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Land Surface Temperature Variation in Bangkok Metropolitan Area, Thailand, During 2001-2020

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Abstract Temperature change is a critical concern for human health, particularly in metropolitan areas. Warmer summer temperatures and cooler winter temperatures raise concerns about power and gas consumption. The Bangkok Metropolitan Area (BMA) includes the entire city as well as the neighboring areas. BMA is regarded as one of the major cities, rapidly expanding and urbanizing with high-rise buildings. Since, climate change is causing anxiety in all of the world's major cities, our study aims to investigate the seasonal patterns and trends of land surface temperature (LST) in the Bangkok Metropolitan Area, Thailand, from January 2001 to December 2020. The data for this study came from the National Aeronautics and Space Administration's website (NASA). The patterns and trends of LST during the last 20 years were investigated using simple linear regression and cubic spline approaches. The first 70% of the data is used as a training set, while the rest is used as a testing set. For building effective LST predictive models, the Autoregressive Integrated Moving Average (ARIMA) has been used for model construction. The LST in Bangkok Metropolitan has increased at a rate of about 0.675C each decade over the last 20 years, according to a simple linear regression fit to seasonally adjusted LST. Finally, ARIMA(3,0,0) was determined to beat all other models by producing the least RMSE. The model's performance, however, varies from dataset to dataset.

MSC: 49K35; 47H10; 20M12

Keywords: land surface temperature; cubic spline model; linear regression; root mean square error; autoregressive integrated moving average

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1. Introduction

Many studies have found that urban areas emit more heat than the surrounding environment, see [1–5] for examples. In fact, cities that are cooler in the winter and warmer in the summer would use more energy to maintain a livable environment for humans.

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This brought up the question of scarcity of resources. Pavement, buildings, concrete, asphalt, and other constructs are used to replace natural ground cover in large cities. This could result in higher land surface temperatures (LST). A study published in 2020 by Jiang and Tian found that land use change was a significant contributor in the increase in LST [6]. Later in 2018, Sogacheva et al. [7] used two decades of numerous satellite datasets, including MODIS data, to study regional and seasonal fluctuations of aerosols over China. They discovered that in the overlapping period, the Aerosol optical depth (AOD) tendencies are quite strong in the summer, autumn, and overall for the yearly average.

BMA is a huge metropolitan city in Southeast Asia with a population of about 15 million people and a land area of 3,199 square kilometers. After Manila and Jakarta, it is Southeast Asia's third largest metropolis. The average air temperature is between 26 and 31 degrees Celsius. According to land use characteristics, BMA can be divided into five zones: conservation zone, economic zone, residence zone, western suburbs zone, and eastern suburbs zone [5]. BMA is situated on the lower Chao Phraya River delta, which runs through the heart of the city. Bangkok has three distinct seasons: rainy, winter, and summer. In reality, the warmest months are March to May, with air temperatures exceeding 40 C [8].

Bangkok is Thailand's capital. The Bangkok Metropolitan Area (BMA) encompasses both the city and its neighboring areas. BMA is one of the biggest cities in the country, quickly growing and urbanizing with high-rise buildings. Several research have focused on temperature changes in Thailand's major cities, including Bangkok [1, 3, 5, 8] and Hat Yai [9].

The research's major goals were to (i) look into the seasonal patterns and trends of LST change in BMA during the last 20 years, and (ii) create a predictive model of LST in BMA. The following is how the paper was structured. The study area was explained in Section 2. Section 3 discussed data collection and methodology. Finally, in Section 4 and 5, the result, discussion, and conclusion are discussed, respectively.

2. Data and Methodology

2.1. Data Source

The information in this paper was gathered from the NASA website, which is used to track numerous events on the planet's surface. The LST data pertains to the MOD11A2 product. In a 1,200 by 1,200 square kilometer grid, the MOD11A2 Version 6 products provide an average 8-day per-pixel LST and Emissivity with 1 squarekilometer spatial resolution. Each MOD11A2 pixel value is a simple average of all the associated MOD11A1 LST pixels recorded throughout the course of the 8-day period. The LST data of product MOD11A2 from 9 regions covering BMA from 2001 to 2020 is used in this research (Figure 1). Each region is 7x7 square kilometers in size and contains 49 LST pixels. Figure 2 depicts the primary illustration.

