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Characterizing the Urban Temperature Trend Using Seasonal Unit Root Analysis: Hong Kong from 1970 to 2015

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ABSTRACT

This paper explores urban temperature in Hong Kong using long-term time series. In particular, the characterization of the urban temperature trend was investigated using the seasonal unit root analysis of monthly mean air temperature data over the period January 1970 to December 2013. The seasonal unit root test makes it possible to determine the stochastic trend of monthly temperatures using an autoregressive model. The test results showed that mean air temperature has increased by 0.169°C (10 yr)$^{-1}$ over the past four decades. The model of monthly temperature obtained from the seasonal unit root analysis was able to explain 95.9% of the variance in the measured monthly data — much higher than the variance explained by the ordinary least-squares model using annual mean air temperature data and other studies alike. The model accurately predicted monthly mean air temperatures between January 2014 and December 2015 with a root-mean-square percentage error of 4.2%. The correlation between the predicted and the measured monthly mean air temperatures was 0.989. By analyzing the monthly air temperatures recorded at an urban site and a rural site, it was found that the urban heat island effect led to the urban site being on average 0.865°C warmer than the rural site over the past two decades. Besides, the results of correlation analysis showed that the increase in annual mean air temperature was significantly associated with the increase in population, gross domestic product, urban land use, and energy use, with the R^2 values ranging from 0.37 to 0.43.

Key words: urban temperature trend, urban heat island effect, seasonal unit root tests, long-term time series

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1. Introduction

Urbanization is a global phenomenon that has transformed landscapes. According to a study by the United Nations' Population Division (UN, 2014), the world's urban population is projected to increase from 3.9 billion in 2014 to 5.0 billion in 2030, and then to 6.3 billion in 2050. By 2025, 7 out of 37 megacities with a population exceeding 10 million are expected to be located in mainland China. By 2050, China will have the largest urban population, totaling about 1 billion. Urbanization transforms lands for residential, commercial, industrial, and transportation purposes. When more people live in a confined space such as a city, they will consume more energy, resulting in large amounts of emissions and waste heat. Moreover, the modified land surface of a city affects the storage and radiative and turbulent transfers of the city's heat. Hence, urban warming trends and the relative warmth of a city compared with its surrounding rural areas—known as the Urban Heat Island (UHI) effect—have become key environmental issues (IPCC, 2007; Ning et al., 2015). Epidemiological studies (Conti et al., 2005; Michelozzi et al., 2007; Ye et al., 2012; Chen et al., 2015) show that people in urban areas have an elevated risk of mortality due to the effect of higher air temperature and heat waves, as compared to those in suburban and rural areas.

Over the past three decades, researchers have studied urban warming trends using annual, quarterly, and monthly mean air temperature data (Kalnay and Cai, 2003; Huang et al., 2009; Kataoka et al., 2009; Ren et al., 2012; Sonali and Kumar, 2013; Chattopadhyay and Edwards, 2016). Ren et al. (2012) indicated that annual mean air temperature increased at a rate ranging from 0.03°C (10 yr)$^{-1}$ to 0.12°C (10 yr)$^{-1}$ in China in the past 100 years, and the warming was more significant in winter and spring and was more evident in northern China. Sonali and Kumar (2013) studied temperature trends across all regions in India. They also reported that significant trends could be found using winter maximum temperature data in India. Kalnay and Cai (2003) studied the impact of urbanization and other land-use changes on monthly mean surface temperature. By comparing trends in observed surface temperatures at U.S. surface stations with that derived from the reconstruction of surface temperatures based on global climate model from 1950–99, they determined that the mean surface warming was about 0.27°C (100 yr)$^{-1}$ in the U.S. due to urbanization as well as other land-use changes.

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Chattopadhyay and Edwards (2016) studied long-term temperature trends using annual mean data at 42 different locations in Kentucky. They reported that only three of the 42 locations had a linear temperature trend of about 0.01°C yr^{-1}. Huang et al. (2009) studied long-term annual surface air temperature and reported that the mean warming rate in Osaka was about 2.0°C $(100\ yr)^{-1}$ during the period 1883–2006. A slightly higher value of temperature increase was reported by Kataoka et al. (2009). Chan et al. (2012) studied temperature trends in Hong Kong from a seasonal perspective. They calculated the daily maximum temperature, daily mean temperature, and daily minimum temperature for every three months, i.e., each season, from 1885 to 2010, and reported that the warming trend was more prominent in winter and spring in Hong Kong. Nevertheless, analyzing urban warming trends using annual and quarterly temperature data has relatively weak statistical power because the availability of data points is limited (Wang et al., 1990; Li et al., 2004; Huang et al., 2009; Chan et al., 2012). Lenten and Moosa (2003) used a general multivariate structural time series model and found that the monthly air temperature series in Australian cities were $I(1)$, i.e., with a trend. They also reported that temperature had an upward trend in most cities between January 1901 and December 1998.

To determine the UHI intensity, researchers have either calculated the temperature difference between an urban site and a rural site (Wang et al., 1990; Camilloni and Barros, 1997; Li et al., 2004; Debbage and Shepherd, 2015) or used remote sensing techniques (Nichol, 1996, 2005; Lo and Quattrochi, 2003; Zhou et al., 2015). Wang et al. (1990) investigated the UHI effect in 42 urban areas in China between 1954 and 1983. Wang et al. (1990) found that the presence of a UHI led to urban areas being on average 0.23°C warmer than rural areas across all seasons and regions in China. On the other hand, Li et al. (2004) reported that the average UHI effect for the whole of China during the 50 years between 1951 and 2001 was less than 0.06°C—a figure that was insignificant when compared to the background trend of increasing temperature. Nichol (1996, 2005) used Landsat data to study the UHI effect in Singapore and Hong Kong. Chen et al. (2006) investigated the relationship between UHIs and land use in the Pearl River Delta using Landsat TM and ETM+ (Enhanced TM Plus) thermal IR images obtained between 1990 and 2000 at an interval of two or threeyears. They found that the UHI was proportionally related to urban size and population density. Li et al. (2011) studied the UHI in Shanghai using Landsat ETM+ images and found that the manmade impervious surface area significantly affects the UHI. Lo and Quattrochi (2003) used different Landsat images from 1973 to 1997 to study changes in land use and land cover and surface temperature in the Atlanta metropolitan area in Georgia. They found that an increase in surface temperature was associated with the decline in vegetation or natural biomass. Zhou et al. (2015) used MODIS data to study the footprint of the UHI effect in China. They indicated that ignoring the footprint may underestimate the UHI intensity in many cities in China.

