Applied Energy 184 (2016) 820–829

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Modeling temporal variations in global residential energy consumption and pollutant emissions

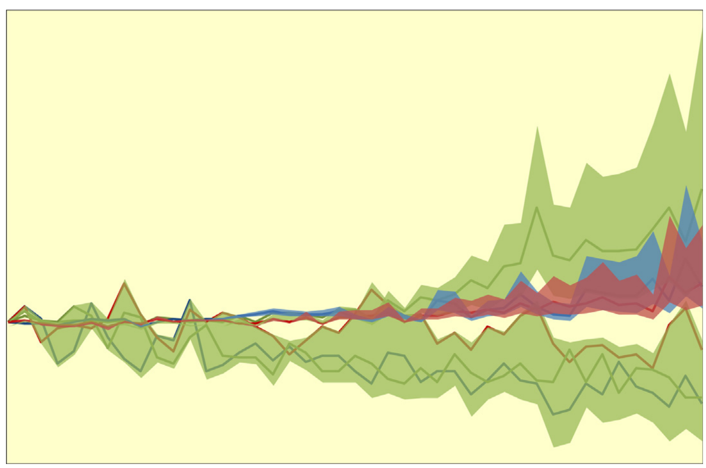
Han Chen, Ye Huang, Huizhong Shen, Yilin Chen, Muye Ru, Yuanchen Chen, Nan Lin, Shu Su, Shaojie Zhuo, Qirui Zhong, Xilong Wang, Junfeng Liu, Bengang Li, Shu Tao *

Laboratory for Earth Surface Processes, College of Urban and Environmental Sciences, Peking University, Beijing 100871, PR China

HIGHLIGHTS

- Space-for-time substitution was tested for seasonality of residential energy.
- Regression models were developed to simulate global residential energy consumption.
- Factors affecting the temporal trend in residential energy use were identified.
- Climate warming will induce changes in residential energy use and emissions.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 8 July 2015
Received in revised form 15 October 2015
Accepted 31 October 2015
Available online 11 November 2015

Keywords:
Residential energy
Seasonality
Pollutants
Emissions
Regression modeling
Climate warming

ABSTRACT

Energy data are often reported on an annual basis. To address the climate and health impacts of greenhouse gases and air pollutants, seasonally resolved emissions inventories are needed. The seasonality of energy consumption is most affected by consumption in the residential sector. In this study, a set of regression models were developed based on temperature-related variables and a series of socioeconomic parameters to quantify global electricity and fuel consumption for the residential sector. The models were evaluated against observations and applied to simulate monthly changes in residential energy consumption and the resultant emissions of air pollutants. Changes in energy consumption are strongly affected by economic prosperity and population growth. Climate change, electricity prices, and urbanization also affect energy use. Climate warming will cause a net increase in electricity consumption and a decrease in fuel consumption by the residential sector. Consequently, emissions of CO_2, SO_2, and Hg are predicted to decrease, while emissions of incomplete combustion products are expected to increase. These changes vary regionally.

* Corresponding author. Tel.: +86 10 62751938.
E-mail address: taos@pku.edu.cn (S. Tao).

http://dx.doi.org/10.1016/j.apenergy.2015.10.185
0306-2619/

1. Introduction

1.1. Energy use in residential sector

Energy production and use are the dominant sources of many air pollutants and greenhouse gases. Temporally resolved emissions inventories are needed to quantitatively assess the public health and climate impacts of these pollutants. The residential sector contributes significantly, not only to ambient and household air pollution [1], but also to temporal trends in energy use and pollutant emissions [2]. In general, the seasonal variability of residential energy use is induced by temperature fluctuations [3]. On the other hand, long-term consumption trends are driven by both climate change and socioeconomic development [4].

