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Future trends of building heating and cooling loads and energy consumption in different climates

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ABSTRACT

Principal component analysis of dry-bulb temperature, wet-bulb temperature and global solar radiation was considered, and a new climatic index (principal component *Z*) determined for two emissions scenarios – low and medium forcing. Multi-year building energy simulations were conducted for generic air-conditioned office buildings in Harbin, Beijing, Shanghai, Kunming and Hong Kong, representing the five major architectural climates in China. Regression models were developed to correlate the simulated monthly heating and cooling loads and building energy use with the corresponding *Z*. The coefficient of determination (R^2) was largely within 0.78–0.99, indicating strong correlation. A decreasing trend of heating load and an increasing trend of cooling load due to climate change in future years were observed. For low forcing, the overall impact on the total building energy use would vary from 4.2% reduction in severe cold Harbin (heating-dominated) in the north to 4.3% increase in subtropical Hong Kong (cooling-dominated) in the south. In Beijing and Shanghai where heating and cooling are both important, the average annual building energy use in 2001–2100 would only be about 0.8% and 0.7% higher than that in 1971–2000, respectively.

1. Introduction

There is a growing concern about energy use and its implications for the environment. Recent reports by the Inter-governmental Panel on Climate Change (IPCC) have raised public awareness of energy use and the environmental implications, and generated a lot of interest in having a better understanding of the energy use characteristics in buildings, especially their correlations with the prevailing weather conditions [1,2]. It was estimated that in 2002 buildings worldwide accounted for about 33% of the global greenhouse gas emissions [3]. In their work on climate change and comfort standards, Kwok and Rajkovich [4] reported that the building sector accounted for 38.9% of the total primary energy requirements (PER) in the United States, of which 34.8% was used for heating, ventilation and air-conditioning (HVAC). In China, building stocks accounted for about 24.1% in 1996 of total national energy use, rising to 27.5% in 2001, and were projected to increase to about 35% in 2020 [5,6]. Although carbon emissions per capita in China are low, its total emissions are only second to the US. When the life cycle energy use and emissions footprint are considered, buildings account for a significant proportion of the energy-related emissions [7,8].

A significant proportion of this consumption was due to the ever growing demand for better thermal comfort in terms of space heating in winter and space cooling during the hot/humid summer months [9,10]. Buildings typically have a long life span, lasting for 50 years or more. It is, therefore, important to be able to analyse how buildings will response to climate change in the future, and assess the likely changes in energy use. Earlier work had revealed an increasing temperature trend over the past decades, resulting in less discomfort in winter and more discomfort during summer [11–13]. The extent to which overall energy use for space conditioning would be affected would depend very much on the prevailing local climates and the actual climate change in future years. Reductions in the space heating could well outweigh the anticipated increase in energy use for space cooling and vice versa. Office building development is one of the fastest growing areas in the building sector, especially in major cities such as Beijing and Shanghai. On a per unit floor area basis, energy use in large commercial development with full air-conditioning can be 10–20 times higher than that in residential buildings and is an important element in building energy conservation programmes [14,15]. The

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objective of the present work was, therefore, to investigate future trends of energy consumption in air-conditioned office buildings in different climate zones across China under different emissions scenarios in the 21st century.

2. Methodology

There have been some works on the impact of climate change on the built environment based on energy simulation using sophisticated building energy simulation tools to perform hour-by-hour computation of heating/cooling loads and energy use. In general, a weather file containing 8760 hourly records of major climatic variables such as dry-bulb temperature, dew point or wet-bulb temperature, solar radiation and wind speed is required for building energy simulation. For instance, Sheppard et al. [16,17] studied the impact of climate change on commercial building energy consumption in the Sydney region (Australia) using predicted 3-hourly data from the Australian Bureau of Meteorological Research Centre's general circulation model (GCM). They found that energy use could be increased by 10–17% due to CO_2 doubling in the global atmosphere. More recent works involved stochastically generated test reference year (TRY) hourly datasets for Portuguese buildings [18] and moderate climate [19], a sample office building in 6 cities ranging from low to high latitudes (10.6°N–51.2°N) [20], 'morphing' technique to stretch and shift existing TRY and design summer year for a number of case studies in UK [21–23], modifying existing weather files to account for changes in diurnal temperature, dry-bulb temperature and cloud cover in 2100 for 20 climate regions worldwide [24], and potential impact assessment of global warming on residential buildings in United Arab Emirates where the air temperatures were raised by 1.6 °C and 2.9 °C to reflect the climate in 2050, and by 2.3 °C and 5.9 °C in 2100 [25].

Archived predictions from GCMs, however, contain mostly monthly and/or daily data (e.g. the WCRP CMIP3 multi-model dataset [26]). Attempts were made to generate future hourly data based on the archived daily values from these climate models [27,28]. An alternative (and certainly simpler) approach would be to correlate building energy use directly with daily/monthly weather data. Although empirical or regression-based models using mean daily/monthly outdoor dry-bulb temperature and degree-days data tend to show good correlations between energy use and the prevailing weather conditions, most of them either consider only one weather variable (e.g. dry-bulb temperature), or do not adequately remove the bias in the weather variables during the multiple linear regression analysis [29]. Our earlier work on existing air-conditioned office buildings and sector-wide electricity consumption in subtropical climates had shown that regression models based on principal component analysis (PCA) of key monthly climatic variables could give a good indication of the corresponding monthly and annual electricity use [30,31]. More recently, it was also found that annual energy use in fully air-conditioned office buildings in subtropical climates from PCA and regression models was very close to that from detailed multi-year hourly simulation, and could give a good indication of future trends of energy use [32,33]. PCA and multi-year dynamic building energy simulations were thus adopted and the study covered the following:

(i) Principal component analysis of historical weather data measured at the local meteorological station and future (21st century) predictions from GCMs to generate a new composite climatic variable, which could account for the long-term variations of the major meteorological variables.
(ii) Multi-year building energy simulation based on measured hourly weather data and generic office buildings with design and operation features based on the local energy codes/

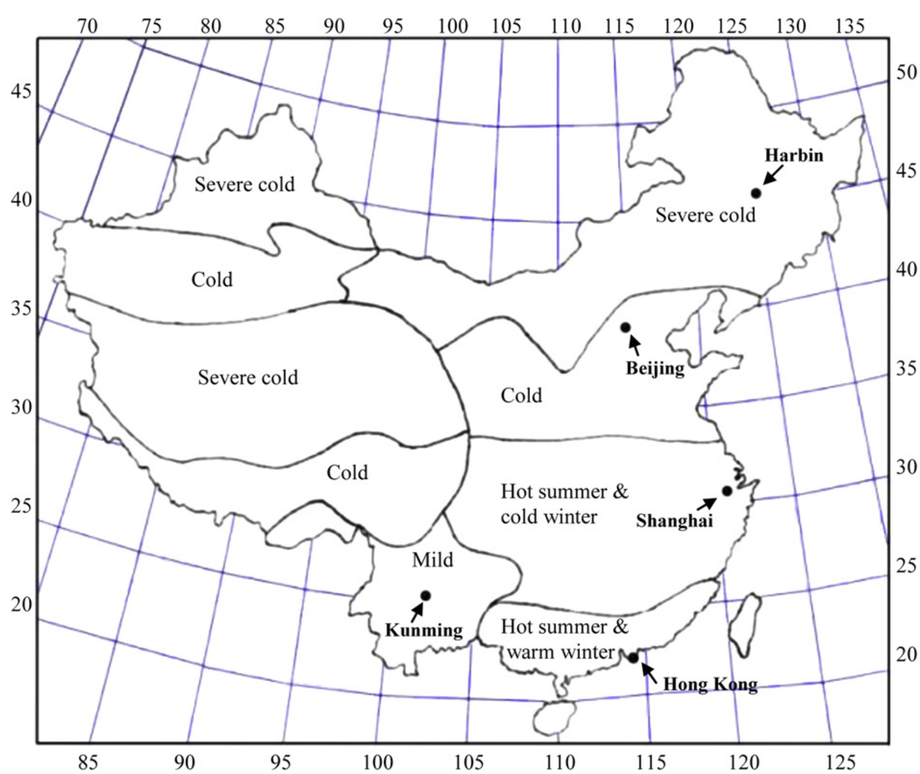

Fig. 1. Overall view of the five major climates and geographical distribution of the five cities.

guidelines and prevailing architectural and construction practices in major climate zones across China.
(iii) Correlation between simulated heating and cooling loads and energy consumption with the corresponding composite climatic variable using regression technique.
(iv) Regression model evaluation via comparison between simulation results and regression-predicted data.
(v) Estimation of the likely changes in heating and cooling loads and total building energy use in future years using the regression model developed.