The objectives of the present study are not only to determine the urban temperature trend in Hong Kong using annual mean air temperature data, but also to demonstrate that urban temperature should be rigorously modeled based on seasonal unit root tests for unadjusted monthly mean air temperatures. The UHI intensity was estimated using the temperature difference between an urban site and a rural site in Hong Kong. The study also explores whether increases in population, gross domestic product (GDP), urban land use, and energy use were significantly associated with the change in urban temperature in Hong Kong. Following this introduction, section 2 describes the area studied and the data used; section 3 presents the results and analysis; and section 4 concludes the study.

2. Methods

2.1. *The study area — Hong Kong*

Hong Kong has a land area of 1104 km^2 and is an international finance center, trade and logistics center, and a popular tourist destination (To, 2015). Hong Kong has experienced substantial demographic, economic, and environmental changes over the past four decades. Hong Kong's population increased from 4.0 million in 1970 to 7.3 million in 2015, while its GDP increased from HKD 195.2 trillion to HKD 2246.4 trillion during the same period of time. The number of visitors increased from 1.3 million in 1970 to 59.3 million in 2015. Electricity consumption and associated greenhouse gas emissions have increased almost tenfold (To et al., 2012)—the same as the increase in the total use of primary energy, including oil products, coal, and natural gas (To, 2014)—over the past four decades. Unfortunately, the number of hours of reduced visibility increased from 184 hours in 1971 to 1398 hours in 2011 (To, 2014).

2.2. *Datasets*

The data for this study, including annual mean air temperature, monthly mean air temperature, population, and GDP, between 1970 and 2015, were extracted from databases provided by the Hong Kong Observatory and Hong Kong Census and Statistics Department. Annual and monthly mean air temperatures were recorded at the weather station in the headquarters of Hong Kong Observatory in Tsim Sha Tsui — an urban site (Chan et al., 2012). Similar to the studies by Ren et al. (2012), Huang et al. (2009), and Kalnay and Cai (2003), mean air temperature was used to determine the urban temperature trend in Hong Kong over the past four decades. The size of developed areas between 1970 and 2015 was obtained from publications of the Hong Kong Buildings and Lands Department and the Hong Kong Planning Department. Energy end-use data were obtained from the reports published by the Hong Kong Electrical and Mechanical Services Department (HKEMSD, 2005a, b).

2.3. *Analysis method*

Annual mean air temperature data between 1970 and 2013 were analyzed using the ordinary least-squares (OLS) approach with linear trend, like most other UHI studies (Li et al., 2004; Huang et al., 2009; Chan et al., 2012). The major problem with using annual mean air temperature data rather than monthly data is the reduction in the number of observations, thus reducing the statistical power of the estimation and the reliability of the estimates. Hence, we applied seasonal unit root tests to the monthly mean air temperature data between January 1970 and December 2013, as described by Franses (1991), Beaulieu and Miron (1993), and Franses and Hobijn (1997). The seasonal unit root test produces a much more accurate estimate of the temperature trend because the monthly data are fully utilized, with in which the loss of information is small (Nijman and Palm, 1990).

In monthly time series, the test of the presence of multiple unit roots cannot be accomplished by the standard augmented Dickey–Fuller Test (Dickey and Fuller, 1981). As different unit roots might exist in a monthly seasonal process due to the stochastic nature of climatic conditions, we adopted the method developed by Franses (1991) and used the critical values suggested by Franses and Hobijn (1997). Specifically, the test for the presence of seasonal unit roots was based on the following auxiliary regression (Franses, 1991):

$$\begin{aligned}\emptyset(B)y_{8,t} = \mu_t + \pi_1 y_{1,t-1} + \pi_2 y_{2,t-1} + \pi_3 y_{3,t-1} + \pi_4 y_{3,t-2} +\\ \pi_5 y_{4,t-1} + \pi_6 y_{4,t-2} + \pi_7 y_{5,t-1} + \pi_8 y_{5,t-2} + \pi_9 y_{6,t-1} +\\ \pi_{10} y_{6,t-2} + \pi_{11} y_{7,t-1} + \pi_{12} y_{7,t-2} + \varepsilon_t \,, \qquad (1)\end{aligned}$$

where B is the backward shift operator, in which $B^k y_t = y_{t-k}$ and $\emptyset(B)$ is an autoregressive polynomial, μ_t is the constant term, π_i is the coefficient of y_i, and ε_t is the error term. The autoregressive model was used because monthly mean air temperature depends on the current weather condition as well as the past states of the climate system. The y values are given in Eq. (2):

$$\begin{aligned}y_{1,t} &= (1+B)(1+B^2)(1+B^4+B^8)y_t\,;\\ y_{2,t} &= -(1-B)(1+B^2)(1+B^4+B^8)y_t\,;\\ y_{3,t} &= -(1-B^2)(1+B^4+B^8)y_t\,;\\ y_{4,t} &= -(1-B^4)(1-\sqrt{3}B+B^2)(1+B^2+B^4)y_t\,;\\ y_{5,t} &= -(1-B^4)(1+\sqrt{3}B+B^2)(1+B^2+B^4)y_t\,;\\ y_{6,t} &= -(1-B^4)(1-B+B^2)(1-B^2+B^4)y_t\,;\\ y_{7,t} &= -(1-B^4)(1+B+B^2)(1-B^2+B^4)y_t\,;\\ y_{8,t} &= (1-B^{12})y_t\,. \qquad (2)\end{aligned}$$

Tests were conducted with the auxiliary equation for π_2 that is equal to zero and a set of joint tests of the hypotheses for pairs of consecutive π_i that is equal to zero for i from 3 to 12. We also tested for two scenarios—one with a trend and another without a trend—using the set of critical values established by Franses and Hobijn (1997). The model obtained from the seasonal unit root analysis was used to predict monthly mean air temperatures between January 2014 and December 2015. The accuracy of this model was assessed using the mean absolute error, the RMSE, and the root-mean-square percentage error.

