IJISET - International Journal of Innovative Science, Engineering & Technology, Vol. 7 Issue 7, July 2020
ISSN (Online) 2348 – 7968 | Impact Factor (2020) – 6.72
www.ijiset.com

Modeling and Forecasting of the Temperature in Bandung, Indonesia: The Next Ten Years

IGN Mindra Jaya[1], Anna Chadidjah[2]

[1]Department of Statistics, Universitas Padjadjaran, Indonesia

Abstract

Climate change is a real issue and can be a great challenge for our future. It is related to rising temperatures, extreme weather events, that will affect shifting wildlife populations and habitats, rising seas, and a range of other impacts. We realized that nature is not controllable. However, we can design and implement some scenarios to avoid the worst effect of climate change. Statistical modeling is needed to provide an accurate prediction in the future about the rising temperature and extreme weather. In this study, we focus on developing the prediction model for small area level and small observation of yearly time-series data. We apply our model to get an accurate prediction of minimum, mean, and maximum temperatures in Bandung city, Indonesia. We compared frequentist and Bayesian approaches in order to get the best prediction model.

Keywords: Climate change, temperature, Bandung, frequentist, Bayesian.

1. Introduction

The real challenge faced by humanity and all living things on this planet is climate change [1]. Climate change is a real issue and can be a great challenge for our future. It is related to rising temperatures, extreme weather events, that will affect shifting wildlife populations and habitats, rising seas, and a range of other impacts [2]. Climate plays an important role in our lives. Agriculture, ecology, health, business and other fields are strongly influenced by climate changes. However, our knowledge about the climate change particularly for small area is very limited [3]. We realized that nature is not controllable. However, we can design and implement some scenarios to avoid the worst effect of climate change. The raising temperature is related to some other weathers variables. There is a strong relationship between temperature rainfall that may cause the extreme weather [4]. The relationship between precipitation and temperature have been explored in several research papers (see [5],

[6], [4], [7], [8], [9], [10]). In order to anticipate the worst effect of climate change particularly related to the rising temperature, we have to develop an early warning system that provide some relevant and important information about temperature including minimum, maximum, and mean temperature in the future. This information will be useful for the government and policy maker to design some policy that can slow down the climate change process.

Forecasting is a technique of predicting some future event or events. In planning and decision making processes, prediction of future events is very critical and forecasting can help in making rational decisions [11]. Forecast is not an easy task. Statistical modelling is commonly used for forecasting purpose [12]. However, the very complex system of climates, the statistical modelling have to be integrated with subjective knowledge about the data. Modeling is an art that we cannot focus only on statistical aspect [13]. In this study, we performed and compared frequentist and Bayesian approaches to modelling minimum, mean and maximum temperature in order to get an accurate prediction for the next ten years in small area Bandung city, Indonesia.

2. Material and Method

2.1. Material

We obtained historical data of yearly minimum, mean and maximum temperature from the website http://data.bandung.go.id/. The data were presented in Figure 1.

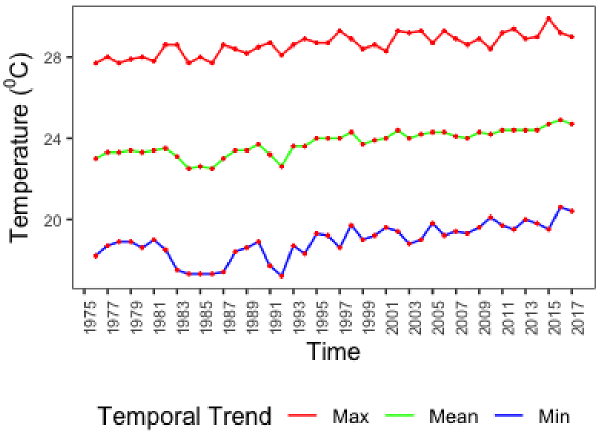

Figure 1. Rainfall data in Bandung city, 2000-2017

Figure 1 presents the temporal pattern of yearly temperature data, 1976-2017. We observed that there is s temporal trend however, it clearly presents seasonal pattern.