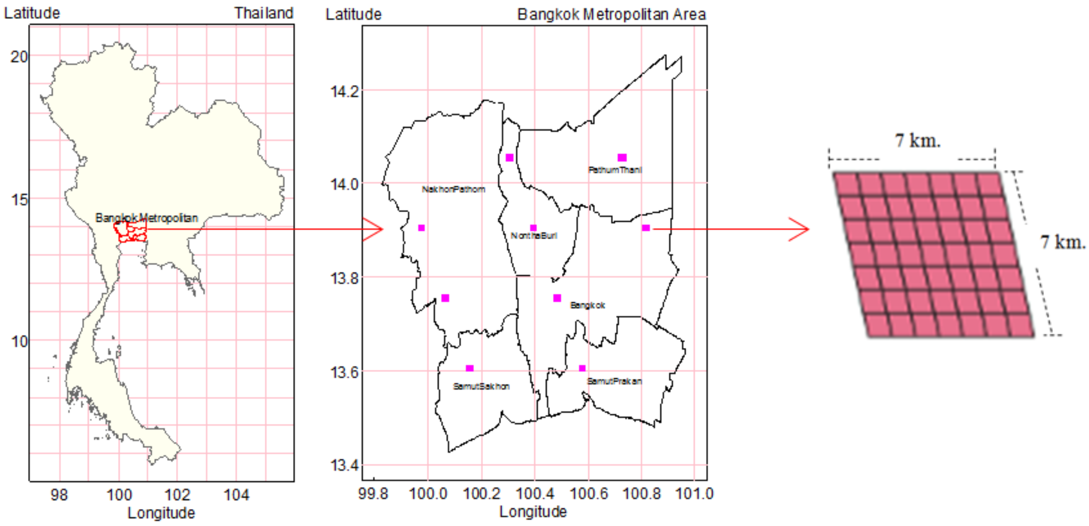

FIGURE 1. Map of Bangkok Metropolitan Area in Thailand

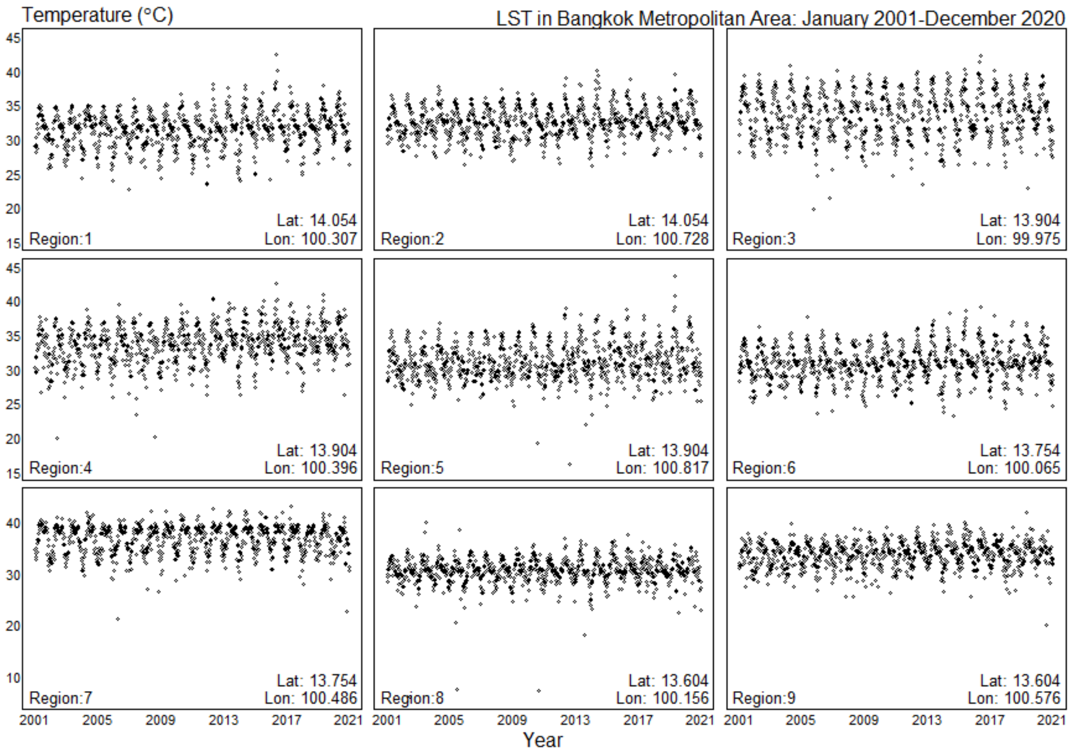

FIGURE 2. LST in Bangkok Metropolitan Area, Thailand from 2001-2020 (920 observations for each region)