3. Climate zones and selection of cities

China is a large country with an area of about 9.6 million km^2. Approximately 98% of the land area stretches between a latitude of 20°N and 50°N, from the subtropical zones in the south to the temperate zones (including warm-temperate and cool-temperate) in the north [34]. The maximum solar altitudes vary a great deal and there is a large diversity in climates, especially the temperature distributions during winters. Characteristics associated with continental climates can be identified, with warmer summer, cooler winter and a larger annual temperature range than other parts of the world with similar latitudes. China also has a complex topography ranging from mountainous regions to flat plains. These diversity and complexity have led to many different regions with distinct climatic features [35]. The most commonly used climate classification is for the thermal design of buildings. It has five climate types, namely severe cold, cold, hot summer and cold winter, mild, and hot summer and warm winter [36]. The zoning criteria are mainly based on the average temperatures in the coldest and hottest months of the year. The numbers of days that daily average temperature is below 5 °C or above 25 °C are counted as the complementary indices for determining the zones. Fig. 1 shows an overall layout of the five major climates. Because of the varying topology and hence elevations, there are nine regions – both the severe cold and cold climates have three regions. A city within each of the five major climate zones was selected for the analysis. These were Harbin (severe cold, 45°45′N/126°46′E), Beijing (cold, 39°48′N/116°28′E), Shanghai (hot summer and cold winter, 31°10′N/121°26′E), Kunming (Mild, 25°01′N/102°41′E) and Hong Kong (hot summer and warm winter, 22°18′N/114°10′E).

4. Principal components analysis (PCA) of major meteorological variables

In the analysis of long-term meteorological variables, it is often advantageous to group key weather variables directly affecting building energy performance. PCA is a multivariate statistical technique for analysis of the dependencies existing among a set of inter-correlated variables [37,38]. Because of its ability to categorise the complex and highly inter-correlated set of meteorological variables as one or more cohesive indices, PCA tends to give a better understanding of the cause/effect relationship. PCA is conducted on centred data or anomalies, and is used to identify patterns of simultaneous variations. Its purpose is to reduce a dataset containing a large number of inter-correlated variables to a dataset containing fewer hypothetical and uncorrelated components, which nevertheless represent a large fraction of the variability contained in the original data. These components are simply linear combinations of the original variables with coefficients given by the eigenvector.

Initially five climatic variables were considered, namely dry-bulb temperature (DBT, in °C), wet-bulb temperature (WBT, in °C), global solar radiation (GSR, in MJ/m^2), clearness index and wind

Table 1
Summary of error analysis of predicted dry-bulb temperature (DBT), wet-bulb temperature (WBT) and global solar radiation (GSR).

City	Model	DBT				WBT				GSR				Average score[c]
		MBE[a]		RMSE[b]		MBE		RMSE		MBE		RMSE		
		°C	Rank	°C	Rank	°C	Rank	°C	Rank	MJ/m^2	Rank	MJ/m^2	Rank	
Harbin	BCCR-BCM2.0	−3.81	4	6.15	4	−3.21	5	5.25	4	1.38	4	3.98	4	4.2
	GISS-AOM	−1.59	2	3.49	2	0.16	1	2.61	2	0.70	1	3.32	2	1.7
	INM-CM3.0	−4.02	5	5.22	3	−2.77	4	4.10	3	1.05	3	3.83	3	3.5
	MIROC3.2-H	−0.35	1	2.67	1	0.29	2	2.35	1	3.65	5	5.69	5	2.5
	NCAR-CCSM3.0	−2.66	3	8.69	5	−1.65	3	7.27	5	1.03	2	2.90	1	3.2
Beijing	BCCR-BCM2.0	−6.89	4	7.54	3	−4.59	4	5.24	3	1.46	1	2.76	1	2.7
	GISS-AOM	−3.24	2	4.02	2	−2.44	2	3.33	2	2.01	4	3.09	3	2.5
	INM-CM3.0	−7.28	5	7.96	4	−5.58	5	6.15	4	1.87	2	2.90	2	3.7
	MIROC3.2-H	−2.69	1	3.47	1	−1.86	1	2.70	1	4.20	5	4.81	5	2.3
	NCAR-CCSM3.0	−5.62	3	8.40	5	−4.35	3	6.75	5	1.92	3	3.93	4	3.8
Shanghai	BCCR-BCM2.0	−0.91	1	1.93	1	−0.63	1	1.92	1	2.53	2	4.01	1	1.2
	GISS-AOM	3.28	5	4.76	4	2.70	5	4.07	3	4.01	3	4.80	3	3.8
	INM-CM3.0	−3.16	4	4.71	3	−2.51	4	4.10	4	4.57	4	5.37	4	3.8
	MIROC3.2-H	1.00	2	2.08	2	1.37	3	2.18	2	5.20	5	6.03	5	3.2
	NCAR-CCSM3.0	−1.79	3	5.13	5	−0.86	2	4.52	5	2.24	1	4.15	2	3.0
Kunming	BCCR-BCM2.0	−3.00	5	3.52	5	0.52	1	1.97	1	0.13	1	3.56	1	2.3
	GISS-AOM	−0.52	4	1.47	1	2.23	5	2.60	3	4.41	4	5.79	4	3.5
	INM-CM3.0	0.14	1	3.40	4	1.32	3	3.46	5	3.77	2	5.41	2	2.8
	MIROC3.2-H	−0.23	2	1.68	2	1.87	4	2.29	2	4.15	3	5.50	3	2.7
	NCAR-CCSM3.0	−0.23	2	3.34	3	−0.59	2	2.98	4	4.82	5	6.76	5	3.5
Hong Kong	BCCR-BCM2.0	−1.32	4	2.12	2	−0.36	2	1.85	2	2.53	1	4.50	1	2.0
	GISS-AOM	−0.60	2	2.61	3	−0.18	1	1.99	3	6.18	5	7.22	5	3.2
	INM-CM3.0	−2.92	5	3.64	5	−2.45	5	3.11	5	5.45	4	7.01	4	4.7
	MIROC3.2-H	0.06	1	1.77	1	0.69	3	1.75	1	5.08	3	6.37	3	2.0
	NCAR-CCSM3.0	−0.99	3	2.62	4	−0.84	4	2.62	4	3.55	2	4.59	2	3.2

[a] MBE $= \{\sum_{i=1}^{n}(P_i - M_i)\}/n$ (P_i = prediction, M_i = measured data, $n = 252$ for Hong Kong, $n = 348$ for the 4 mainland cities).
[b] RMSE $= \{\sum_{i=1}^{n}(P_i - M_i)^2/n\}^{1/2}$.
[c] Arithmetic mean of the 6 rankings.

Table 2
Summary of principal component analysis (for Harbin).