Residential energy consumption was responsible for 7.0% and 13.6% of primary and total energy consumption, respectively, globally in 2011 [5]. End-use shares are relatively high in developed countries such as the United Kingdom (29%) [6] and the United States (22%) [7]. In China, end-use energy consumed by residents reached 400 million tonnes of coal equivalent in 2012, which represented 11% of the country's total energy use [8]. Because of relatively low combustion efficiency and no abatement measures various solid fuels in residential stoves, comparing with those in industrial facilities, emission factors (EFs, the mass of pollutants emitted from combustion per unit mass of fuel) of various pollutants, especially the incomplete combustion products, from residential sector are much higher than those in other sectors. For residential stoves using solid fuels, combustion efficiencies are often very low and there is no abatement device at all. As a result, emission factors (EFs, the mass of pollutants emitted from combustion per unit mass of fuel) of various air pollutants, especially the incomplete combustion products, for the residential sector are much higher than those for other sectors. Therefore, residential energy use contributes relatively large shares of emissions of many air pollutants, although this sector contributes only a relatively small fraction of total primary energy consumption. For example, 32.6%, 88.6%, and 21.5% of the global emissions of black carbon (BC), benzo(a)pyrene (BaP), and primary particulate matter less than 2.5 μm ($PM_{2.5}$), respectively, come from residential fuel burning [9–11]. Therefore, quantification of residential energy use and pollutant emissions are critical for a better understanding of air pollution.

1.2. Temporal variation of residential energy consumption

Temporally resolved energy consumption data are essential to the development of emissions inventories [12]. The significant contributions of residential energy use to emissions and the impact of that use on the temporal variation of emissions necessitate an increased understanding of the seasonal and interannual trends of energy consumption. Unfortunately, energy consumption statistics are often provided on an annual basis. To our knowledge, such information on a global scale does not exist. With the exception of a few developed countries [13–16], it is difficult to find information on the seasonal variation of residential fuel and electricity consumption, especially in the developing world, where the majority of air pollutants are emitted [1,17].

Attempts have been made to address this issue by modeling the temporal variation of energy consumption. In many cases, simple interpolation has been used to derive seasonal energy consumption and CO_2 emissions. For example, data on monthly natural gas deliveries in the United States were used in one study as a proxy for residential fuel consumption and CO_2 emissions [18]. This method is difficult to apply in developing countries due to the diversity in heating fuels and data gaps. Similarly, a full accounting approach was used to estimate monthly CO_2 emissions in individual states of the United States [19], and a proportional method was developed to generate monthly CO_2 emissions from fossil fuel sources on a global scale [13]. A 2-harmonic Fourier series was also applied to simulate the seasonal variation of global CO_2 emissions from anthropogenic sources by using latitude-dependent parameters developed from monthly energy use statistics in the United States [20].

Regression models are often useful for quantifying temporal trends. Most modeling exercises conducted thus far have focused on a single country or a part of a country [21]. For example, econometric autoregressive models were developed to derive robust elasticity coefficients for various economic indicators and to provide both short- and long-term predictions for Spain [22], the United States [23], and Thailand [24]. Many parameters such as income, expenditures, climate, and lag terms based on historical data are often adopted as independent variables. In addition to climate and socioeconomic factors, household characteristics such as floor space, appliance ownership, and operating frequency are often taken into consideration using data from household surveys [25,26]. Although these regression models can provide refined predictions, they are difficult to apply in developing countries, where similar survey data are rare. In addition to simulating monthly and diurnal variations in energy consumption, these models have been used to predict future trends under the influence of various climate change at various scenarios [27], serving as a supplement to physical simulations [28,29].

Several studies of energy consumption have been conducted at the multi-national or global scale. For example, a general moments method used energy statistics panel data obtained from the IEA for the 1978–2000 period to estimate the long-term elasticity of temperature related to energy consumption in the industrial, residential, and commercial sectors of OECD and several non-OECD countries [30]. The study analyzed data on coal, petroleum, natural gas, and electricity and found that temperature change would have impacts on residential energy consumption and would slightly influence the service and industrial sectors in these countries. Temperature elasticities associated with demand for different energy goods were also studied for 31 countries, and the inherent interactions between temperature and personal income were explored [31]. The study revealed that the intensity of the relationship varies with temperature in a non-linear and discontinuous pattern and that electricity consumption in hot and cold countries are more sensitive to summer and winter temperatures; no major differences in coal and gas use changes were observed between country categories. Additionally, households with higher incomes tended to be more responsive to temperature change.