2.2. Conceptual Framework

Figure 3 depicts the conceptual framework, which begins with data collecting from NASA's website. The data was then prepared using preprocessing techniques such as data imputation and transformation. After that, the trend analysis was studied by fitting

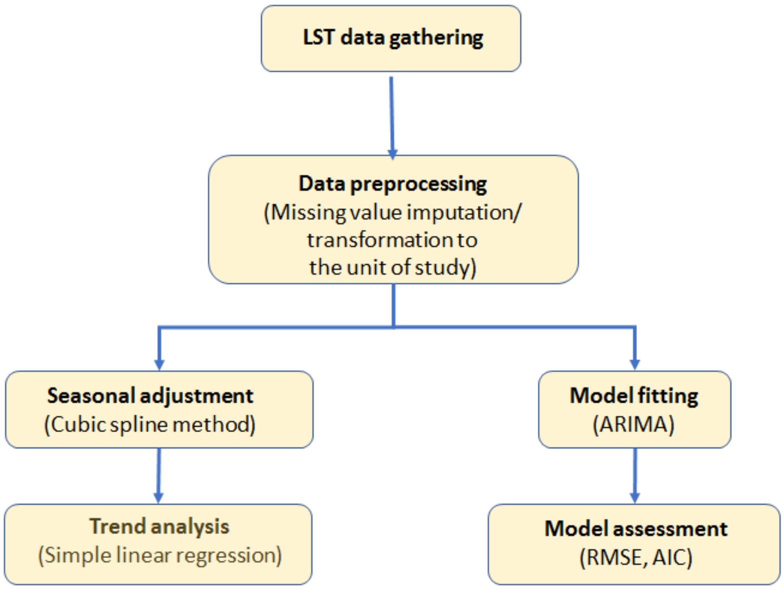

FIGURE 3. Conceptual Framework.

the seasonally adjusted LST to a simple linear model. The ARIMA model was used to choose the optimal model based on an appropriate and relatively minimal AIC and RMSE for prediction.

2.3. Statistical Methods

A piecewise cubic polynomial with continuous second derivatives is known a cubic spline function, and it is the smoothest of all functions. The nature cubic spline approach was used to determine the seasonal patterns and trends of LST in each region. In terms of natural, it means the function is linear outside the range [11]. The cubic spline function is defined by the following formula:

$$s_t = a + bt + \sum_{r=1}^{n} c_r(t - t_r)_+^3 \tag{2.1}$$

where, s_t is the spline function with parameters a, b and c_r.The index $r = 1, 2, \ldots, n$ and t_r is the location of the knots with n is the total number of knots. In the formula, t denotes time with $t_1 < t_2 < \ldots < t_n$ and $(f)_+$is a positive function such that its value will be f itself if f is nonnegative and will be 0 otherwise.The capacity to tolerate a substantial quantity of missing data is one advantage of using the cubic spline function in modeling [10]. The variation in LST for every eight-day period was then seasonally adjusted by subtracting the spline values LST in each period and adding back the overall mean of each region. Indeed, the seasonal adjusted LST is calculated as follows:

$$X_t = (y_t - s_t) + \bar{y}, \tag{2.2}$$

where X_t is the seasonally adjusted LST (Figure 4), y_t is the LST observation at t, s_t is the seasonal pattern achieved from natural cubic spline model, $t = 1, , 920$, and $\bar{y}$ is the overall mean of the observed LST. To determine the trends, the seasonally adjusted LST were fitted using simple linear regression as illustrated in Figure 5. Now, the ARIMA(p, d, q) model was considered as a predictive model. This model has been applied for developing a predictive model in many studies [12, 14, 15]. The parameters p is the number of autoregressive terms, d is the number of differences (in case the original time series is not stationary), and q is the number of moving averages [12]. The first assumption for the model is that the data needs to be stationary. By primary exploration through its ACF and PACF, it turned out that the LST time series are all stationary. In particular, the parameter d in the model will be zero. ARIMA model is due to its statistical properties and the well-established BoxJenkins methodology [13, 14] in the model building process. In fact, the formular for ARIMA(p, d, q) can be expressed as:

$$z_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \quad - \theta_q \epsilon_{t-q}, \quad (2.3)$$

where $\phi_p, i = 1, \ldots, p$ and $\theta_q, k = 1, \ldots, q$ are the coefficients, p and q are the orders of autoregressive and moving average polynomials, respectively. The basis of this approach consists of three phases: model identification, parameter estimation and diagnostic testing [14]. The Root Mean Square Error (RMSE) and the Akaike Information Criterion (AIC), [16], were used to assess the model's performance. The RMSE formula is as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (X_t - \hat{X}_t)^2}, \quad (2.4)$$

where X is the LST observation, $\hat{X}$ is its prediction and n is the number of observations.

3. Results and Discussion

3.1. Seasonal Pattern and Trend of LST

The seasonal patterns of LST covering BMA shown in Figure 4 were obtained by fitting 8-knot cubic spline functions. The resulting patterns reflected the local season of this region. It can be seen that the patterns could approximately be divided into 2 groups. Regions 1-6 and 8 have similar patterns and hence should be in one group while regions 7 and 9 should be in another. The first group exhibits a kind of winter (low temperature) at the beginning of the year. Then it is increasing, indicating an obvious summer season. After that during the middle of the year, the LST starts dropping again. This is not yet winter, but it is cooler because of the rainy season. At the end of the rainy season, the temperature starts inclining again showing like the second hump around September. Yet, this is not another summer because the peak is not as high as the first hump. Finally, after October, the LST drops again for the beginning of winter. In fact, all 9 regions have similar patterns for several months of the beginning and the end of the year. However, the second group does not show a clear hump. It is more like a plateau showing once the temperature rises to the highest level around April, it stays there with little deviation below the peak until October. Region 7 is the center downtown Bangkok of dense and high-rise buildings. Region 9 is Samut Prakan Province, one of the major cities homes to industrial factories in Thailand. This is possibly the reason why the temperature does not decline even during the rainy season. However, the precise causes are still open for further study.