2.2. Method

SARIMA Model

Box-Jenkins ARIMA is one of the most popular time series forecasting technique for stationary and non-stationarity data. The basic Box-Jenkins expressed by the following form [14]:

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} - \sum_{j=1}^{q} \beta_j e_{t-j}\,, i = 1, \dots, p \text{ and j} = 0,1, \dots, q \tag{1}$$

where y_t, denotes a temperature data, α_0 is a intercept term, and e_t is error term with β_j coefficients. The *i* and *j* terms are autoregressive and moving average parts of the model. Eq.1 classified as an $ARMA(p, q)$ model, where p denotes the number of lag, and q is the number of lagged forecast errors. Integrated with number differencing d may be applied to satisfy the stationarity assumption. Eq.1 can be extended for seasonal model becomes $ARIMA(p, d, q)(P, D, Q)[s]$, where P, D, Q are similar to p, d, q but here as a part of seasonal components with s denotes the seasonal order. The forecast packages in R is the one of the best for time series model that used in this paper.

Bayesian Model

Bayesian approach is an alternative model that commonly used for model prediction [15]. It becomes a popular approach for several reasons such as the easy to deal with a missing value. In this paper, we assume the minimum, mean, and maximum temperature follow Gaussian distribution with the model:

$$y_t = \alpha + \beta t + \varphi_t + \kappa_t \; t = 1, \dots, T, \tag{1}$$

where α denotes the intercept, β is slope to account the linear temporal trend, φ_t and κ_t are the random effect components representing the nonlinear trend and seasonal effects. A common nonlinear (dynamic) temporal trend (φ_t) is a random walk of order one (RW1) [16]:

$$\varphi_{t+1} - \varphi_t | \tau_\varphi \sim \mathcal{N}\left(0, \frac{1}{\tau_\varphi}\right) \forall i \text{ and } t = 1, \dots, T-1, \quad (2)$$

with τ_φ is the precision parameter of φ. The seasonal random component (κ_t) with periodicity m is defined as:

$$\kappa_t + \kappa_{t+1} + \cdots + \kappa_{t+m-1} | \tau_\kappa \sim \mathcal{N}\left(0, \frac{1}{\tau_\kappa}\right) \forall i \text{ and } t = 1, \dots, T-m+1, \quad (3)$$

where τ_κ denotes the precision parameter of κ_t. To estimate the Bayesian model we used INLA approach and implemented in R-INLA [15]

Forecast evaluation methods

To compare SARIM and Bayesian model we used Mean absolute deviance (MAE), as given below [17]:

$$MAE = \frac{1}{H} \sum_{h=1}^{H} |y_{t+h} - \hat{y}_{t+h}| \quad (10)$$

where y_{t+h} denotes data testing at $t + h$ period and $\hat{y}_{t+h}$ is the forecast value for $t + h$ period with H is length of forecast and means square error (MSE):

$$MSE = \frac{1}{H} \sum_{h=1}^{H} (y_{t+h} - \hat{y}_{t+h})^2 \quad (11)$$

Smaller value of MAE and MSE is preferable for the best model. All computation process will be done by R-software using several packages.

3. Empirical result

In this section we present the parameters estimate of SARIMA and Bayesian model. We avoid the detail discussion about the step of the modeling process[1]. Table 1 presents the SARIMA estimation parameter.

Table 1. SARIMA parameter estimate

[1] Detail process are provided upon by request

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Temperature	Model	AR	MA	Seasonal
Min	SARIMA(0,1,1)(0,00)	-	-0.3851 (0.1858)	-
Mean	SARIMA(0,1,0)(0,00)	-	-	-
Max	SARIMA(0,1,1)(0,00)	-	-0.7035 (0.0993)	-

For minimum temperature, the best model based on AIC, MAE and MSE is SARIMA SARIMA(0,1,1)(0,00); for mean temperature is SARIMA(0,1,0)(0,00) and for the maximum temperature has similar model with min temperature SARIMA(0,1,1)(0,00). Next, we discuss the model based on Bayesian approach using combination of Random walk order one and seasonal random components. Table 2 and 3 present the parameters estimate of fixed and random effect components of the Bayesian model.