Of the few studies that have analyzed global data, Petrick et al. [21] expanded on De Cian's study [31], which used four regression equations to analyze temperature-derived variables. More recent work by Isaac and van Vuuren [32] has focused on the impact of climate change on the relationship between worldwide household heating and cooling energy consumption and CO_2 emissions. Energy demand theory and a number of country-specific temperature-derived variables, including heating degree days (The number of degrees that a day's average temperature is below a base temperature and people start to use heating facilities, *HDD*), cooling degree days (The number of degrees that a day's average temperature is above a base temperature and people start to use cooling devices, *CDD*), and unit energy consumption (*UEC*), have also been used to project future energy consumption and CO_2 emissions for scenarios generated by the TIMER/IMAGE model [33].

Zhu et al. have proposed a space-for-time substitution method to fill the data gaps in temporally resolved energy consumption in residential sector [4]. To do so, a hypothesis assuming that the major factors affecting spatial and temporal variations of residential energy consumption are similar was successfully tested. Based on this assumption, spatially resolved data were collected and used to develop two regression models for residential electricity and fuel consumptions in China and the models were then applied to simulate temporal variations successfully [4]. It was revealed that quantities of residential fuel consumption was significantly affected by both *HDD* and heating days (The number of days, the mean temperature of which is above a base temperature and people use heating facilities, *HD*), while residential electricity consumption depends strongly on income, urbanization rate (*R*u), and *CDD* [4].

1.3. Objectives

The primary objectives of this study were (1) to test the hypothesis that factors affecting spatial and temporal variations of energy consumption are similar to each other at global scale; (2) to develop statistical models using the space-for-time substitute method for predicting the amounts of electricity and fuels used in residential sector at global scale; and (3) to project temporal, as well as spatial variations of air pollutant emissions. The result can be used in atmospheric chemical transport modeling as important input. To be specific, models were developed based on spatial data and validated against temporal data. The evaluated models were applied for the following purposes: (1) simulate past (1960–2011) and future (2012–2050) intra- and interannual variations in residential electricity and fuel consumption, (2) calculate CO_2 emissions and a number of air pollutants generated by the residential sector, and (3) derive climate warming-induced net changes in residential energy use and emissions.

2. Methodology

2.1. Modeling

Stepwise regression was applied to model the dependence of per capita residential electricity (*E*cap) and fuel (*F*cap) consumption. Bidirectional elimination was applied to have a better test and 0.05 and 0.10 were used as criteria for including or excluding variables, respectively. Physical and socioeconomic parameters to be tested were selected based on a literature review and a series of correlation analysis to identify major factors affecting the residential energy use. The selection was also affected by data availability. For example, house units (*H*, average number of houses owned by a resident) are not available for most countries except the United States. The parameters finally used include per capita residential electricity (*E*cap) and fuel (*F*cap) consumptions, per capita income (*I*cap), per capita gross domestic product (*G*cap), *HD*, *HDD*, *CDD*, *R*u, electricity price (*P*e), gas price (*P*g), *H*, and mean floor area per capita (*F*). All parameters involved are listed in Table S2 together with *p*-values derived from the regression analysis for all variables tested and 95% confidence intervals for all variables selected. The variables were either arithmetic or ln-transformed. In some cases, a product of two independent variables was used to characterize the interaction of those variables based on a series of trial-and-error. These parameters were selected from the literature based on their influences on energy use.

Variance inflation factor (VIF) were calculated as collinearity statistics the results are listed in Table S3 together with other parameters for evaluating the models. In most cases, collinearity of variables was not substantial with exception of a few. For example, relatively high VIF values were found for the two models for China, which are adopted from another study [4]. On the other hand, exogeneity of the independent variables cannot be totally ensured. Both collinearity and endogeneity can lead to uncertainty of the models to certain extent, which is the major limitation of the models and should not be overlooked.

Since unified models could not be satisfactorily derived, likely because of substantial differences in the dependence of energy consumption on socioeconomic conditions among countries and between electricity and fuels, a set of models were developed electricity and fuel separately for various country categories using a trial-and-error approach. Single-country models were developed for the large countries with sub-national data available. The other countries were pre-groups based on their similarity in energy mix and consumption such as cooling and heating needs. The criteria is to achieve the best fitting.

