecast at Ranong was assessed by comparing the RMSE, RRMSE and the AIC values from the models. The ARIMAX model produces a lower RMSE (0.65) and AIC (1.514) values relative to the ARIMA model (0.75) in the forecast of temperature at Ranong during 2016 (Table 1). However, both the ARIMAX and the ARIMA models have approximately the same RRMSE values (0.85). Thus, the ARIMAX model did better than the ARIMA model relative to RMSE values. This result is similar to a study by Anggraeni (2015) which also revealed the better performance of the ARIMAX model in time series forecasting concerning lower AIC, MAPE and RMSE values relative to the ARIMA models. Jalalkamali et al. (2015) also confirmed the superiority of the ARIMAX models among other time series models in forecasting a monthly time series of drought observations.

Modelling mean monthly temperature at Phuket

The seasonal patterns present in the monthly average temperature observations were adjusted for seasonal effect by taking the seasonal difference. The ADF method was used to examine the stationarity of the observations. The result gave t-values of -6.96, -0.63, -6.314 for the temperature, humidity and rainfall, respectively, with corresponding p-values of 0, 0.86 and less than 0.001, respectively. Analysis of the results revealed that the monthly temperature and rainfall observations were stationary at 5% level of significance (p-values < 0.05), but the monthly humidity observations were non-stationary. The humidity observations were then converted to stationary using the difference method.

The parameter estimates of the fitted ARIMA $(3,0,2)(0,1,0)_{12}$ and ARIMAX $(3,0,2)(0,1,0)_{12}$ models are given in Table 2. Analysis of the estimated parameters of the models (ARIMA $(3,0,2)(0,1,0)_{12}$ and ARIMAX $(3,0,2)(0,1,0)_{12}$) interestingly revealed that the estimated parameters were very influential and significant in the fitted models. Most of the parameters had p-values < 0.001. Therefore, the temperature forecasting equation of the ARIMA model is given by Eq. (7) and that of the ARIMAX is given by Eq. (8) where R and H are the rainfall and humidity observations, respectively.

Table 1 The estimated parameters of ARIMA$(1,0,0)(0,1,0)_{12}$ and ARIMAX $(1,0,0)(0,1,0)_{12}$ at Ranong during 2016

Methods	Model	Variable	Coefficient	p Value	AIC	SSE
ARIMA	$(1,0,0)(0,1,0)_{12}$	AR(1)	0.522	0.0000	1.910	41.531
ARIMAX	$(1,0,0)(0,1,0)_{12}$	AR(1)	−0.617	0.0000	1.514	26.655
		Rain	−0.031	0.0007		
		Moisture	−0.035	0.0000		