To evaluate the UHI intensity, we compared annual and monthly air temperatures at the urban site and at a rural site—Tu Kwu Ling, Hong Kong. Correlation analyses were performed between annual mean air temperature data, population, GDP, urban land use, and energy use.

3. Results and analysis

3.1. *Urban temperature trend*

Figure 1 shows Hong Kong's annual mean air temperature for the period 1970 to 2013. The correlation between "year" and annual mean air temperature was 0.600 and significant at the 0.001 level. A linear trend was identified by using the OLS approach. The analyzed result shows that annual mean air temperature increased by 0.174°C (10 yr)$^{-1}$ during this period of time. The coefficient of determination, R^2, indicated that the temperature model identified using the OLS approach explained 36% of the variance in the measured data, similar to other studies (Wang et al., 1990; Li et al., 2004; Huang et al., 2009; Kataoka et al., 2009).

Figure 2 shows that, although the variations in the monthly data were quite significant (ranging from 16°C in

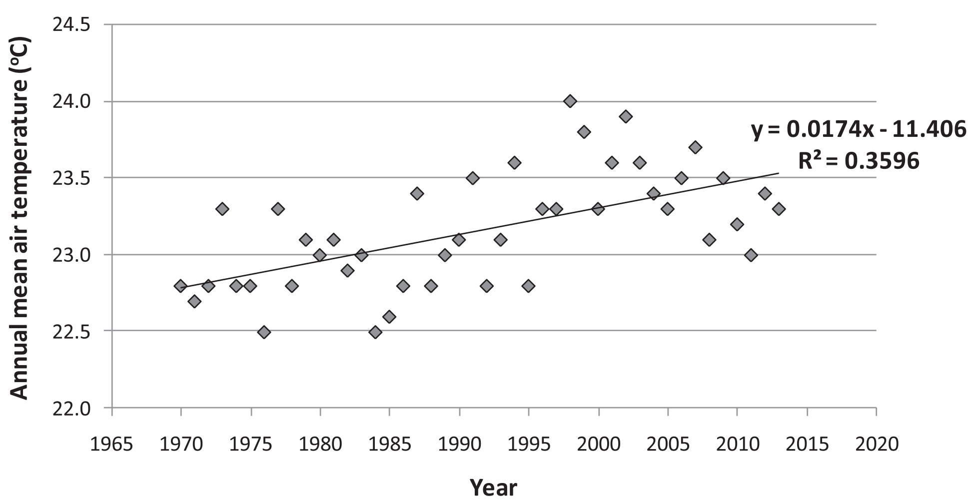

Fig. 1. Annual mean air temperature in Hong Kong from 1970 to 2013.

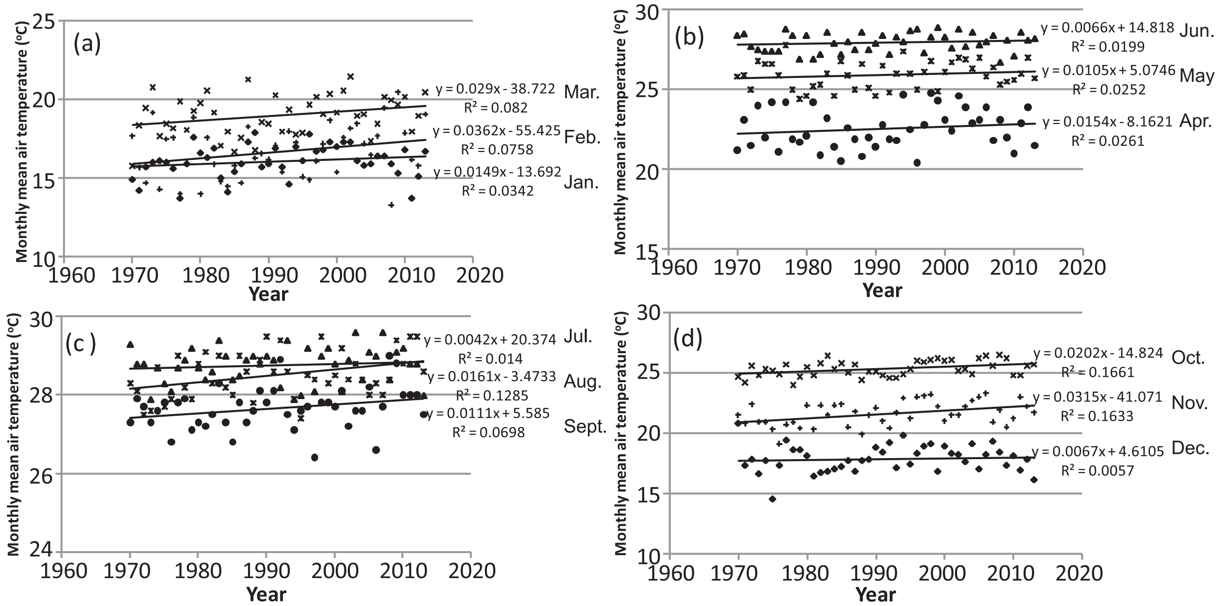

Fig. 2. Monthly mean air temperature in Hong Kong for January–Decembr (from 1970 to 2013): (a) January (filled diamonds), February (plus signs) and March (multiplication signs); (b) April (filled circles), May (multiplication signs) and June (filled triangles); (c) July (filled triangles), August (multiplication signs) and September (filled circles); (d) October (multiplication signs), November (plus signs) and December (filled diamonds).