For electricity, seven models was developed: (1) China (modified Zhu's model) [4]; (2) the United States; (3) Australia; (4) other developed countries with cooling needs; (5) other developed countries without cooling needs, except Canada; (6) other developing countries with cooling needs; and (7) other developing countries without cooling needs. Similarly, five regression models were developed for fuels: (1) China [4]; (2) the United States; (3) Australia; (4) other developed countries, except Canada; and 5) other developing countries. For the last category, data for 17 small countries representing 4% of total fuel use did not fit well and were excluded. The country categories are listed in Table S4. With many rounds of trail-and-error, electricity and fuel consumptions of Canada cannot be modeled separately. In fact, neither electricity nor fuel consumption in Canada is correlated with *hdd*. Therefore, an electricity-fuel combined model has to be applied. It is likely due to the unique feature of energy mix in Canada which are rich in both hydropower and fossil fuel and are quite different among provinces.

National (for multi-nation models) or subnational (for single-nation models) fuel and electricity consumption data from 2001–2008 were from the International Energy Agency and national statistics. [7,34–36]. For *HDD*, 5 °C and 15 °C were adopted as the base temperatures for developing and developed countries, respectively [4,37]. Similarly, base temperatures of 18 °C and 25 °C were chosen for *CDD* for the two country categories [4,38]. Monthly national/provincial *HDD* and *CDD* were calculated based on population-weighted, gridded temperature data. Globally gridded ($0.1° \times 0.1°$) temperature (6-h resolution) and population data came from NOAA–NCEP/NCAR and the Oak Ridge National Laboratory, respectively [39,40]. *R*u and purchasing power parity adjusted *G*cap and *I*cap came from the World Bank and national statistics [41–45]. *P*e came from the IEA and Eurostat [46,47]. *H* values for the United States came from the US Census Bureau [48].

2.2. Model validation

The regression models developed using spatial data were validated for predicting temporal variation. To do so, the monthly electricity or fuel consumption data for several countries were collected from the literature [49–58] and are compared with the model predicted monthly energy consumption.

Data limitations restricted this study's evaluation to several countries with available seasonal data. For these countries, models developed based on annual national data were evaluated against monthly *E*cap and *F*cap [49–58].

2.3. Simulation

Historical (1960–2011, monthly) and future (2012–2050, annual) temporal trends in electricity and fuel consumption were simulated. Three IPCC (Intergovernmental Panel on Climate Change) scenarios, A1B, B1, and A2, were included in the future simulations [59]; climate warming-induced net changes (defined as the difference between situations with or without climate change) in residential electricity and fuel consumption were calculated.

Future predictions for country populations, Gcap, gridded monthly temperature data for the three scenarios, and the Pe and Pg of developed countries were from the literature [60–62]. Gcap and Icap were adjusted for purchasing power parity [63]. It was assumed that future electricity markets would be saturated when Gcap reaches 80,000 USD [32]. For temporal simulations, the calculated monthly results were adjusted based on annual data from the literature to avoid bias.

2.4. Emission estimation

Emissions of CO_2, CO, SO_2, NOx, PM_{10} (particulate matter less than 10 m), $PM_{2.5}$, BC, OC (organic carbon), PAHs (polycyclic aromatic hydrocarbons), BaP, and Hg were calculated. The results were derived by multiplying the amount of fuel consumed and country specific EFs. The EFs were from a previous study [4]. Amounts of fuel used for electricity generation were derived based on the relative contributions of various fuel types, including renewable energy, to power generation and the generating efficiencies of individual countries, which were derived based on the fuel consumption and total electricity and heat production of power plants [5]. CO_2 emissions from biomass fuels were excluded because of carbon neutrality [64]. For future simulations, the relative contributions of various fuels to electricity generation were taken from the literature [65].

2.5. Uncertainty analysis

A Monte Carlo simulation was conducted to characterize overall uncertainty. The simulation was run 5000 times with parameters randomly selected from normal distributions; the coefficient of variation equaled 0.05 in 2008 and linearly increased to 0.2 by 2050 [4]. The results are presented as ranges between the 25th and 75th percentiles, showing pre-defined uncertainty range of the model simulated values.

3. Results and discussion

3.1. Modeling residential electricity consumption

Variation in electricity consumption is often associated with cooling and heating requirements, which depend strongly on weather and socioeconomic factors. The influence of temperature on electricity consumption is often quantified using *HDD* and *CDD* [32]. Based on the results of a correlation analysis, associations between electricity consumption, temperature, and a number of socioeconomic parameters were identified (Table S5). For example, a positive correlation ($p < 0.05$) was found between Ecap and *CDD* rather than *HDD* in certain developing countries, where air conditioners for cooling are becoming popular among fast-growing middle-class families. However, these air conditioners are seldom used for heating because cheap fuels are often readily available [66]. Both air conditioners and electric heaters are popular in many developed countries [50,52]. For these countries, a significant correlation ($p < 0.05$) was found between Ecap and *HDD* or *CDD*.