Scenario	Principal component	Eigenvalue	Cumulative explained variance (%)	Coefficient		
				DBT	WBT	GSR
SRES B1 (low forcing)	1st	2.725	90.82	0.983	0.975	0.899
	2nd	0.274	99.96	−0.182	−0.221	0.438
	3rd	0.001	100	−0.027	0.025	0.002
SRES A1B (medium forcing)	1st	2.709	90.29	0.982	0.974	0.892
	2nd	0.290	99.95	−0.186	−0.226	0.452
	3rd	0.001	100	−0.028	0.026	0.002

speed. DBT affects the thermal response of a building and the amount of heat gain/loss through the building envelope and hence energy use for the corresponding sensible cooling/heating requirements, whereas WBT dictates the amount of humidification required during dry winter days and latent cooling under humid summer conditions. Information on solar radiation is crucial to cooling load determination and the corresponding design and analysis of air-conditioning systems, especially in tropical and subtropical climates where solar heat gain through fenestrations is often the largest component of the building envelope cooling load [39,40]. Clearness index indicates the prevailing sky conditions while wind speed affects natural ventilation and the external surface resistance and hence *U*-values of the building envelope [41]. Contributions to the principal components from the clearness index and wind speed, however, were found to be small (at least one order of magnitude smaller) compared with DBT, WBT and GSR [30]. These 2 climatic variables were, therefore, not considered.

Details of data gathering and subsequent PCA of the three weather variables can be found in Lam et al. [32,33]. Briefly, historical (30 years, 1971–2000 for the four cities on the mainland and 1979–2008 for the Hong Kong SAR) weather data measured at the meteorological stations within the five cities were obtained from the China National Meteorological Centre and the Hong Kong Observatory. Future weather conditions were obtained from the World Climate Research Programme's (WCRP) Coupled Model Intercomparison Project Phase 3 (CMIP3) multi-model dataset [26]. Altogether, there were five GCMs that had archived monthly mean DBT, moisture content, and GSR. Predictions from these five GCMs were downloaded and analysed. These GCMs included the BCCR-BCM2.0 (Norway), GISS-AOM (USA), INM-CM3.0 (Russia), MIROC3.2-H (Japan), and NCAR-CCSM3.0 (USA). They covered predictions for the past 10 decades (1900–1999) based on known emissions, and future years (2000–2099 for NCAR-CCSM3.0 and BCCR-BCM2.0; and 2001–2100 for GISS-AOM, INM-CM3.0, and MIROC3.2-H) based on different emission scenarios [42]. To get an idea about how well these GCMs could predict the temperature, humidity and solar radiation, predictions for the 29-year period (1971–1999) from these 5 GCMs were gathered and analysed (only 21 years (1979–1999) for Hong Kong). To compare like with like predicted moisture content was converted to WBT. The predicted DBT, WBT and GSR were compared with the corresponding measured monthly mean data. A summary of the error analysis is shown in Table 1. The GCMs tended to underestimate DBT in all five cities, except GISS-AOM and MIROC3.2-H for Shanghai, INM-CM3.0 for Kunming and MIROC3.2-H for Hong Kong. There was, however, no distinct pattern showing any tendency of underestimation or overestimation of the WBT. The GSR appeared to be overestimated in all five cities by the five GCMs. The mean bias error (MBE) in DBT varied from 7.28 °C underestimation by INM-CM3.0 for Beijing to 3.28 °C overestimation by GISS-AOM for Shanghai, and root mean square error (RMSE) from 1.47 °C (GISS-AOM in Kunming) to 8.69 °C (NCAR-CCSM3.0 in Harbin). To have a better understanding of the error analysis, performance of the five GCMs was ranked in terms of the MBE and RMSE, and a summary is also shown in Table 1. GISS-AOM performed best in Harbin (average score = 1.7), MIROC3.2-H in Beijing (average score = 2.3), and so on. For simplicity and consistency, an attempt was made to select one GCM for this study by comparing the average scores among all five cities. The overall average score was 2.5, 2.9, 3.7, 2.5 and 3.3 for BCCR-BCM2.0, GISS-AOM, INM-CM3.0, MIROC3.2-H and NCAR-CCSM3.0, respectively. Apparently, MIROC3.2-H tended to perform well in temperature and humidity but only average in solar radiation among the 5 models. Its

Table 3
Summary of the coefficients for the principal component (i.e. Equation (1)).

City	Scenario	*A*	*B*	*C*
Harbin	Low forcing	0.983	0.975	0.899
	Medium forcing	0.982	0.974	0.892
Beijing	Low forcing	0.982	0.974	0.893
	Medium forcing	0.982	0.957	0.839
Shanghai	Low forcing	0.974	0.971	0.849
	Medium forcing	0.973	0.970	0.838
Kunming	Low forcing	0.990	0.925	0.606
	Medium forcing	0.989	0.928	0.597
Hong Kong	Low forcing	0.974	0.956	0.772
	Medium forcing	0.973	0.957	0.765

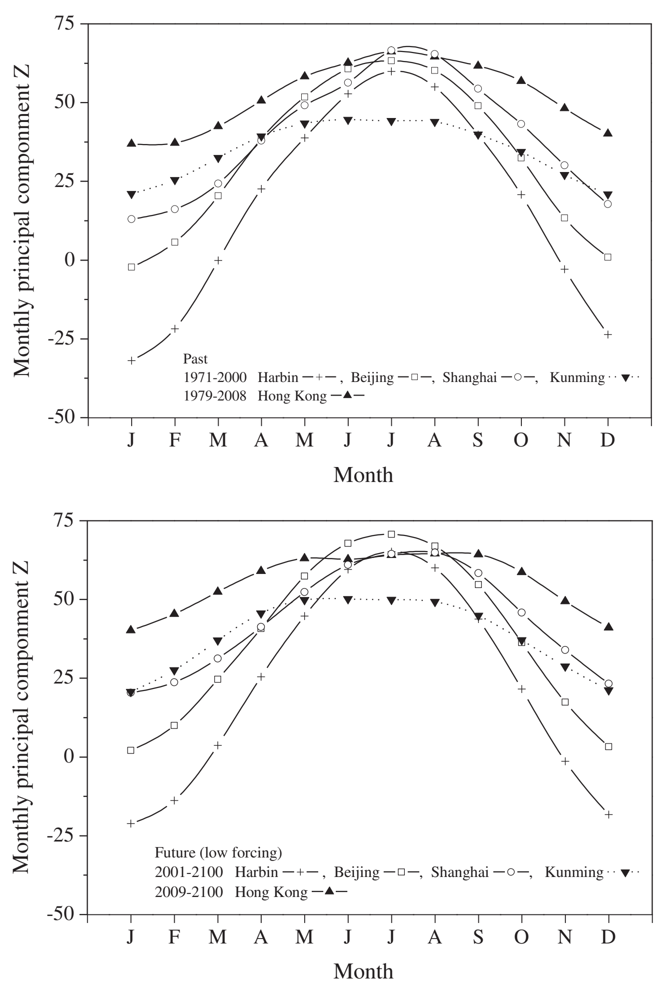

Fig. 2. Monthly profiles of principal component *Z* during 1971–2100 for scenario SRES B1 (low forcing).

overall score was 2.5, the same as BCCR-BCM2.0. In this study, MIROC3.2-H was selected for two reasons. Firstly, temperature and humidity greatly affect air-conditioning load, particularly winter humidification requirements in the north and latent cooling in warmer climates in the south. Secondly, our recent work on human bioclimate had found that MIROC3.2-H tended to show the best agreement between measured data and model predictions [12].