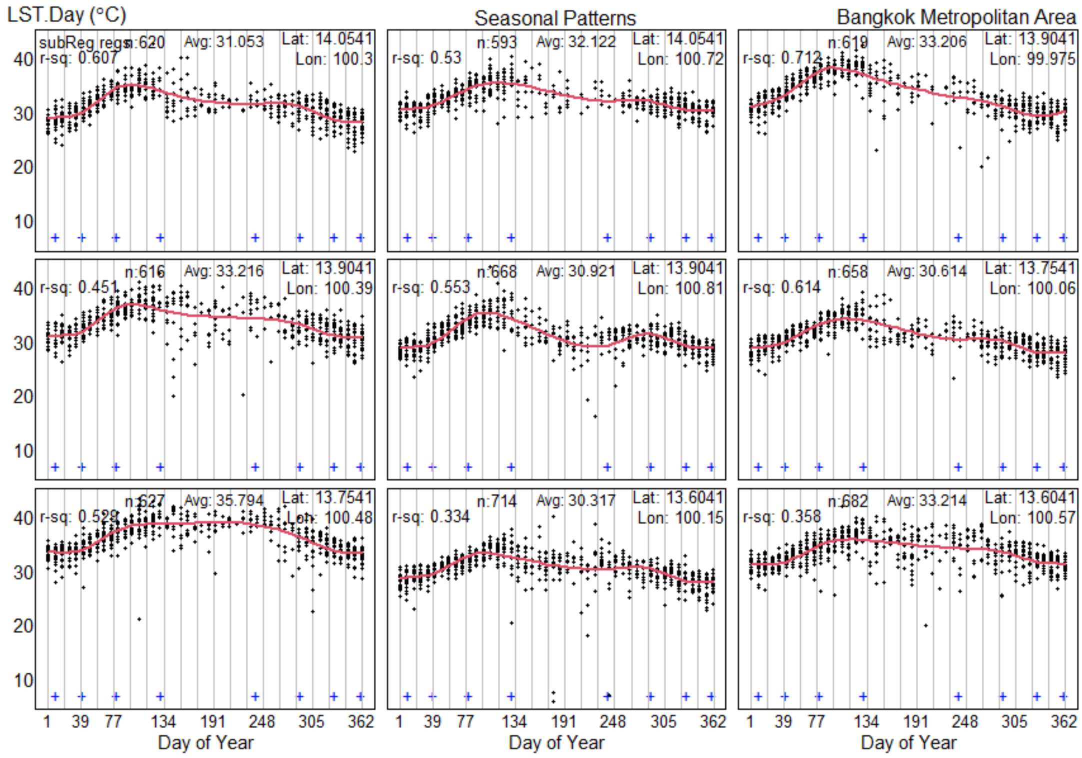

FIGURE 4. Seasonal pattern of LST in BMA over the last 20 years.

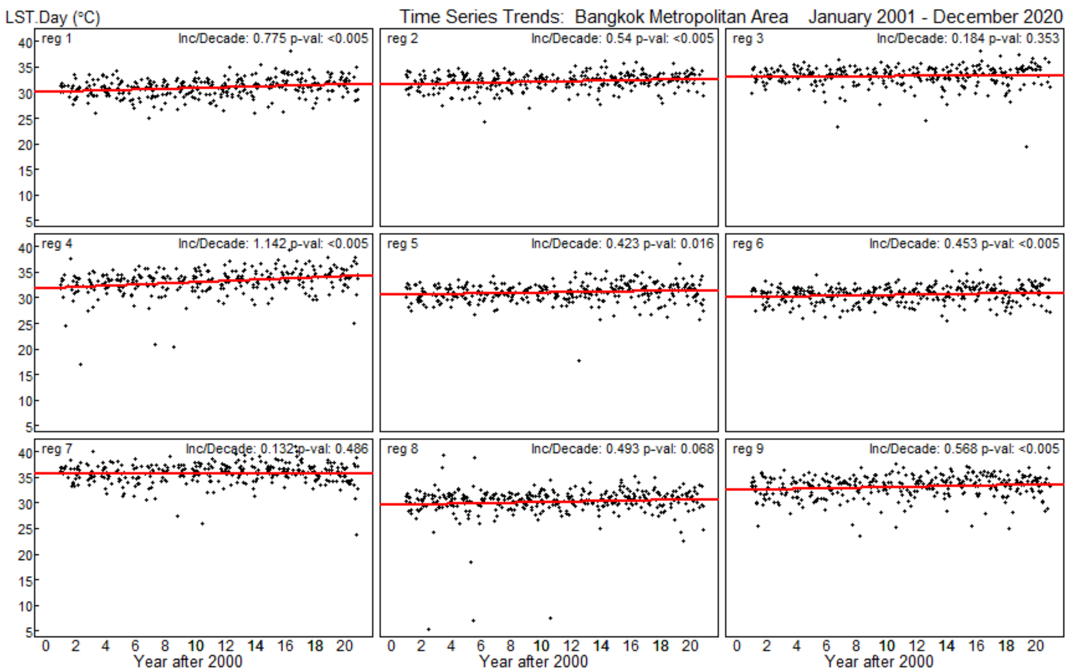

FIGURE 5. LST Trends over BMA in the last 20 years.

The trends of LST in BMA were obtained by simple linear regression. In each region, the slope (increase/decrease in degree Celsius per decade) was shown at the top-right corner with its p-value (Figure 5). For example, the LST in region 9 (Samut Prakan

Province) increased 0.568 degree Celsius per decade. The increase was statistically significant with p-value less than 0.05. In fact, it was discovered that the change in all regions is positive, implying an increase in LST. The increases in six (Regions 1-2, 4-6, and 9) out of nine regions are statistically significant.

3.2. Prediction of LST

It was suggested by the ACF and PACF (Figure 6) of the LST in each region that the value of parameter p could be up to 4-time lags. After varying the values p of the model and measuring its RMSE, the resulting model of all 9 regions are shown in Table 1.