Among various socioeconomic parameters tested, Gcap significantly correlated ($p < 0.01$) with Ecap for both developing and developed countries. A correlation between Ecap and economic development has also been reported in the literature [67]. For a similar reason, Pe appears to play a role in electricity consumption. However, a significant correlation ($p < 0.01$) between Ecap and Pe was only identified for developed countries, likely due to the fact that Pe in many developing countries are not market based. Although the dependence of electricity consumption on Pe should be more sensitive to lower incomes, Pe in developing countries is often skewed by government subsidies [68]. For example, residential electricity in China is sold at relatively constant prices over years, while production costs vary extensively together with fuel prices [69]. A significant correlation was found between Ecap and Ru ($p < 0.05$) for developing countries, where differences between rural and urban areas are more pronounced than that in developed countries [70]. It has been reported that Ru may be used as a proxy for richness to explain the effect of living standard on electricity use, which may not be fully captured by income [71].

Based on the analysis above and a process of trial-and-error, models were established for Ecap (tonnes of oil equivalent/cap, toe/cap) related to seven country categories. The units of the independent variables are Icap and Gcap (RMB/year for China and USD/year for other countries), Pe (USD/MW h), Pg (USD/MW h), H (house/capita), and Ru (%). Ecap and most independent variables are ln-scaled, indicating linear relationship in terms of orders of magnitude among them, with exception of Ru and the product term.

(1) $\ln Ecap = 0.768\ \ln Icap + 6.59 Ru + 1.75 \times 10^{-6}\ CDD_{25} \cdot Icap - 11.512$, $n = 163$, $R^2 = 0.88$
(2) $\ln Ecap = -0.629\ \ln Pe + 0.962 \ln H + 2.60 \times 10^{-3} CDD_{18} + 5.08 \times 10^{-4}\ HDD_{15} - 1.40$, $n = 1224$, $R^2 = 0.64$
(3) $\ln Ecap = 0.425\ \ln Icap - 0.337 \ln Pe + 2.27 \times 10^{-6}\ HDD_{15} \cdot Icap + 4.05 \times 10^{-7}\ CDD_{18} \cdot Icap - 6.74$, $n = 120$, $R^2 = 0.76$
(4) $\ln Ecap = 0.476\ \ln Gcap - 0.685 \ln Pe + 4.83 \times 10^{-7}\ HDD_{15} \cdot Gcap + 8.16 \times 10^{-7}\ CDD_{18} \cdot Gcap - 6.56$, $n = 103$, $R^2 = 0.70$
(5) $\ln Ecap = 0.773\ \ln Gcap - 0.762 \ln Pe + 6.01 \times 10^{-7}\ HDD_{15} \cdot Gcap - 8.60$, $n = 112$, $R^2 = 0.80$
(6) $\ln Ecap = 0.923\ \ln Gcap + 10.6\ Ru + 4.47 \times 10^{-6}\ CDD_{25} \cdot Gcap - 12.5$, $n = 380$, $R^2 = 0.80$
(7) $\ln Ecap = 0.152\ \ln Gcap + 1.23 \times 10^{-6} HDD_5 \cdot Gcap - 6.45$, $n = 99$, $R^2 = 0.62$

Model-simulated Ecap values are plotted against those from the literature in Fig. S1 and the variation is well explained. The means and standard deviations of relative deviations (RD), defined as the absolute model residues divided by the true values, were calculated as 14.5 ± 12.3, 16.7 ± 13.2, 8.8 ± 5.2, 13.49.52, 22.9 ± 16.3, 30.5 ± 42.4, and 10.9 ± 9.11% for the seven models. Of all of the variables, Gcap or Icap appear to be the most important in positively affecting electricity consumption, except in the model for the United States. Several other studies have also found relatively small or negligible income elasticity coefficients in residential electricity consumption models for the United States [72]. No negative influence of Pe on electricity consumption in developing countries was observed [4,31]. Large differences between urban and rural areas made Ru an important factor in the model for developing countries with cooling needs. H was suggested as a proxy for stock of home appliances in the United States [73], and the models for the United States and Canada were significantly improved when this parameter was introduced. Electricity used for heating or cooling was explicitly represented by *HDD* and *CDD*. Most models could be improved by including the product of a temperature parameter (*HDD* or *CDD*) and an economic factor (Gcap or Icap), revealing a