Predictions from the MIROC3.2-H general circulation model were used in the PCA for future years from 2001 to 2100 for two scenarios [42] – SRES B1 (low forcing, rapid change toward a service and information economy, peak global population in mid-21st century and decline thereafter, introduction of clean and resource-efficient technologies, and emphasis on global solutions to economic social and environmental sustainability), and SRES A1B (medium forcing, very rapid economic growth, same population trends as B1, convergence among regions with increased cultural and social interactions, and technological emphasis on a balanced mix of fossil and non-fossil energy resources). The predicted monthly mean DBT, WBT and GSR were calibrated according to the mean bias error shown in Table 1. A dataset consisting of 30-year (1971–2000 for

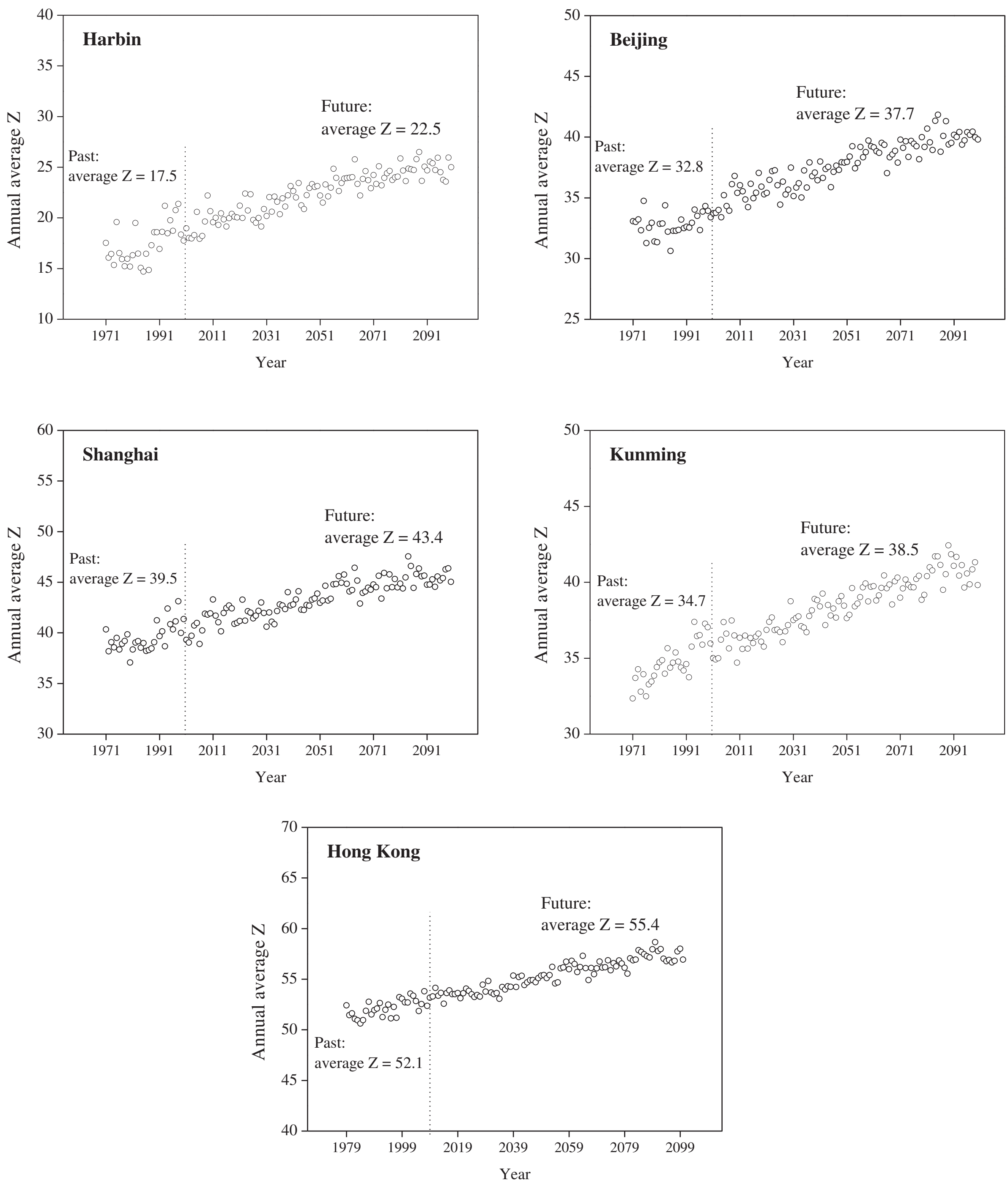

Fig. 3. Long-term trends of annual average principal component *Z* during 1971–2100 for scenario SRES B1 (low forcing).

the four cities on the mainland and 1979–2008 for Hong Kong) measured data and 100-year (2001–2100) predictions (only 92 years for Hong Kong, 2009–2100) was established for each emissions scenario. Altogether 130 (122 for Hong Kong) $\times$ 12 $\times$ 3 monthly data were considered in each PCA. The historic and future data were considered together as one time series in the PCA. The rationale was that the new set of monthly variable Z determined as a linear combination of the original three climatic variables would be applicable to both past and future years. Although the 30 years of historical observations in PCA are much less than 100 years of projection, this would not result in the PCA being skewed [37,38]. Table 2 shows the coefficients of the three principal components and the relevant statistics from the PCA for Harbin. The eigenvalue is a measure of the variance accounted for by the corresponding principal component. The first and largest eigenvalue account for most of the variance, and the second the second largest amounts of variance, and so on. A common approach is to select only those with eigenvalues equal to or greater than one (eigenvalues greater than one imply that the new principal components contain at least as much information as any one of the original climatic variables [43]) or with at least 80% cumulative explained variance [44]. These criteria were adopted for this study. From Table 2, the first principal component had an eigenvalue greater than one with a cumulative explained variance exceeding 90% (i.e. a one-component solution accounted for more than 90% of the variance in the original climatic variables). Similar features were observed for the other four cities. The first principal component was, therefore, retained, and a new set of monthly variable, Z, determined as a linear combination of the original three climatic variables as follows:

$$Z = A \times \mathrm{DBT} + B \times \mathrm{WBT} + C \times \mathrm{GSR} \tag{1}$$

Table 3 shows a summary of the coefficients A, B and C for the five cities. Measured data for the three climatic variables were analysed and the monthly values of Z determined for the 30-year