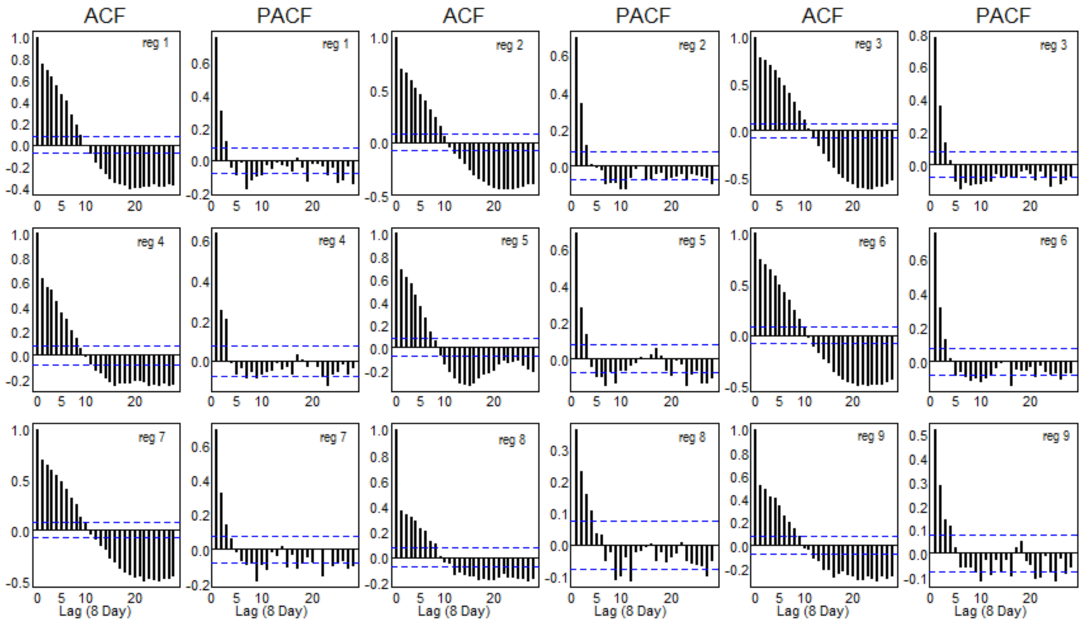

Figure 6. The graphs of ACF and PACF for the 9 regions

Table 1. Results obtained from ARIMA analysis on training and testing dataset.

			RMSE	
Region	Model	AIC	Training Dataset	Testing Dataset
1	ARIMA(3,0,0)	2431.44	1.58544	1.64756
2	ARIMA(3,0,0)	2349.55	1.48699	1.32693
3	ARIMA(3,0,0)	2648.55	1.87507	1.94705
4	ARIMA(3,0,0)	2756.34	2.03951	1.77129
5	ARIMA(3,0,0)	2593.01	1.79652	1.81239
6	ARIMA(3,0,0)	2369.97	1.5106	1.57771
7	ARIMA(3,0,0)	2683.38	1.92695	1.73533
8	ARIMA(3,0,0)	3025.79	2.51497	1.71855
9	ARIMA(4,0,0)	2711.73	1.96728	2.16702

It turned out that with the training dataset, ARIMA(3,0,0) fit well with almost all regions except for the region 9, the most appropriate model is ARIMA(4,0,0). The fitted

LST of all regions on the training dataset were illustrated in Figure 7. Finally, the performance of these selected models of each region on the testing dataset is shown in Figure 8.