Table 2. The parameter estimate of fixed effect component

		Mean	SD	q(0.025)	q(0.975)
Min	(Intercept)	-0.4911	22155.2500	-43498.7200	43461.4300
	Linear trend	0.0384	0.0080	0.0227	0.0541
Mean	(Intercept)	-63.8325	70060.9300	-137617.1000	137374.6000
	Linear trend	0.0412	0.0080	0.0255	0.0569
Max	(Intercept)	13.7523	0.7531	12.2738	15.2296
	Linear trend	0.0490	0.0077	0.0339	0.0640

The three models for three different temperatures had different intercept, but a similar linear trend. The means estimate of linear trend has positive lower and upper credible interval which indicates those linear trends are statistically significant.

Table 3. The parameter estimate of random effect component

		Mean	SD	q(0.025)	q(0.975)
Min	Error	0.1353	0.0000	0.1353	0.1353
	RW	0.1353	0.0000	0.1353	0.1353
	Seasonal	0.1353	0.0000	0.1353	0.1353
Mean	Error	0.1354	0.0000	0.1354	0.1354
	RW	0.1353	0.0000	0.1353	0.1353
	Seasonal	0.1353	0.0000	0.1353	0.1353
Max	Error	0.1353	0.0000	0.1353	0.1353
	RW	0.1353	0.0000	0.1353	0.1353
	Seasonal	0.1353	0.0000	0.1353	0.1353

The mean of random effect components was similar for all temperatures and components which indicate the random walk, seasonal and error term have similar contributions in explaining the variation of the temperatures.