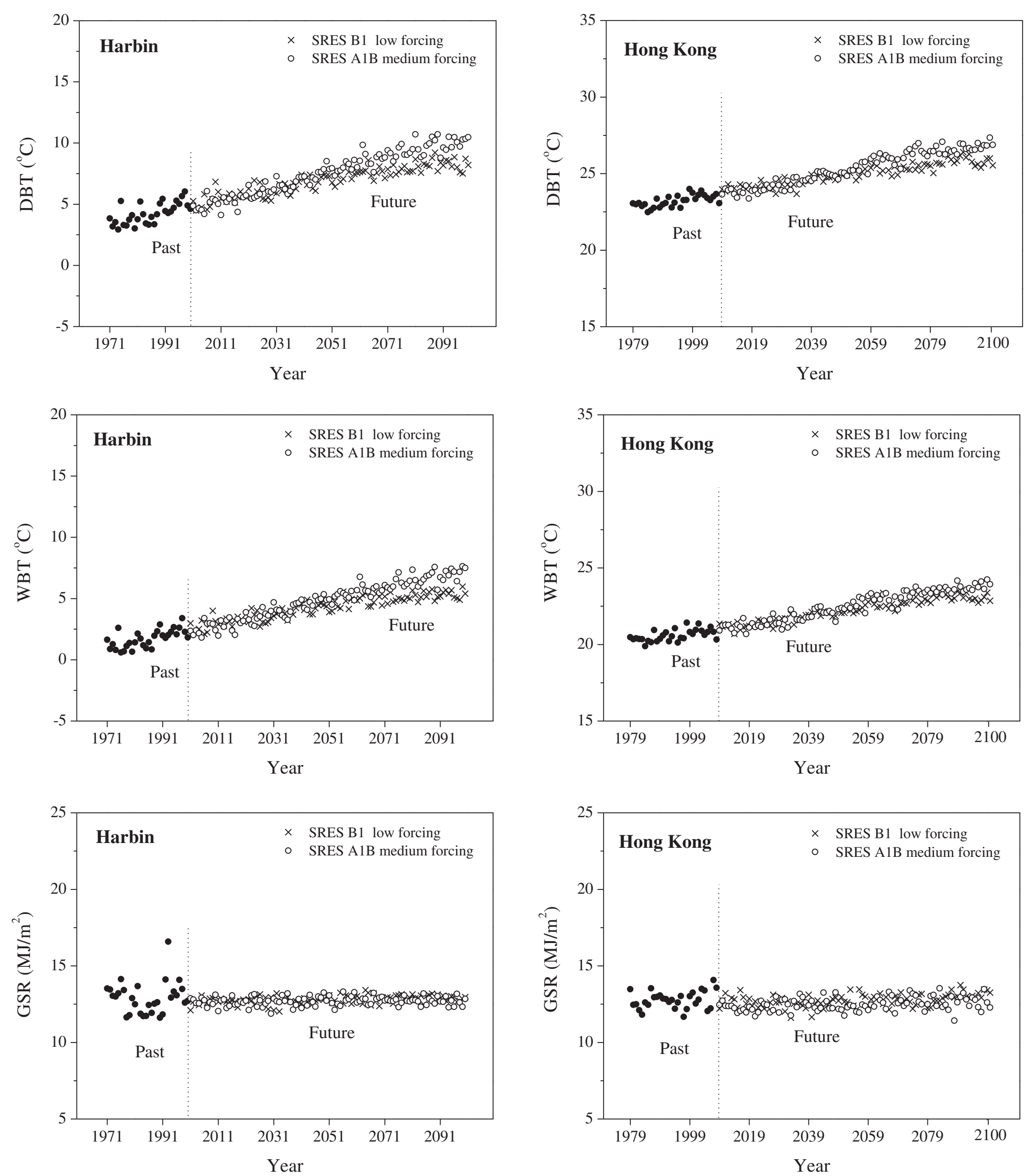

Fig. 4. Long-term trends of dry-bulb temperature (DBT), wet-bulb temperature (WBT) and global solar radiation (GSR) in Harbin and Hong Kong.

Table 4
Summary of annual averages of dry-bulb temperature (DBT), wet-bulb temperature (WBT) and global solar radiation (GSR) during 1971–2100.

City	Scenario	DBT (°C)	WBT (°C)	GSR (MJ/m^2)
Harbin	1971–2000	4.2	1.7	12.9
	2001–2100 (low forcing)	6.9	4.3	12.8
	2001–2100 (medium forcing)	7.6	4.9	12.7
Beijing	1971–2000	12.3	8.4	14.1
	2001–2100 (low forcing)	15.0	10.7	14.1
	2001–2100 (medium forcing)	15.6	11.3	13.9
Shanghai	1971–2000	16.2	13.8	12.3
	2001–2100 (low forcing)	18.2	15.7	12.3
	2001–2100 (medium forcing)	18.6	16.1	12.0
Kunming	1971–2000	14.9	12.1	14.5
	2001–2100 (low forcing)	16.9	13.9	14.7
	2001–2100 (medium forcing)	17.3	14.4	14.5
Hong Kong	1979–2008	23.2	20.6	12.8
	2009–2100 (low forcing)	25.0	22.2	12.7
	2009–2100 (medium forcing)	25.4	22.5	12.5

period, and a summary is shown in Fig. 2. The principal component profiles show distinct seasonal variations. Z tended to be at its lowest during the winter months (December, January and February) and peaked in the summer (June–August). Likewise, predictions from the GCM were used to determine monthly Z for the low and medium forcing scenarios during 2001–2100, and a summary for the low forcing is also shown in Fig. 2. To get an idea about the underlying trend, annual average Z was determined, and the past and future long-term trends for low forcing are shown in Fig. 3. Both the past and future years show a clear (though slightly) increasing trend. Similar trends were observed for the medium forcing, but with greater rates of increase and larger average Z. Fig. 4 shows the annual averages of the three climatic variables (i.e. DBT, WBT and GSR) in Harbin and Hong Kong during 1971–2100 and 1979–2100, respectively. Clear increasing trends in DBT and WBT can be observed, but not GSR. Similar trends were observed for the other three cities. These seem to be consistent with findings from investigation work on cloud cover, solar radiation and climate changes in Hong Kong [45] and elsewhere [20,28,46]. Table 4 shows a summary of the past and future average DBT, WBT and GSR. There seemed to be an increase in temperature rise (i.e. 2001–2100 average over the 1971–2100 average) as we moved from warmer climates in the south to colder climates in the north.

5. Multi-year building energy simulation

Hour-by-hour energy simulations were conducted for each of the 30 years (1971–2000 for the four mainland cities and 1979–2008 for Hong Kong) using the simulation tool VisualDOE4.1 [47]. Building energy simulation is an accepted and widely used analysis technique, but there would always be differences between simulation and the actual energy consumption in practice. In terms of comparative energy study, the simulated results would nevertheless give a good indication of the likely percentage change and any underlying trend. Two major inputs were considered for the simulation: (i) 8760 hourly records of weather data (DBT, WBT, GSR, wind speed and wind direction) [48], and (ii) a generic office building for each city, details of which can be found in Lam et al. [10,33]. Briefly, it was a 35 m × 35 m, 40-storey building with curtain walling design, 3.4 m floor-to-floor height and 40% window-to-wall ratio. The total gross floor area (GFA) is 49,000 m^2 (41,160 m^2 air-conditioned and 7840 m^2 non-air-conditioned). The air-conditioned space had five zones – four at the perimeter and one interior. Obviously, each city would in reality have rather different building envelope designs to suit the local climates. Generic building envelopes and HVAC designs were developed based on the prevailing architectural and engineering practices and local design/energy codes in the four cities on the mainland [49,50] and Hong Kong [51,52]. Table 5 shows a summary of the key design parameters. The computed results were analysed and compared in three aspects: building heating load, building cooling load and total building energy use (i.e. electricity consumption for HVAC, lighting and equipment).

6. Correlation between simulated results and principal component

To investigate the strength of correlation between building load/energy use and principal component, regression analysis was conducted for the monthly simulated results (which were normalised to account for the difference in the number of days per

Table 5
Summary of key design data for the five cities.

City	Building envelope				Indoor design condition		Internal load density			HVAC		
	U-value (W/m^{2}K)			Window shading coefficient	Summer (°C)	Winter (°C)	Occupancy (m^2/person)	Lighting (W/m^2)	Equipment (W/m^2)	AHU	Cooling	Heating
	Wall	Window	Roof									
Harbin	0.44	2.50	0.35	0.64	25	20	8	18	13	4-Pipe fan coil	Centrifugal chiller	Gas-fired boiler
Beijing	0.60	2.60	0.55	0.70	25	20	8	18	13		(Water-cooled,	
Shanghai	1.00	3.00	0.70	0.55	25	20	8	18	13		COP = 4.7)	
Kunming	1.47	3.50	0.89	0.50	25	20	8	18	13			
Hong Kong	2.01	5.60	0.54	0.40	24	21	13	15	10	VAV		Electric

HVAC = heating, ventilating and air-conditioning; AHU = air-handling unit; VAV = variable-air volume.