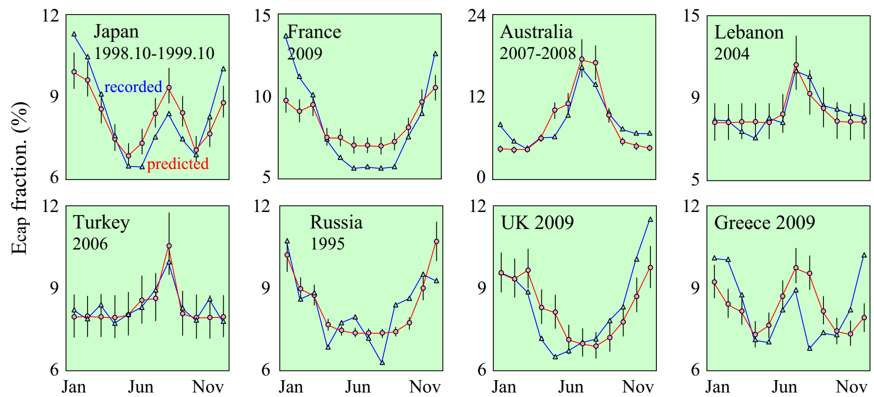


Fig. 1. Comparison of model-calculated and observed monthly electricity consumption in eight countries. The data are normalized as fractions (*F*). The results are shown in percentages of monthly electricity consumption over the annual total.

positive interaction. This suggests that factors such as *CDD* and *I*cap do not act independently or cumulatively and that their impacts are non-linear. Similar interactions have been reported [4,31].

The models were evaluated by comparing monthly *E*cap of eight countries between the model calculated and literature reported values [49–56], suggesting reasonably good agreement with relative differences between 70% of the data below 10% (Fig. 1).

3.2. Modeling residential fuel consumptions

The results of the correlation analysis between fuel consumption, temperature, and several socioeconomic parameters are shown in Table S3. There was a significant positive correlation ($p < 0.05$) between *F*cap and *HDD* for all country categories. A similar relationship was reported in many other studies [74]. A positive correlation ($p < 0.05$), albeit not as significant as that between F_{cap} and *HDD*, was also shown between *F*cap and *G*cap, which can be explained by the fact that households with relatively high incomes often occupy relatively large floor areas and use more fuel for heating [32]. Unlike with electricity, the influences of other socioeconomic factors such as fuel price and *R*u on fuel consumption were not found. This is because both fossil and biomass fuels are widely used; the latter are difficult to price and often associated with accessibility [75,76]. Accordingly, *F*cap (toe/cap) models were developed for five country categories. Unlike the electricity models, the dependent variable of the fuel models was not logarithmic transformed, and orders of magnitude variation in *I*cap and *G*cap can cause changes of *F*cap on arithmetic scale.

(1) $F\text{cap} = 5.93 \times 10^{-5}\, HDD_5^{0.9} + 3.89 \times 10^{-4}\, HD_5 + 0.012,$ $\quad n = 163,\quad R^2 = 0.66$

(2) $F\text{cap} = 2.33 \times 10^{-4}\, HDD_{15} + 1.95 \times 10^{-4} Pe - 0.058,$ $\quad n = 100,\quad R^2 = 0.83$

(3) $F\text{cap} = 2.56 \times 10^{-4}\, HDD_{15} - 3.11 \times 10^{-4}\, Pg + 1.91 \times 10^{-4}\, Pe - 8.32 \times 10^{-4},$ $\quad n = 70,\quad R^2 = 0.84$

(4) $F\text{cap} = 1.18 \times 10^{-4}\, HDD_{15} + 1.24 \times 10^{-2}\, \ln G\text{cap} - 2.77 \times 10^{-4}\, Pg + 1.59 \times 10^{-4}\, Pe - 0.084,$ $\quad n = 189,\quad R^2 = 0.71$

(5) $F\text{cap} = 3.64 \times 10^{-4}\, HDD_5 + 5.11 \times 10^{-3}\, \ln G\text{cap} - 0.025,$ $\quad n = 180,\quad R^2 = 0.77$

Unlike electricity consumption, fuel consumption was modeled more accurately without a log-transformation. The means and standard deviations of RDs are 18.0 ± 16.5%, 18.4 ± 16.6%, 34.4 ± 26.2%, 44.3 ± 58.6%, and 43.5 ± 69.6% for the five models, respectively. The relationships between model-simulated and recorded *F*cap are shown in Fig. S2.