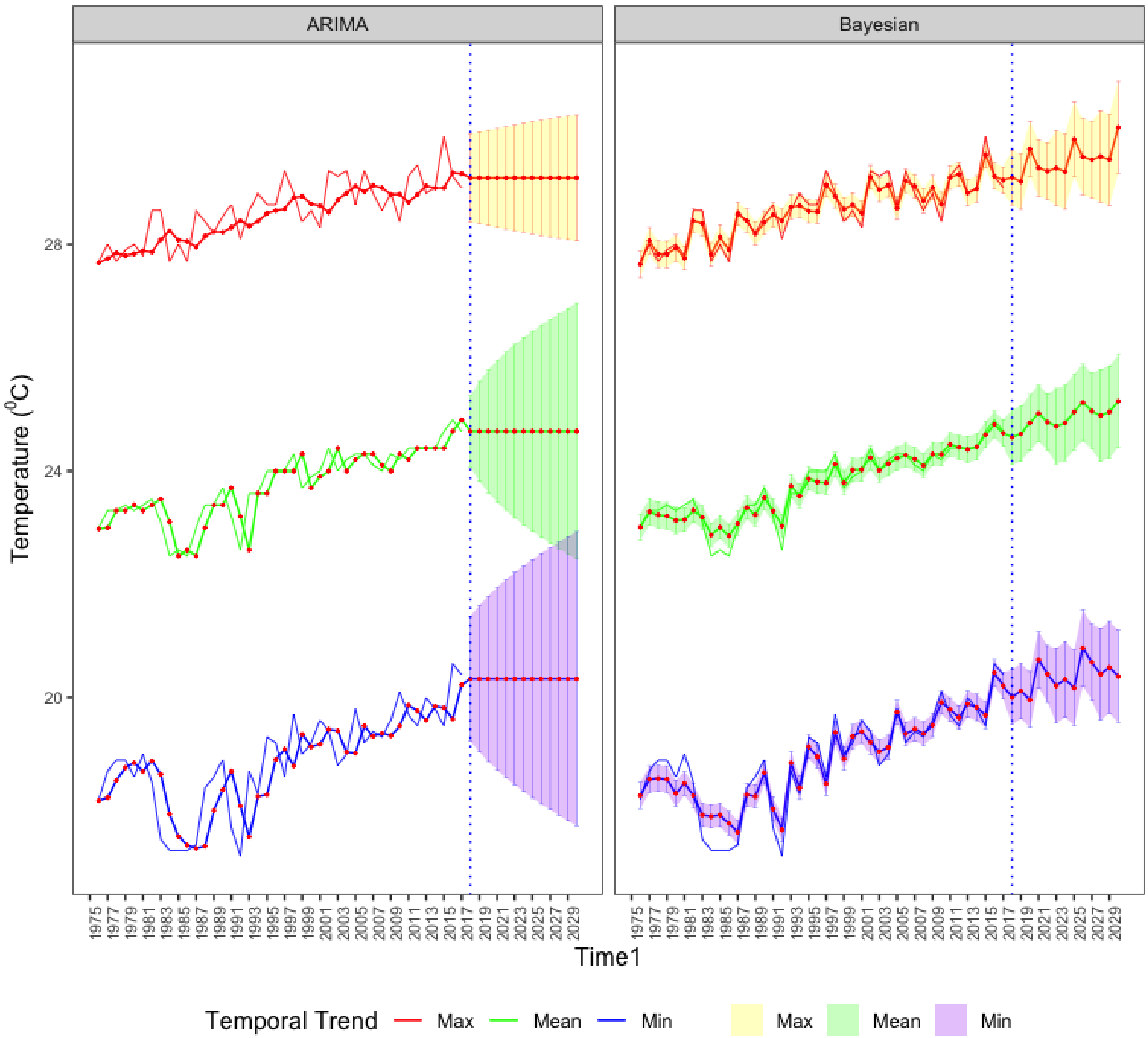

Figure 2. Temperature prediction based on ARIMA and Bayesian models.

Figure 2 shows the comparison of temperature prediction based on ARIMA and Bayesian model. It shows clearly that the ARIMA has wider interval confidence compare that Bayesian model and the prediction estimates of the Bayesian model are very close to the observation data. In order to have objective comparison we have calculated the MAE and MSE for each model and each type of temperature. The result is presented in Table 4.

Table 4. Model comparison

Model	Minimum Temperature		Mean Temperature		Maximum Temperature		Joint	
	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE
ARIMA	0.430	0.301	0.227	0.099	0.316	0.149	0.324	0.183
Bayesian	0.222	0.072	0.124	0.027	0.133	0.026	0.160	0.041

Based on MAE and MSE we found that the Bayesian model outperformed than SARIMA model for all type of temperature. In table 5 we presents the forecasting value for the next ten years. The minimum, mean, and maximum temperatures in Bandung city, Indonesia are predicted increase with small variation in the next ten years.

Table 5. Prediction of temperature for the next ten years.

Year	Minimum Temperature			Mean Temperature			Maximum Temperature		
	Mean	q(0.025)	q(0.975)	Mean	q(0.025)	q(0.975)	Mean	q(0.025)	q(0.975)
2021	20.668	20.170	21.166	25.017	24.519	25.515	29.349	28.853	29.845
2022	20.415	19.917	20.913	24.861	24.363	25.358	29.291	28.795	29.787
2023	20.210	19.546	20.874	24.788	24.125	25.452	29.347	28.688	30.007
2024	20.324	19.661	20.989	24.847	24.184	25.512	29.280	28.621	29.941
2025	20.168	19.498	20.838	25.041	24.372	25.711	29.854	29.189	30.519
2026	20.874	20.200	21.547	25.209	24.536	25.883	29.548	28.878	30.218
2027	20.621	19.948	21.295	25.053	24.379	25.726	29.489	28.819	30.159
2028	20.416	19.605	21.227	24.980	24.170	25.791	29.553	28.749	30.358
2029	20.530	19.721	21.341	25.040	24.230	25.850	29.494	28.690	30.299
2030	20.374	19.558	21.190	25.234	24.418	26.049	30.066	29.256	30.876

Discussions and Conclusions

Climate change is one of the big issues where science such as the forecasting model is crucial in the future prediction of climate to provide accurate information for the government and policy-making [18]. The accurate prediction of the climates in the future can be used to effectively control and stabilize the effects of global warming and climate change [19]. Statistical analysis support the forecasting of the climate variables such temperature. However, the subjective views is needed to get the reasonable forecast. In this study, we evaluate the frequentist and Bayesian approaches to forecast minimum, maximum and mean temperature for small area level, Bandung city, Indonesia for the next ten years. Frequentist approach is represented by seasonal autoregressive moving average (SARIMA) and numerical Bayesian was used to estimate the Random walk seasonal model. Mean absolute error and mean square error were used to evaluate the model prediction and Bayesian approach. Bayesian approach outperform in providing more accurate prediction for the next ten years. Based on the Bayesian approach, we found the minimum, maximum, and mean temperatures increased consistently. This situation must be addressed properly by the government of Bandung and policy maker to be able to prevent the adverse effects of the extremely climate change.

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