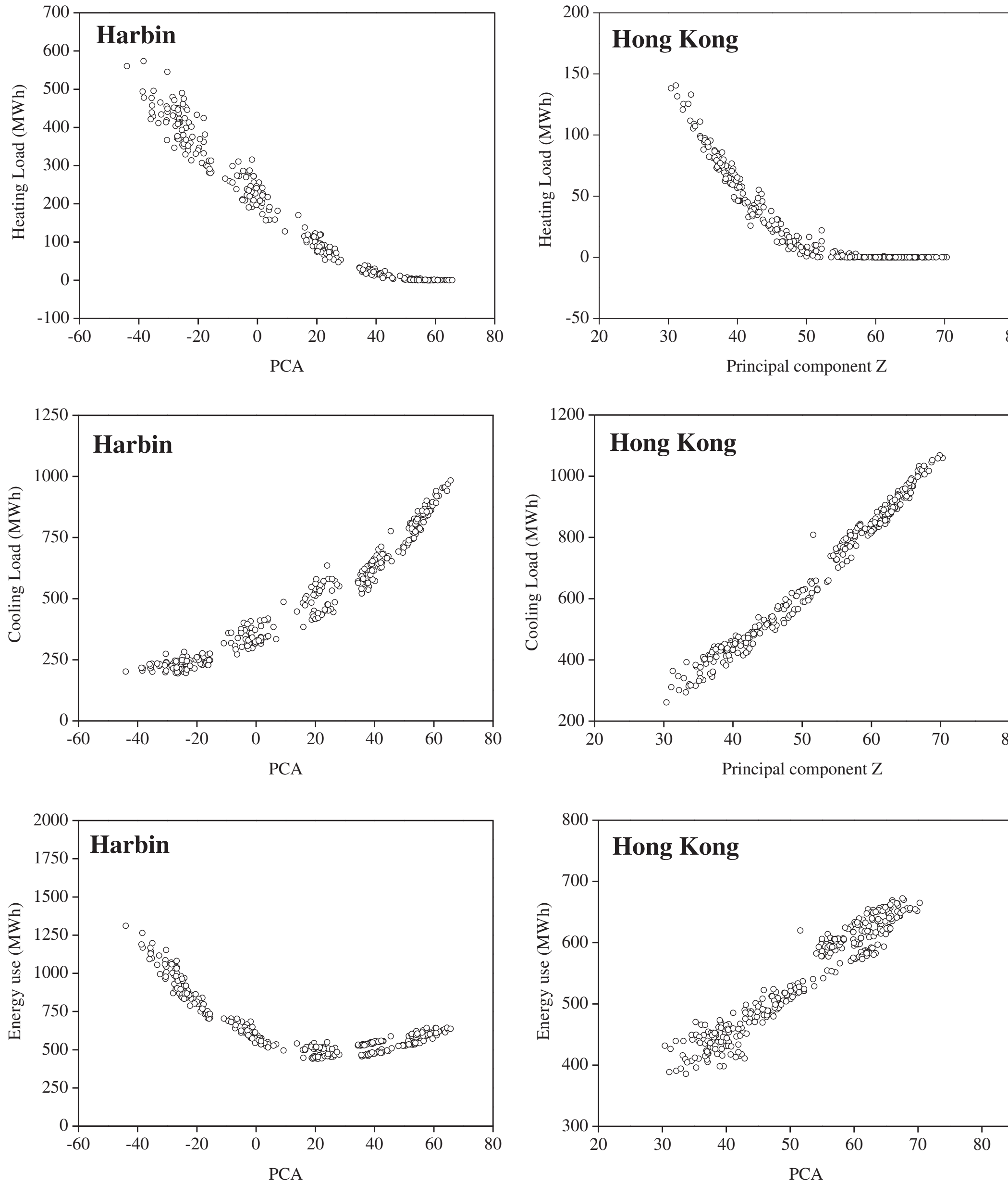

Fig. 5. Correlation between monthly building load/energy use and the corresponding principal component Z (Harbin and Hong Kong).

month) and the corresponding principal component. Only 27 years (1971–1997 for the four mainland cities and 1979–2005 for Hong Kong) data were used, the remaining 3 years being reserved for regression model evaluation. Fig. 5 shows a summary of the correlation for the SRES B1 (low forcing) scenario in Harbin and Hong Kong. It can be seen that both the building loads and energy use correlated quite well with the corresponding Z. A quadratic regression (i.e. $Y = a + bZ + cZ^2$, where Y is the monthly building load/energy use) was obtained for the cooling load, and a 3rd order polynomial (i.e. $Y = a + bZ + cZ^2 + dZ^3$) for the heating load and building energy use. Similar characteristics were observed for the SRES A1B (medium forcing) scenario and for the other cities. A summary of the regression statistics is shown in Table 6. It can be seen that, except energy use in Kunming, the regressions have a rather high coefficient of determination ($R^2 = 0.78–0.99$), indicating reasonably strong correlation between the simulated building load/energy use and the corresponding principal component (i.e. 78–99% of the changes in the simulated results can be explained by variations in the corresponding principal component). Building heating and cooling loads tended to have better correlation (i.e. larger R^2) than total building energy consumption. This is not surprising as the latter included non-weather-sensitive components such as lighting and equipment. The relatively poor correlation for Kunming might be due to its mild climates, resulting in comparatively lower energy use for heating and cooling as well as smaller seasonal variations in the weather-sensitive component of the total building energy consumption [9,10]. Coefficients of the regression models for the low and medium forcing scenarios are very close to each other because the only difference in the two sets of regression analysis is the slightly different monthly Z value

Table 6
Summary of regression analysis of building loads and energy use.

City	Scenario		R^2	a	b	c	d
Harbin	SRES B1	Heating	0.98	216.0	−6.7	0.03	0.0004
		Cooling	0.97	338.5	5.4	0.06	–
		Energy use	0.96	581.5	−8.2	0.19	−0.0007
	SRES A1B	Heating	0.98	215.6	−6.7	0.03	0.0004
		Cooling	0.97	338.8	5.5	0.06	–
		Energy use	0.96	581.1	−8.2	0.19	−0.0007
Beijing	SRES B1	Heating	0.99	208.4	−8.4	0.10	−0.0004
		Cooling	0.98	331.9	5.6	0.06	–
		Energy use	0.78	551.6	−9.5	0.30	−0.0020
	SRES A1B	Heating	0.99	205.1	−8.4	0.10	−0.0004
		Cooling	0.97	334.0	5.8	0.06	–
		Energy use	0.78	547.9	−9.4	0.30	−0.0021
Shanghai	SRES B1	Heating	0.99	337.8	−12.4	0.13	−0.0003
		Cooling	0.99	309.2	−0.7	0.17	–
		Energy use	0.88	640.9	−15.0	0.36	−0.0019
	SRES A1B	Heating	0.99	336.9	−12.4	0.13	−0.0003
		Cooling	0.99	309.5	−0.7	0.17	–
		Energy use	0.88	639.6	−15.0	0.36	−0.0019
Kunming	SRES B1	Heating	0.87	143.4	2.5	−0.29	0.0037
		Cooling	0.87	400.6	−3.9	0.21	–
		Energy use	0.62	573.4	−13.4	0.38	−0.0025
	SRES A1B	Heating	0.87	143.4	2.5	−0.29	0.0037
		Cooling	0.87	400.3	−3.8	0.21	–
		Energy use	0.62	570.8	−13.2	0.38	−0.0025
Hong Kong	SRES B1	Heating	0.98	1001.9	−45.9	0.69	−0.0035
		Cooling	0.99	45.9	3.4	0.16	–
		Energy use	0.94	996.1	−44.1	1.02	−0.0066
	SRES A1B	Heating	0.98	1002.7	−46.0	0.70	−0.0035
		Cooling	0.99	46.8	3.4	0.16	–
		Energy use	0.94	991.6	−43.9	1.02	−0.0066

used for the 2 scenarios (i.e. small difference in the coefficients shown in Table 3).