January to 29°C in July), there were upward trends in all monthly time series during the period of 1970–2013. Correlation analyses showed that only three sets of monthly data (August, October and November) were significantly associated with "year" at the 0.05 level (for August, with a Pearson's correlation coefficient of 0.36) and at the 0.01 level (for October and November, with a Pearson's correlation coefficient of 0.41), respectively.

To rigorously examine the long-term stochastic trend with the seasonal phenomenon, we applied seasonal unit root tests and included all monthly data from January 1970 to December 2013 in the analysis. We performed seasonal unit root tests using the approach described by Beaulieu and Miron (1993), Franses (1991) and Franses and Hobijn (1997).

When the auxiliary equation contained a trend (or a trend was absent), seasonal components and a constant, the test statistics showed that there was a unit root at zero frequency based on the t-statistics. Besides, π_2 was significantly different from zero at the 0.01 level. The joint F-tests of the pairs, from π_3–π_4 to π_{11}–π_{12}, rejected the presence of a unit root at the 0.01 level. As suggested by Franses and Hobijn (1997), we conducted joint tests for $\pi_1 \ldots \pi_{12}$ and $\pi_2 \ldots \pi_{12}$, and found that the results were significant. Thus, the results confirmed that a non-seasonal unit root existed.

Table 1 presents the estimation results of two models: one without a trend and another with a trend. All coefficients were significant at the 0.01 level. From the Akaike information criterion, Bayesian information criterion, and Hannan–Quinn information criterion, the model with a trend showed a better ability in minimizing the information loss. This provided evidence of the presence of a stochastic linear trend in the series. The coefficient of determination, R^2, which indicates

Table 1. The estimation results of seasonal models: one without a trend and another with a trend.

	Model without a trend		Model with a trend	
Variable	Coefficient	t-statistic	Coefficient	t-statistic
Constant	16.075	107.919	15.713	97.038
Trend			0.0014	5.097
Feb-component	0.595	2.827	0.594	2.887
Mar-component	2.927	13.896	2.924	14.215
Apr-component	6.470	30.716	6.466	31.430
May-component	9.841	46.716	9.835	47.805
Jun-component	11.880	56.394	11.873	57.707
Jul-component	12.677	60.181	12.669	61.577
Aug-component	12.436	59.037	12.427	60.399
Sep-component	11.586	55.002	11.575	56.260
Oct-component	9.282	44.062	9.269	45.051
Nov-component	5.518	26.196	5.504	26.751
Dec-component	1.784	8.469	1.769	8.596
R^2	0.957		0.959	
Adjusted R^2	0.956		0.958	
Sum squared residual	503.742		479.554	
F-statistic	1049.377		1010.654	
Prob (F-statistic)	0.000		0.000	
Akaike information criterion	2.836		2.791	
Bayesian information criterion	2.933		2.896	
Hannan-Quinn information criterion	2.874		2.832	

how well the model fits the measured values, was 0.959. In other words, the temperature model obtained from the seasonal unit root analysis explained 95.9% of the variance in the measured monthly data—much higher than that of the model obtained using the OLS approach with annual mean air temperature data.

Table 1 shows that the coefficient of trend was significant for the model with a trend. The results showed that mean air temperature changed with respect to time by accounting for the fluctuation of temperature due to the seasonal phenomenon. In other words, time is an important determinant of mean air temperature. The coefficient of trend was obtained based on monthly data. Thus, mean air temperature increased by 0.0014045°C $(\text{month})^{-1}$ [or 0.169°C $(10\ \text{yr})^{-1}$]. This trend was not noticeable in normal statistical analysis due to the variance of monthly temperature data. However, after accounting for the variances due to the seasonal components, our econometric testing results revealed and confirmed such an impact of time on temperature. In summary, the change in mean air temperature was 0.169°C $(10\ \text{yr})^{-1}$ [or 0.174°C $(10\ \text{yr})^{-1}$ using annual data] in Hong Kong, which was higher than the increase in global mean air temperature [0.13°C $(10\ \text{yr})^{-1}$ using the data from 1956 to 2005, or 0.07°C $(10\ \text{yr})^{-1}$ between 1906 and 2005 due to global warming] (IPCC, 2007; Ye et al., 2012). The seasonal unit root model of mean air temperature in Hong Kong is given in Eq. (3):

$$\begin{aligned} T_t = {} & 15.7126 + 0.5941\pi_2 + 2.9245\pi_3 + 6.4662\pi_4 + \\ & 9.8353\pi_5 + 11.8725\pi_6 + 12.6688\pi_7 + 12.4265\pi_8 + \\ & 11.5751\pi_9 + 9.2692\pi_{10} + 5.5041\pi_{11} + 1.7686\pi_{12} + \\ & 0.0014t\,, \end{aligned} \tag{3}$$

where Tt is mean air temperature in month t, $\pi_n = 1$ when $n = t + 12k$, in which t is the number of the month from January 1970, $k = 0, 1, 2, \ldots$; while $\pi_n = 0$ for all others. The coefficients of π values were obtained from Table 1.