For all models, *HDD* is the most important variable and explained 64.8% and 74.3% of total variations for developed and cold developing countries, respectively. Regression coefficients of the models varied within a relatively small range, with the exception of China, for which a relatively low elasticity was attributed to the introduction of an extra variable, HD_5, which is correlated with *HDD* ($p < 0.05$). According to Zhu et al., HD_5 was introduced because a minimum amount of fuel (initial fuel) is always needed to start a fire for heating, no matter how far the temperature is below the base temperature [4]. Regression coefficients for the *HDD* of developing countries are generally higher than those for developed countries, likely because of the strong dependence of the former on fuel for heating, whereas electricity is commonly used for this purpose in developed countries [77]. *G*cap appears in several models owing to its positive influence on floor area, except in Australia and China. Australians have the largest per capita living area of any country, leaving no room for further increase as *G*cap grows [78]. In China, there is often easy access to free biomass fuels [4]. The significance of *G*cap indicates that *F*cap varies among countries within similar climate zones but different development success. For instance, *F*cap for Albania (0.093 toe/cap) was less than that for Bulgaria (0.175 toe/cap), which is in the same climate zone [5] but is less economically prosperous (*I*cap 7216 vs. 11,985 USD in 2008). Similarly, although both countries are within the Mediterranean region, Turkmenistan (*I*cap 6497 USD; *F*cap 0.09 toe/cap) consumed much less fuel than Turkey (*I*cap 12,405 USD; *F*cap 0.27 toe/cap) [5].

The *F*cap models were evaluated against monthly resolved data to perform seasonal simulations. Fig. 2 compares the calculated and literature-based monthly average *F*caps for three countries [51,57,58] and reveals good agreement in the winter peaks.

Canada is enriched with almost all energy types, including petroleum, coal, natural gas, uranium, and hydropower [36], which gives it a more diverse energy consumption pattern. According to the results of a household survey, 47% of households in Canada use natural gas as their main heating fuel, while 37% use electricity [79]. Neither *E*cap nor *F*cap is individually correlated with *HDD* or *I*cap because neither electricity nor fuels dominates residential energy use. Therefore, the two energy types had to be modeled together using the following equations for total per capita energy consumption (*T*cap) and the ratio of electricity consumption to *T*cap ($R_{E/T}$), in which *T*cap, *Pe*, and *H* are ln-transformed similar to the electricity models:

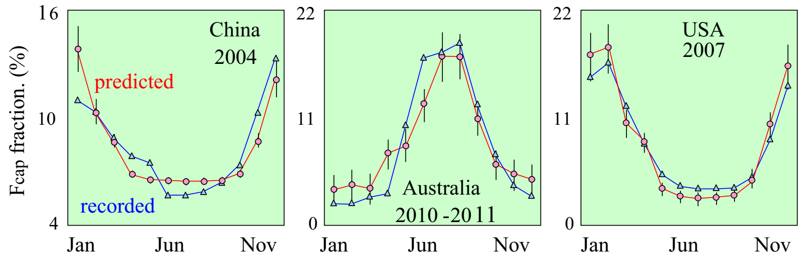


Fig. 2. Comparison of model-calculated and observed monthly fuel consumption for three countries. The data are normalized as fractions (*F*). The results are shown in percentages of monthly fuel consumption over the annual total.

$$\ln Tcap = 0.363\ \ln Pe + 1.551 \times 10^{-3}\ HDD_{15} - 3.624, \qquad n = 80, \quad R^2 = 0.808$$

$$R_{E/T} = -0.410\ \ln Pe + 2.146\ \ln H + 3.212, \qquad n = 80, \quad R^2 = 0.698$$

As expected, *T*cap in Canada is dependent on both HDD_{15} and *G*cap, and there was an interaction between the two variables. The model for $R_{E/T}$ is similar to the electricity model for the United States. The mean with standard deviation of RD for ln*T*cap is 7.21 ± 5.65%.