7. Model evaluation

Performances of the regression models were evaluated. An error analysis was conducted by comparing the simulated results of 1998–2000 (Harbin, Beijing, Shanghai and Kunming) and 2006–2008 (Hong Kong) with those determined from the regression equations using the corresponding principal component. To quantify the differences, mean bias error (MBE) and root mean square error (RMSE) were determined as follows:

$$\mathrm{MBE} = \frac{\sum_{i=1}^{12}(R_i - S_i)}{12} \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{12}(R_i - S_i)^2}{12}} \tag{3}$$

Table 7
Summary of regression model evaluation (SRES B1, low forcing).

City		1998/2006[a]				1999/2007[a]				2000/2008[a]			
		MBE (MWh)	NMBE (%)	RMSE (MWh)	CVRMSE (%)	MBE (MWh)	NMBE (%)	RMSE (MWh)	CVRMSE (%)	MBE (MWh)	NMBE (%)	RMSE (MWh)	CVRMSE (%)
Harbin	Heating load	13.8	10.8	21.3	16.6	7.7	5.4	13.4	9.4	19.7	13.6	28.8	20.0
	Cooling load	−5.3	−1.0	36.7	6.7	0.5	0.1	32.8	6.4	−5.3	−1.0	42.4	8.1
	Energy use	5.9	0.9	26.7	4.2	−5.6	−0.9	29.0	4.6	3.9	0.6	28.3	4.2
Beijing	Heating load	0.9	1.4	5.6	8.9	−0.01	−0.02	6.2	9.7	4.7	6.7	11.5	16.4
	Cooling load	16.8	2.7	40.1	6.5	13.4	2.2	34.2	5.6	4.2	0.7	27.6	4.4
	Energy use	9.5	1.8	33.8	6.3	7.0	1.3	27.5	5.1	−2.8	−0.5	28.5	5.1
Shanghai	Heating load	−1.1	−2.1	10.4	19.6	−0.8	−1.5	6.7	12.2	−2.7	−4.5	9.4	15.4
	Cooling load	3.8	0.6	19.5	3.0	3.6	0.6	21.3	3.6	3.6	0.6	26.9	4.3
	Energy use	−0.1	−0.03	27.8	5.1	5.7	1.1	28.3	5.4	3.2	0.6	29.1	5.4
Kunming	Heating load	3.0	11.1	12.3	45.9	1.5	5.2	13.2	44.5	2.7	8.6	14.1	44.3
	Cooling load	−3.4	−0.6	31.7	5.6	0.6	0.1	23.7	4.2	−4.0	−0.7	26.8	4.9
	Energy use	1.2	0.3	24.5	5.1	1.9	0.4	26.7	5.6	0.6	0.1	25.1	5.3
Hong Kong	Heating load	−0.2	−0.9	3.9	20.4	1.9	12.9	4.5	30.9	0.8	3.1	2.9	11.5
	Cooling load	−10.6	−1.5	25.0	3.6	1.9	0.3	28.7	4.0	−5.6	−0.8	26.0	3.7
	Energy use	−9.8	−1.8	22.5	4.1	2.0	0.4	21.4	3.9	−0.8	−0.15	20.9	3.8

[a] 1998, 1999, 2000 for Harbin, Beijing, Shanghai and Kunming, and 2006, 2007, 2008 for Hong Kong.

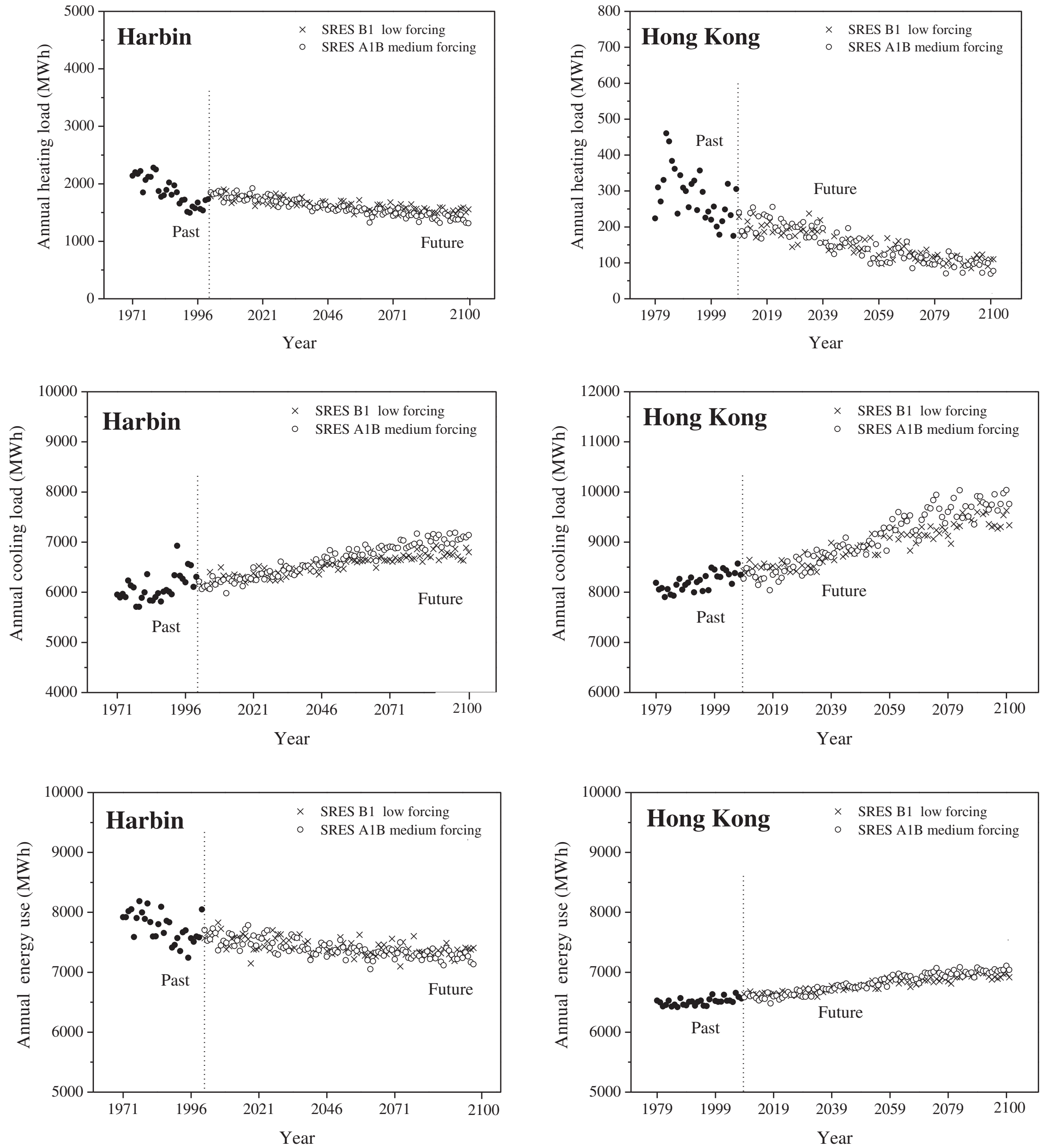

Fig. 6. Long-term trends of annual building load/energy use (Harbin and Hong Kong).

where R_i = regression-predicted monthly data (MWh); S_i = DOE-simulated monthly data (MWh).