Figure 3 shows the measured mean temperature versus predicted temperature using the seasonal unit root model

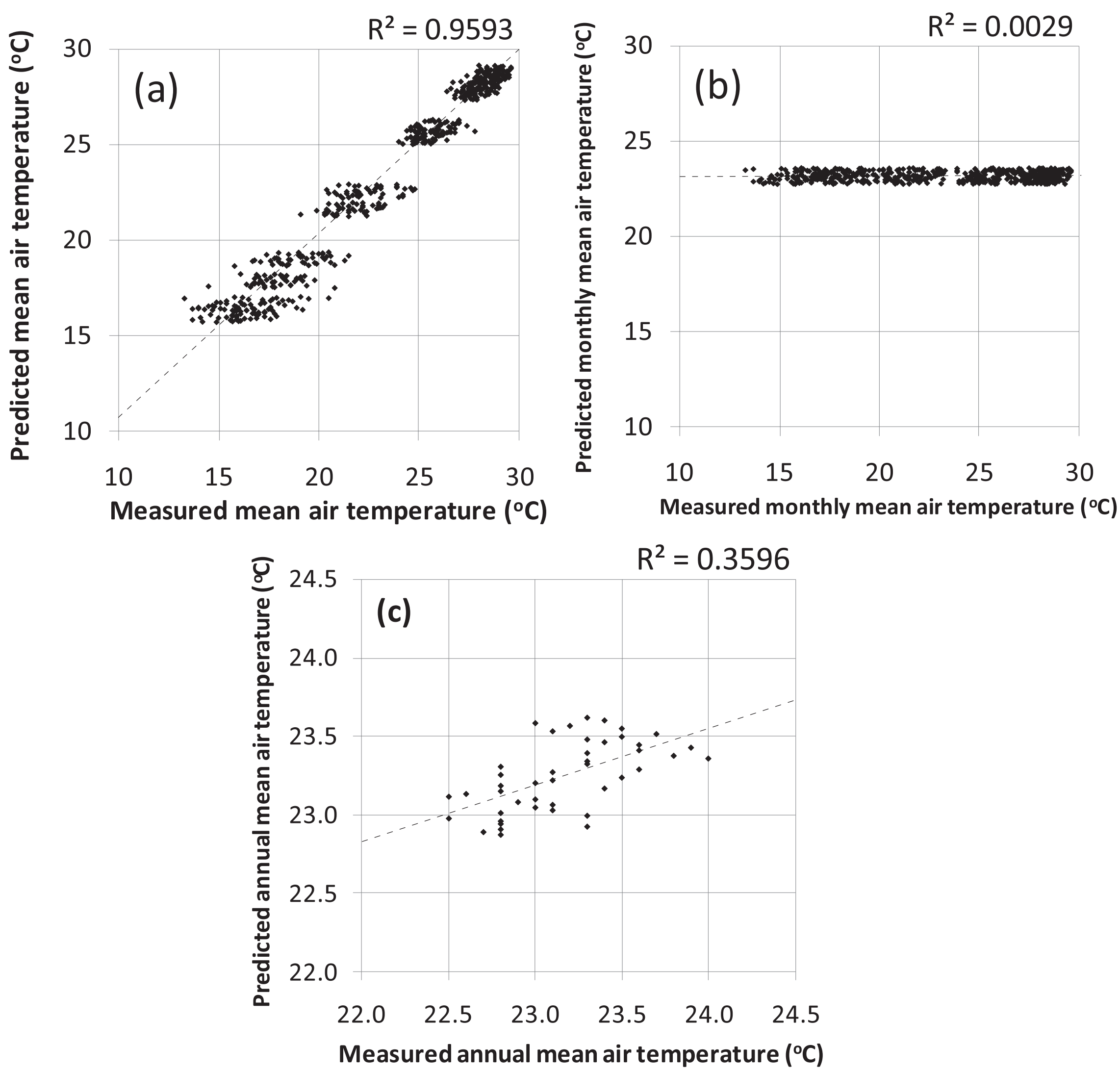

Fig. 3. The measured mean air temperature versus the predicted mean air temperature in Hong Kong (1970–2013), based on (a) the seasonal unit root model, (b) the OLS model using monthly data, and (c) the OLS model using annual data.

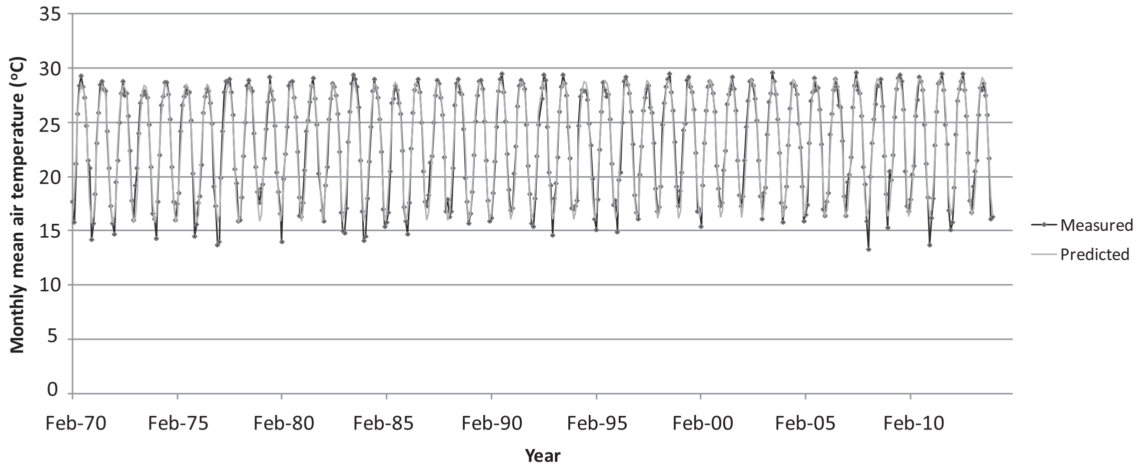

Fig. 4. The predicted monthly mean air temperature using a deterministic trend with seasonal components versus the measured monthly air temperature, in Hong Kong (January 1970 to December 2013).

based on monthly data, using the OLS model based on monthly data, and using the OLS model based on annual data. This figure demonstrates that the overall accuracy of the former model was better than that of the latter models. The R^2 values showed that the model obtained from the seasonal unit root analysis was able to explain 95.9% of the variance in the measured monthly mean air temperature data, while the model obtained using OLS was only able to explain 0.29% of the variance of the measured monthly mean air temperature data. The model obtained using OLS based on annual data was able to explain 36% of the variance of the measured annual mean air temperature data.