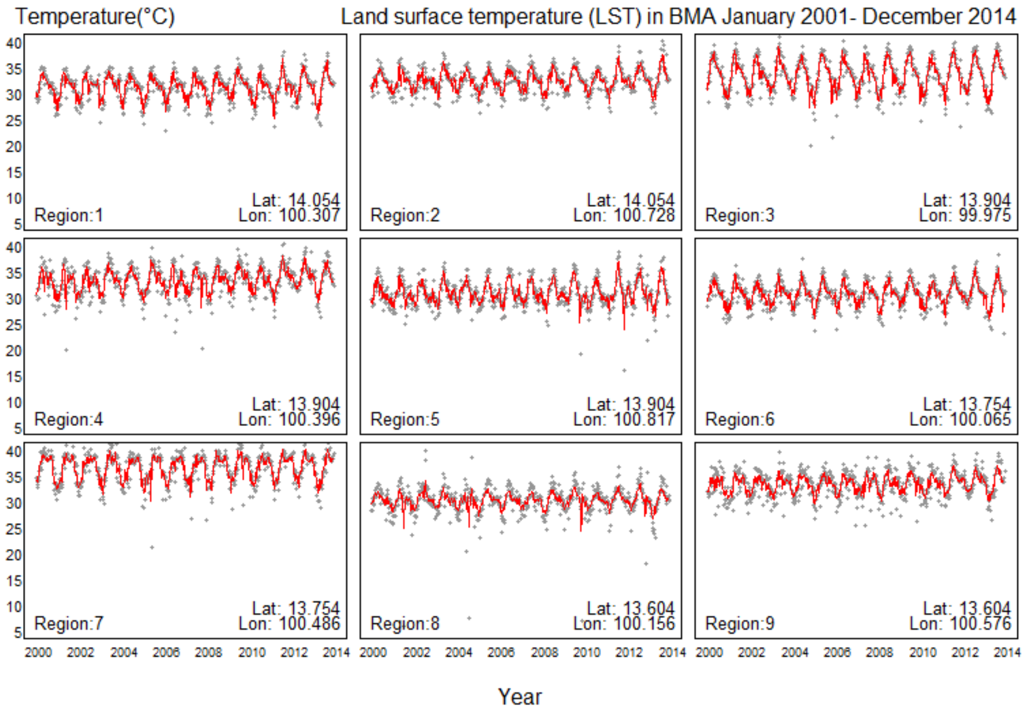

FIGURE 7. Predicted LST of Training datasets (2001-2014) in BMA.

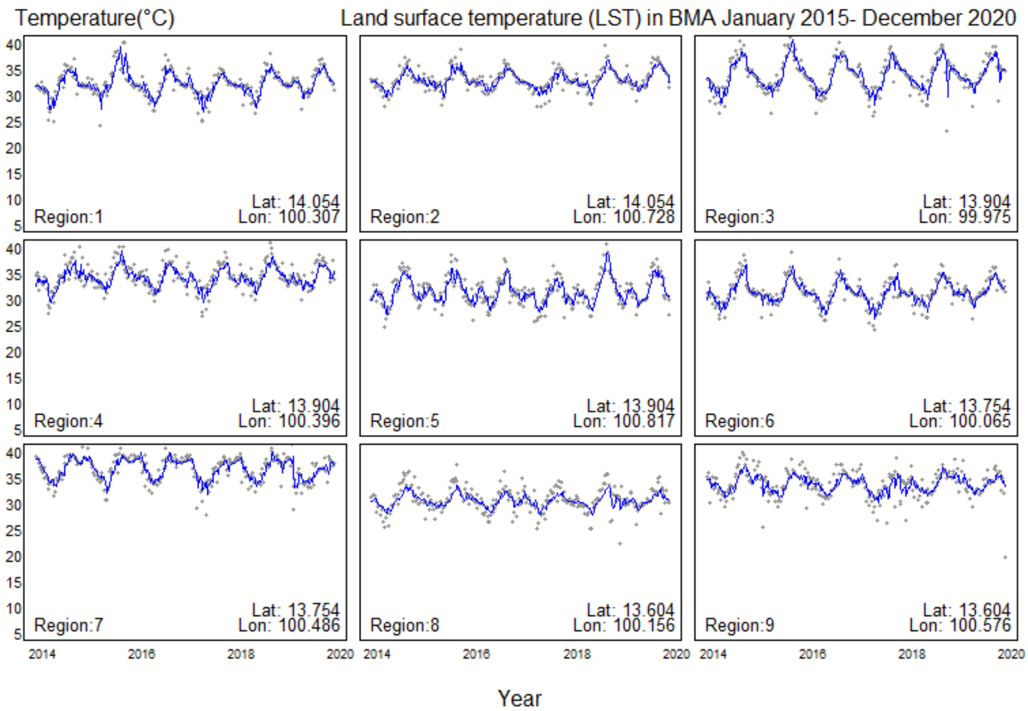

FIGURE 8. Predicted LST of Testing datasets (2015-2020) in BMA.

4. Conclusion

Finally, nine LST locations covering BMA throughout the previous 20 years were investigated. Simple linear regression, natural cubic spline method, and ARIMA models were used to study the variance of LST in BMA. The average change in LST across BMA was found to be roughly 0.675C per decade by taking the average value of each region's LST change. This shows that the LST above BMA has been steadily growing over the last 20 years. Consequently, it may have an impact on the city's energy usage in order to maintain a livable environment. As a result, this outcome could be interpreted as a warning to BMA to prepare for the future warming effect. However, because the results differ from one data set to the other, it is recommended that the next inquiry be conducted using the most recent accessible data.

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