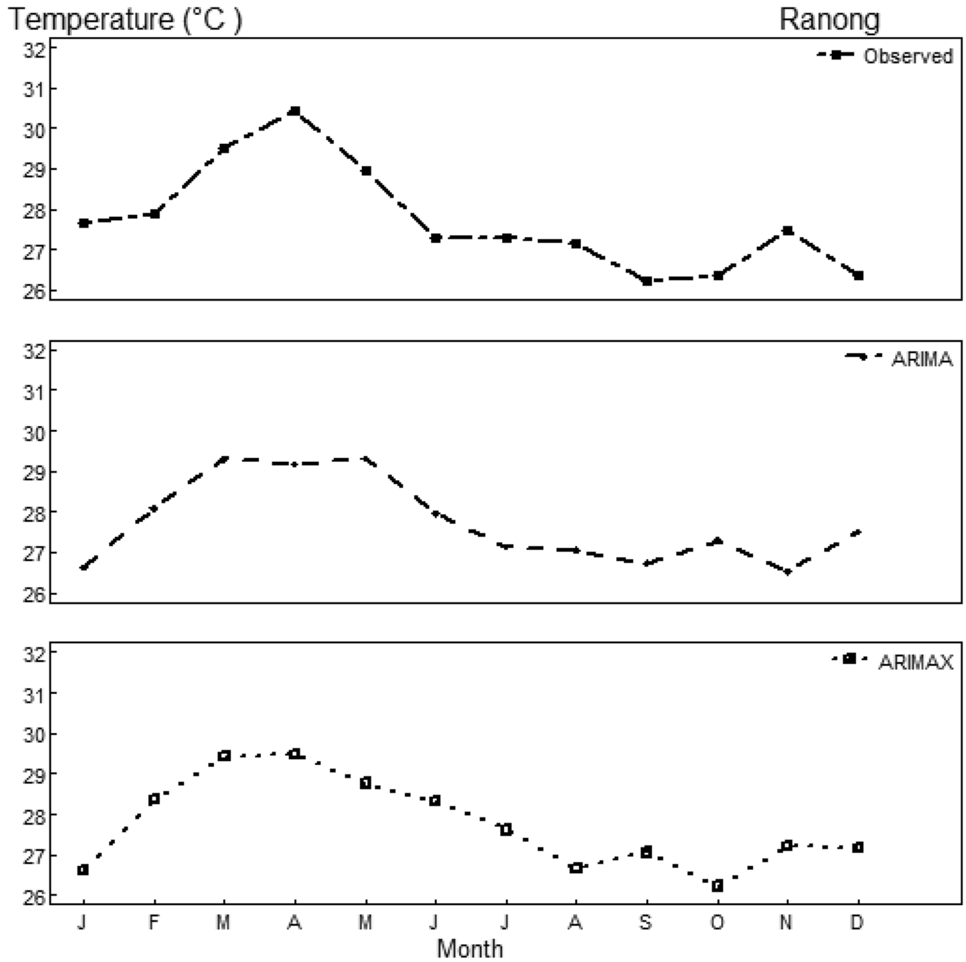

Fig. 4 The observed and the monthly mean temperature forecast in Ranong during 2016. The broken lines with points show the observed mean monthly temperature (the first panel of Fig. 4) while the dotted black lines with boxes show the temperature forecast using the ARIMAX (the third panel of Fig. 4) model. The broken grey lines (the second panel of Fig. 4) show the mean monthly temperature using the ARIMA model

Table 2 The parameters estimates for the ARIMA(3,0,2)(0,1,0)$_{12}$ and ARIMAX(3,0,2)(0,1,0)$_{12}$

Methods	Model	Variable	Coefficient	*p* Value <	AIC	SSE
ARIMA	(3,0,2)(0,1,0)$_{12}$	AR(1)	−0.652	0.001	1.653	29.191
		AR(2)	−0.449	0.0001		
		AR(3)	0.313	0.001		
		MA(1)	1.057	0.001		
		MA(2)	0.965	0.001		
ARIMAX	(3,0,2)(0,1,0)$_{12}$	Rain	0.012	0.043	1.164	17.049
		Moisture	0.066	0.001		
		AR(1)	0.957	0.001		
		AR(2)	−1.181	0.001		
		AR(3)	0.570	0.001		
		MA(1)	0.361	0.001		
		MA(2)	0.968	0.001		

$$\begin{aligned}\hat{Y}_t = &-0.652(Y_{t-1} - Y_{t-13}) - 0.449(Y_{t-2} - Y_{t-14}) \\ &+ 0.313(Y_{t-3} - Y_{t-15}) + Y_{t-12} + \varepsilon_t - 1.057\varepsilon_{t-1} \\ &- 0.965\varepsilon_{t-2}\end{aligned} \tag{7}$$

$$\begin{aligned}\hat{Y}_t = &-0.957405(Y_{t-1} - Y_{t-13}) - 1.181(Y_{t-2} - Y_{t-14}) \\ &+ 0.570(Y_{t-3} - Y_{t-15}) + Y_{t-2} + \varepsilon_t + 0.361\varepsilon_{t-1} \\ &- 0.968\varepsilon_{t-2} - 0.012(R_t - R_{t-12}) \\ &- 0.066(H_t - H_{t-1} - H_{t-12} + H_{t-13})\end{aligned} \tag{8}$$

The fitted models were then applied to forecast the monthly temperature of Phuket during 2016, and the results have been shown in Fig. 5. Analysis of Fig. 5 revealed that the models did reasonably well in forecasting monthly temperature at Phuket. The models fairly revealed the monthly patterns of the temperature. Distinct, peculiar patterns of the models are the indicated peaks and low values of the observations together with their timings that have been fairly captured by the models. Even though the ARIMAX model revealed this value better than the ARIMA model in Phuket the low observed monthly temperature values were better modelled by the ARIMA model. The decreasing monthly mean temperature and the low mean monthly temperature observed between April and November in Phuket may be due to the onset of the rainy season. The southwest of Thailand, where Phuket is located has quite a long rainy period of about 9 months. The season begins in late March until November (Eso 2015).

Besides, the reliability of the models in forecasting the mean temperature at Phuket was evaluated by comparing the RMSE, AIC and the RRMSE values from the models. The ARIMA model produces a lower RMSE value (0.78) relative to the ARIMAX model (0.87) in the forecast of temperature at Phuket during 2016 (Table 2). Also, the RRMSE of both models were approximately the same (1.11). Thus, the optimal time series model for estimating the mean temperature in Phuket is the ARIMA model (ARIMA (3,0,2)(0,1,0)12). A time series modelling by Peter and Silvia (2012) also revealed the superior predictive ability of the ARIMA over the ARIMAX model.