Figure 4 shows the measured and predicted monthly air temperatures from 1970 to 2013. It demonstrates the superior performance of using the seasonal unit root model to regenerate the measured monthly mean air temperatures from January 1970 to December 2013.

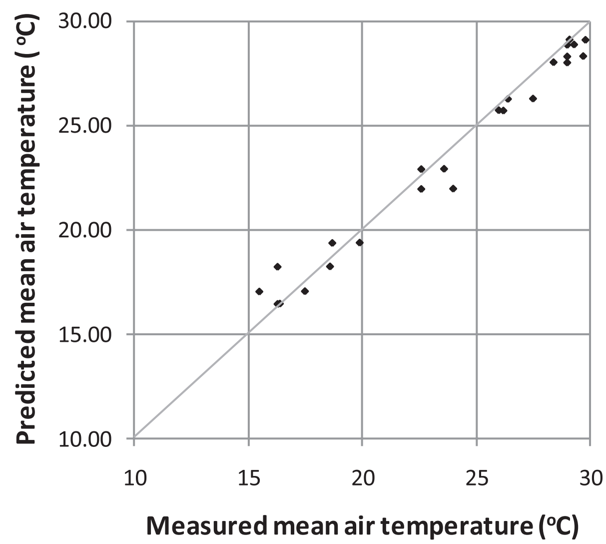

Fig. 5. The measured mean air temperature versus the predicted mean air temperature in Hong Kong (January 2014 to December 2015).

3.2. *Prediction of monthly mean air temperature using the seasonal model*

Equation (3) was used to predict the monthly mean air temperature from January 2014 to December 2015. Figure 5 shows the predicted mean air temperatures and the mean air temperatures recorded at the Hong Kong Observatory in Tsim Sha Tsui. The correlation between the predicted and the measured values was 0.989, while the mean absolute error, the RMSE, and the root-mean-square percentage error were 0.659°C, 0.861°C and 4.2%, respectively. Hence, the results confirmed that the seasonal unit root model of monthly mean air temperature has a high predictive power. When the OLS model based on monthly data was tested, the correlation between the predicted and the measured values was 0.247, while the mean absolute error, the RMSE, and the root-mean-square percentage error were 4.5°C, 5.04°C and 25.1%, respectively.

3.3. *UHI effect*

Generally, the UHI is characterized by comparing air temperatures recorded at an urban site and a rural site (Wang et al., 1990; Camilloni and Barros, 1997; Li et al., 2004; Chan et al., 2012; Debbage and Shepherd, 2015; Hu et al., 2016). The differences between these two time series are attributed to the effect of the UHI. Unfortunately, nearly all rural stations were established in Hong Kong after the mid-1980s, and some rural areas have been converted to developed areas with suburban or urban land-use (Leung et al., 2007; Chan et al., 2012; Siu and Hart, 2013). The measured air temperatures at Hong Kong's island stations, such as Cheung Chau and Waglan Island, have been found to have been substantially modulated by temporal variations in temperature of the near-shore waters (Leung et al., 2007). Hence, annual mean air temperature and monthly mean air temperature data recorded at Ta Kwu Ling were taken as those for the rural station (Leung et al., 2007). Figure 6 shows the difference between the annual mean air temperature at the urban station, i.e., Hong Kong Observatory at Tsim Sha Tsui, and

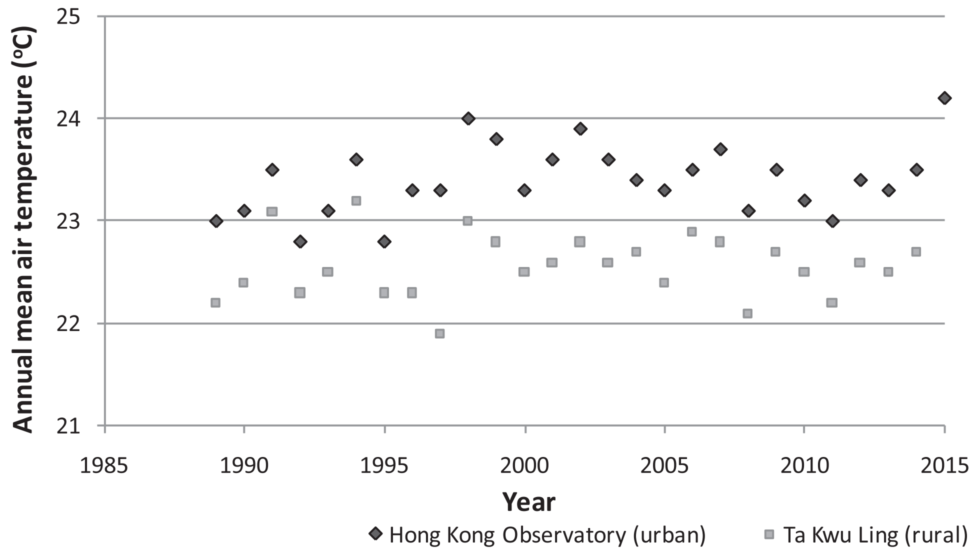

Fig. 6. Annual mean air temperature at an urban site (diamonds) and a rural site (squares) in Hong Kong (1970–2015). Note that air temperature was recorded at the same location of Ta Kwu Ling (rural area) after 1988, and that the annual and monthly mean air temperatures at Ta Kwu Ling for the year 2015 had not been released by the Hong Kong Observatory at the time of writing.

that at the rural station, i.e., Ta Kwu Ling, between 1989 and 2014. It can be seen that the annual mean air temperature at the urban site was 0.808°C (standard deviation: 0.230°C) higher than that of the rural site.