MBE provides information on the long-term performance of the modelled regression equation. A positive MBE indicates that the predicted annual electricity consumption is higher than the actual consumption and vice versa. It is worth noting that overestimation in an individual observation can be offset by underestimation in a separate observation. The RMSE is a measure of how close the regression-predicted monthly data are to the DOE-simulated values. Normalised mean bias error (NMBE) and coefficient of variation of the root mean square error (CVRMSE) were also determined by dividing MBE and RMSE by the mean simulated monthly values, and a summary is shown in Table 7 for low forcing. It can be seen that NMBE for the cooling load ranged from 1.5% underestimation in 2006 (Hong Kong) to 2.7% overestimation in 1998 (Beijing). Most of the errors were about 1% or less. Cooling load CVRMSE varied from 3% in 1998 (Shanghai) to 8.1% in 2000 (Harbin). This suggests that while regression-predicted cooling load, on an annual basis, could be very good (mostly about 1% or less), individual monthly values could differ from the DOE-simulated data by up to 8.1% in Harbin. Heating load tended to have much larger percentage errors, especially in Kunming. Total building energy consumption NMBE varied from 1.8% underestimation in 2006 (Hong Kong) to 1.8% overestimation in 1998 (Beijing) (again, most of the errors were 1% or less), and CVRMSE from 3.8% in 2008 (Hong Kong) to 6.3% in 1998 (Beijing). There was no clear pattern indicating whether the regression models would tend to overestimate or underestimate the building load/energy use. Similar characteristics were found for medium forcing.

8. Future trends of building loads and energy use due to climate change

The regression models developed were used to estimate the heating and cooling loads and energy use in future years for the two scenarios (i.e. low and medium forcing). As expected, a decreasing

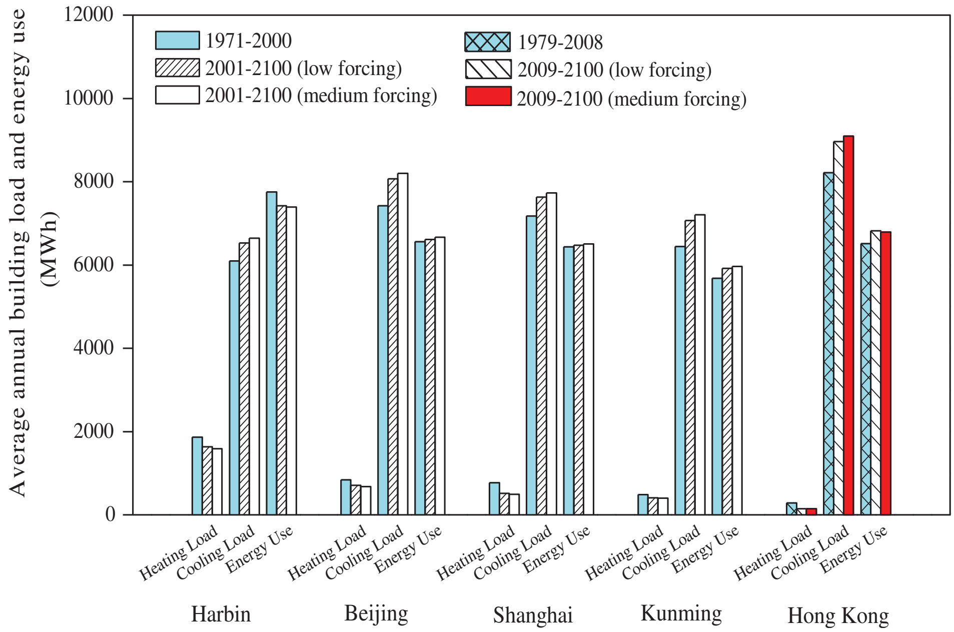

Fig. 7. Comparisons of annual average building load/energy use between past and future years.

trend was observed for the heating load and an increasing trend for the cooling load in all five cities. Fig. 6 shows the long-term trends of the building loads and energy use for Harbin and Hong Kong. In Harbin the total building energy use showed a decreasing trend suggesting that reduction in heating requirements would outweigh the increase in energy use for cooling in future years, and vice versa in Hong Kong. The situation in Beijing, Shanghai and Kunming was similar to Hong Kong. To get a better idea about the impact of climate change on energy use, average building loads and energy use during the 1971–2000 and 2001–2100 periods (1979–2008 and 2009–2100 for Hong Kong) were determined, and a summary is shown in Fig. 7. In Harbin, the average annual heating load in 2001–2100 would be 12.2% and 14.9% less than that in 1971–2000 for low and medium forcing, respectively; cooling load 7.1% and 9% more; and the total building energy use 4.7% and 4.2% less. The overall impact on total building energy use would vary from 4.2% reduction in Harbin to 4.3% increase in Hong Kong for low forcing. In Beijing and Shanghai with substantial heating and cooling requirements, reduction in heating could, to a certain extent, compensate for the increase in cooling, and the average annual building energy use in 1971–2000 would only be about 0.8% and 0.7% higher than that in 2001–2100, respectively, for low forcing. Medium forcing had similar features, but with slightly higher increases/reductions (about 0.5%) than low forcing. It is worth pointing out that, if only the last 30 years (i.e. 2071–2100) were considered, changes in the total building energy consumption would be higher: for low forcing −5.3%, 1.4%, 1.9%, 5.7% and 6.3% in Harbin, Beijing, Shanghai, Kunming and Hong Kong, respectively; and −6.1%, 1.9%, 3.4%, 7.9% and 7.6% for medium forcing.

9. Conclusions

Principal component analysis of three major climatic variables – dry-bulb temperature (DBT), wet-bulb temperature (WBT) and global solar radiation (GSR) – was considered, and a new climatic index (principal component Z) determined for two emissions scenarios (SRES B1 low forcing and SRES A1B medium forcing). Multi-year building energy simulations were carried out for generic air-conditioned office buildings in Harbin, Beijing, Shanghai, Kunming and Hong Kong, representing the five major architectural climates (severe cold, cold, hot summer and cold winter, mild, and hot summer and warm winter) in China. Regression models were developed to correlate the simulated monthly heating and cooling loads and building energy use with the corresponding Z. The coefficient of determination (R^2) was largely within 0.78–0.99, indicating strong correlation between building load/energy use and the corresponding principal component. A decreasing trend of heating load and an increasing trend of cooling load due to climate change in future years were observed. For low forcing, the overall impact on the total building energy use would vary from 4.2% reduction in severe cold Harbin (heating-dominated) in the north to 4.3% increase in subtropical Hong Kong (cooling-dominated) in the south. In Beijing and Shanghai where heating and cooling are both important, the average annual building energy use in 2001–2100 would only be about 0.8% and 0.7% higher than that in 1971–2000, respectively, indicating some compensation between changes in heating and cooling requirements. Similar characteristics were found for medium forcing, but with slightly higher increases/reductions (about 0.5%) than low forcing. If only the last 30 years (2071–2100) were considered, changes in the total building energy consumption could be up to 6.1% reduction in Harbin and 7.6% increase in Hong Kong.

We believe the regression models developed can be used to estimate the impact of climate change on future trends of building heating/cooling loads and energy use in office buildings in different climates based on the monthly predictions (i.e. DBT, WBT and GSR) from general circulation or regional climate models. This would give the building professions and energy/environmental policy makers a good idea about the likely order of magnitude changes in energy consumption in the building sector so that appropriate mitigation measures (e.g. more stringent building energy codes and more energy-efficient building services equipment) could be considered. Although the work was conducted for the five major architectural climates across China, it is envisaged that the approach could be applied to other locations with similar or different climates. Given the growing concerns about climate change and its likely impact on energy use in the built environment, this might have important energy and environmental implications.

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