Conclusion

This study compares and selects the optimal method between two time series models in forecasting temperature in Ranong and Phuket in Thailand. The models comprised the ARIMA and ARIMAX models.

The result revealed that both the ARIMA and ARIMAX models were suitable for the estimating of the average monthly near-surface temperature in Ranong and Phuket. In general, the ARIMAX models revealed the maximum monthly temperature values better than the ARIMA models while the ARIMA models revealed the minimum observed monthly temperature during 2006–2016 better than the

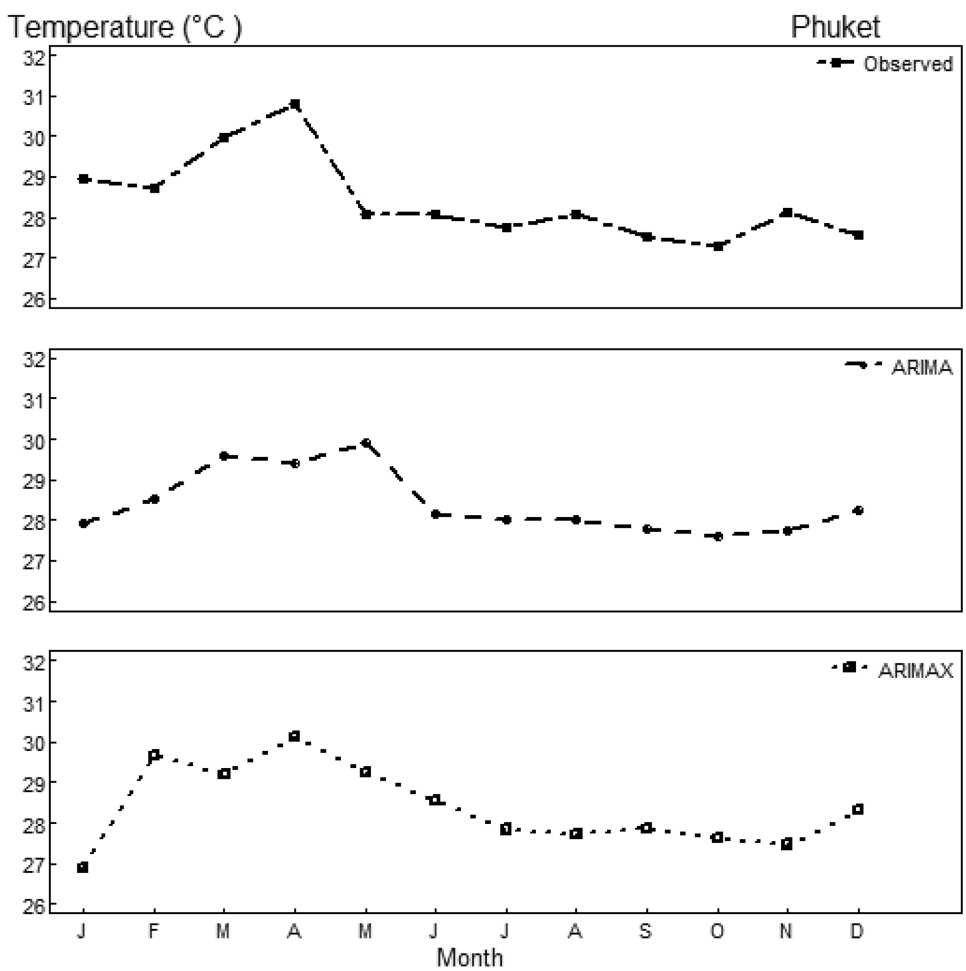

Fig. 5 The observed and the monthly mean temperature forecast in Phuket during 2016. The broken lines with points show the observed mean monthly temperature (the first panel of Fig. 5) while the dotted black lines with boxes show the temperature forecast using the ARIMAX model (panel three of Fig. 5). The broken lines show the mean monthly temperature using the ARIMA model (panel two of Fig. 5)

ARIMAX models. Analysis of the root mean square and the relative root mean square errors from both models revealed that the optimal time series model for forecasting near-surface monthly temperature observations at Ranong was the ARIMAX model while the ARIMA model was the optimal time series model in forecasting monthly temperature at Phuket.

The ARIMA and ARIMAX methods used for the monthly temperature observations modelling for the two selected stations, Phuket and Ranong can be used to estimate and forecast temperature values for areas with missing and insufficient monthly temperature observations. Thus, these methods can be essential to decision-makers and various stakeholders informing policies when preparing themselves for possible extreme climate events.

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