Monthly mean air temperature data at Ta Kwu Ling between January 1999 and December 2014 were obtained from the database of the Hong Kong Observatory. It was found that the distribution of differences between the monthly air temperature at the urban site and that at the rural site ranged between 0°C and 2.9°C, with a mode of 0.50°C–0.75°C. Results showed that the difference between the monthly mean air temperature at the urban site and that at the rural site was greater during the winter months, with an average of 1.38°C for November, 1.88°C for December, and 1.51°C for January. This phenomenon has also been observed in mainland China (Wang et al., 1990), Seoul (Kim and Baik, 2002), Alaska (Hinkel et al., 2003), and Hong Kong using quarterly data (Chan et al., 2012). Monthly mean air temperature was found to be on average 0.865°C (standard deviation: 0.538°C) warmer at the urban site than at the rural site during the period of January 1999 to December 2014.

3.4. *Population, GDP, urban land use, energy use, and annual mean air temperature*

Figure 7a shows that Hong Kong's population increased from 4.0 million in 1970 to 7.3 million in 2015.Figure 7b shows that Hong Kong's GDP increased from HKD 195.2 trillion to HKD 2246.4 trillion during the same period of time. Figure 7c shows the urbanization of Hong Kong between 1970 and 2015. Data were compiled from reports of the Hong Kong Buildings and Lands Department (on or before 1989) and the Hong Kong Planning Department (from 1990 onwards). The use of energy will definitely lead to an increase in air pollutants (To et al., 2012; To, 2014, 2015), and has an effect on ambient temperature—particularly in a built environment such as Hong Kong. However, the impact of energy use on air temperature is a complex phenomenon. Not all the consumption of primary energy will eventually transform in to thermal energy in air. For example, Hong Kong's power plants have an overall efficiency of about 34%. In other words, about 1/3 of fuel energy in the power plant is converted to electrical energy and 2/3 of fuel energy is wasted through mechanical loss, transmission loss, waste heat discharged to the atmosphere through stack gases, and waste heat discharged to the air and sea through the cooling water of condensers (Erdem et al., 2010). Within the urbanized area of Hong Kong, the use of electricity, gases (including liquefied petroleum gas and town gas), motor gasoline by private vehicles, and diesel oil by buses, trucks and industrial boilers, will cause an increase in the amount of waste heat discharged from chillers, boilers, flue gases, etc. Hence, the use of these forms of energy was included in this study. Data were extracted from Hong Kong's energy end-use reports published by the Hong Kong Electrical and Mechanical Services Department (HKEMSD, 2005a, b). Figure 7d shows the use of energy in terajoule (TJ) for the period 1984–2013.

Figure 8 presents scatter plots of annual mean air temperature versus Hong Kong's population, annual mean air temperature versus Hong Kong's GDP, annual mean air temperature versus Hong Kong's urbanized area, and annual mean air temperature versus the total energy use in Hong Kong. Trend and correlation analyses show that there was a moderate and significant relationship between annual mean air temperature and Hong Kong's GDP ($R^2 = 0.3746$; $p < 0.001$), and moderate (slightly stronger) and significant relationships between annual mean air temperature and Hong Kong's population ($R^2 = 0.4244$; $p < 0.001$), between annual mean air temperature and Hong Kong's urbanized area ($R^2 = 0.4319$;

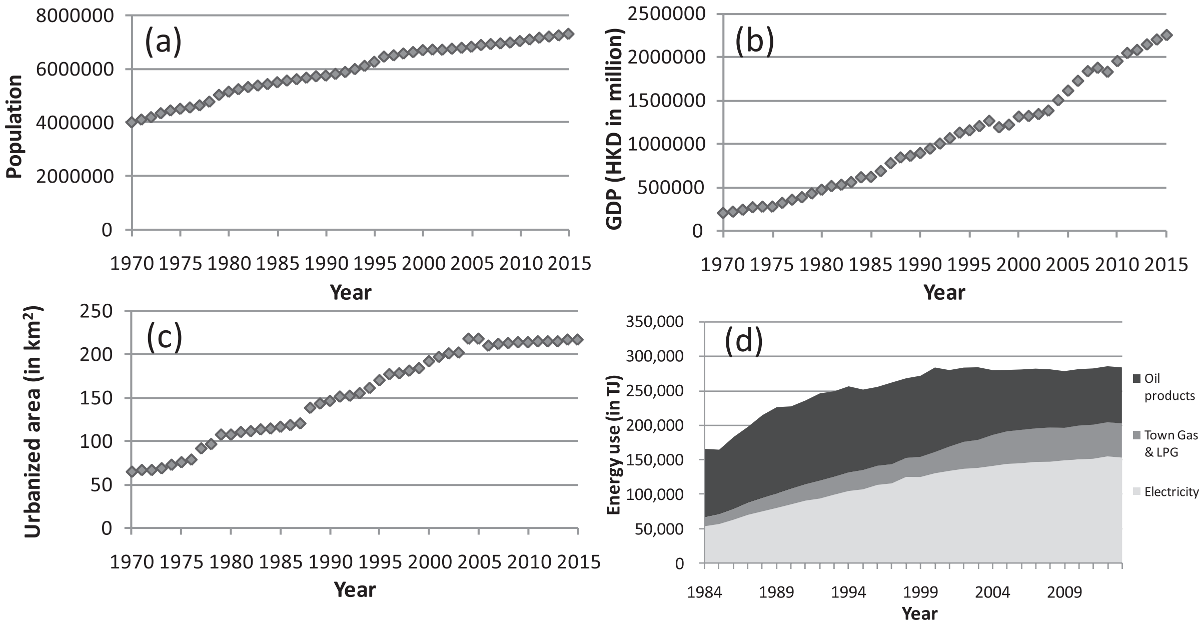

Fig. 7. Hong Kong's (a) population (1970–2015), (b) GDP (1970–2015), (c) urbanized area (1970–2015) and (d) energy use (1984–2013). The data in (c) exclude temporary structures/livestock farms, reservoirs, cemeteries, crematoria, mines, quarries etc. The data in (d) were only available after 1984.

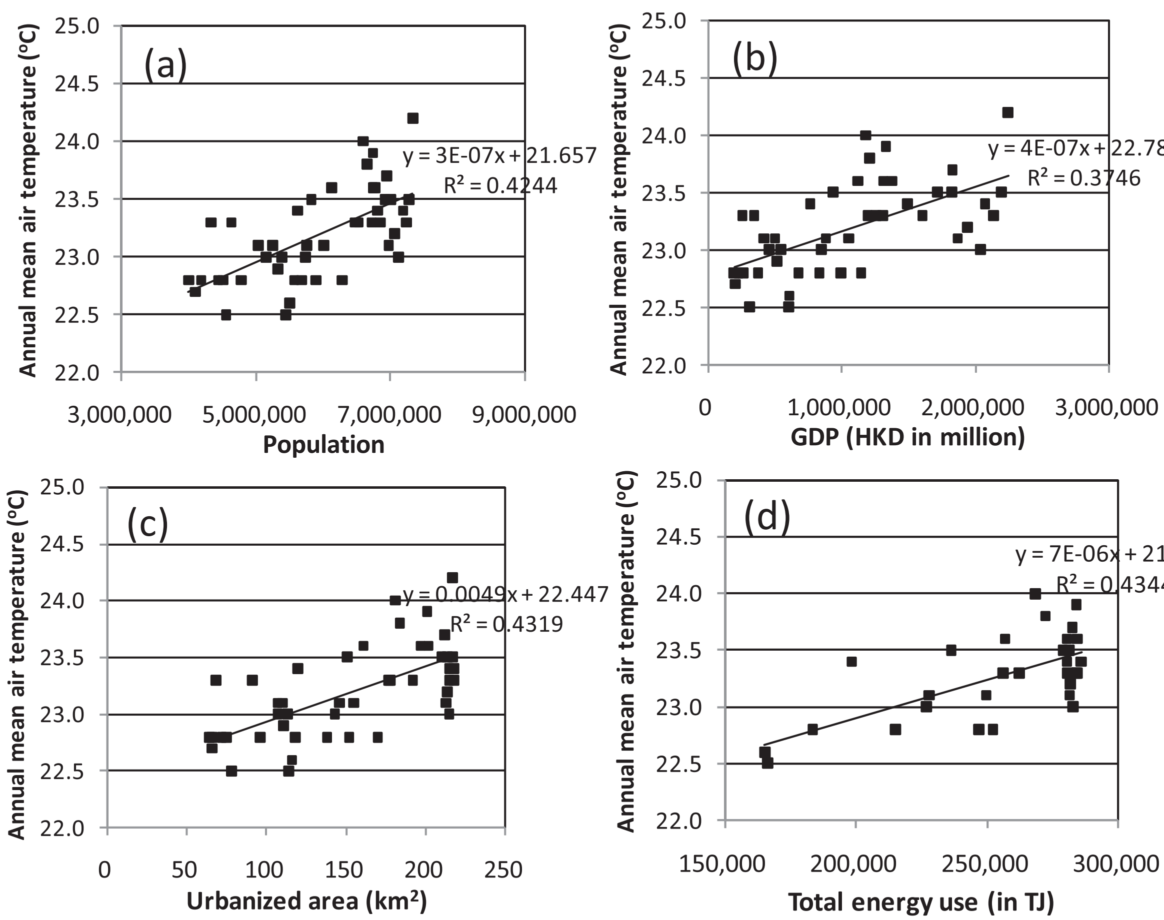

Fig. 8. Scatter plots of annual mean air temperature versus Hong Kong's (a) population, (b) GDP, (c) urbanized area, and (d) total energy use.

$p < 0.001$), and between annual mean air temperature and Hong Kong's total energy use ($R^2 = 0.4344$; $p < 0.001$).The findings are not surprising, because it is known that urban warming is associated with population and GDP (Oke, 1973; Hu and Jia, 2010). Besides, the correlation between annual mean air temperature and urbanized area was consistent with the findings reported by He et al. (2013), who indicated that the total urban area of a city was associated with the annual mean air temperature recorded in the city's meteorological stations.

To identify the relationships between population, GDP, urban land use, energy use, and annual mean air temperature, multiple-linear regression was applied to these five time series (Ning and Bradley, 2014). Population, GDP, urban land use, and energy use were chosen as the independent variables, while annual mean air temperature was selected as the dependent variable. A stepwise procedure was used to identify significant predictors of annual mean air temperature. Results showed that energy use and GDP were able to explain 48.1% of the variance in annual mean air temperature.

4. Conclusion

Urban warming is an important environmental issue and its trend should be closely monitored. The present study is one of the first to use annual as well as monthly mean air temperature data and an econometric approach to characterize the long-term urban temperature trend in a built environment such as Hong Kong. Unlike many other studies, which have primarily used annual mean air temperature data (Li et al., 2004; Huang et al., 2009; Chan et al., 2012), our analysis made use of monthly data, resulting in much higher statistical power to identify the stochastic trend of mean air temperature. The seasonal unit root analysis produced a much more accurate estimate of the urban temperature trend because the monthly data were fully utilized and the loss of information was small (Nijman and Palm, 1990). The results of the seasonal unit root analysis showed that monthly mean air temperature has a stochastic trend and seasonal components. It was found that the mean air temperature in Hong Kong increased by 0.169°C $(10\ \mathrm{yr})^{-1}$ over the past four decades using monthly temperature data [or 0.174°C $(10\ \mathrm{yr})^{-1}$ using annual temperature data], and the trend is likely to persist. By comparing mean air temperatures at an urban site and that at a rural site, it was found that mean air temperature was on average 0.865°C higher at the urban site than at the rural site. The results of correlation analysis illustrated that the increase in annual mean air temperature was significantly associated with the increase in population, GDP, urban land use, and energy use. The results of multiple-linear regression showed energy use and GDP to be the most significant predictors of annual mean air temperature.

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