3.3. Historical trends in energy consumption and emissions

The models developed here can be used to simulate seasonal variations in energy consumption and pollutant emissions. The calculated monthly results were adjusted based on real data on an annual basis. The time series of *E*cap for 10 large countries, either developed or developing, were calculated for the period 1960 to 2011 at a monthly resolution (Fig. S3A) and serve as typical examples. There was an increasing trend of *E*cap for all countries except Russia. In Russia, *E*cap decreased beginning in 2004 as a result of an electricity market reform that came into effect, and electricity tariffs in the residential sector began to increase [80]. In all developed countries, the increasing trends have slowed or plateaued recently, likely because of a saturation of appliances, efficiency improvements, and the economic depression of 2008–2009 [81]. Although *E*cap showed strong seasonality in all countries, the patterns varied. In high-latitude countries such as Russia and Poland, electric heaters supplement fuel stoves, especially on extremely cold days [82], and result in strong winter peaks in electricity use. Similar winter peaks are evident for Germany and France, where electric heaters are popular [22]. Although winters in most of Germany and France are much warmer than those in Russia, more Russian households rely on less expensive fuels than electricity for heating. Therefore, the winter *E*cap peaks in Russia (27.8% higher than other months) were much smaller than those in Germany and France (15.9% and 9.6% higher, respectively). Additionally, the winter peaks for these two countries were wider than those for Russia and Poland, owing to differences in willingness to pay more for heating. It was reported that the deviations of residential electricity consumption from the annual average in Hong Kong were −2.8% and 5.8% in January and July, respectively [83], which varied slightly from our estimations of −3.0% and 3.7%.

For developing countries where summers are hotter and winters are warmer than in Russia, here represented by China and Turkey, *E*cap peaks occurred in the summer from July to August. For India, neither a winter nor a summer peak was recognized. Because this country is located in a warm climate zone, heating is not needed. On the other hand, although India is the hottest of the nine countries studied, air conditioners are not widely used, largely owing to relatively low incomes [84]. The seasonality of *E*cap in the United States and Japan differed from that of other countries, featuring two peaks per year. Electricity is heavily used for both heating in summer and cooling in winter in these two countries. Because of the difference in meteorological conditions, summer peaks in the United States were much higher than those in winter, while the opposite was true in Japan.

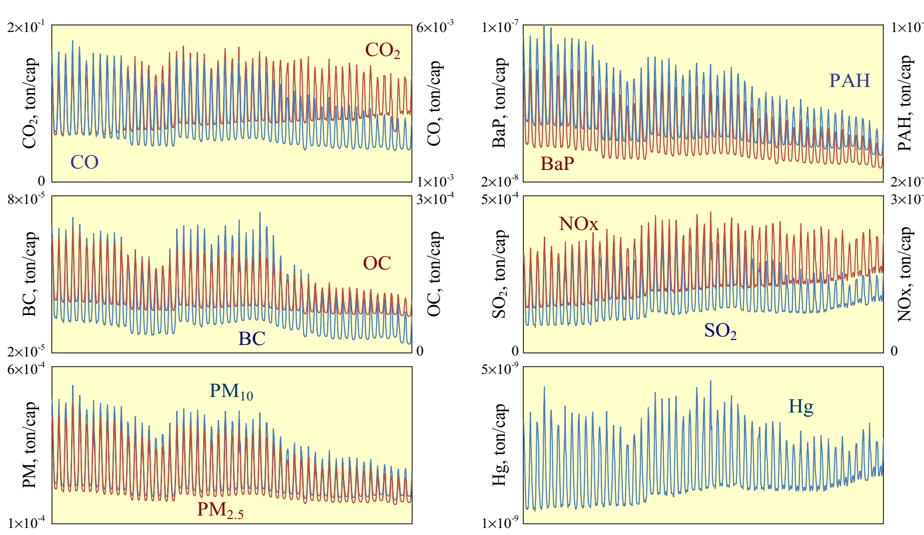


Fig. 3. Historical variations in global per capita emissions of CO_2, CO, BC, OC, PM_{10}, $PM_{2.5}$, PAHs, BaP, SO_2, NOx, and Hg from 1990 to 2011. The pollutants are grouped according to scale.

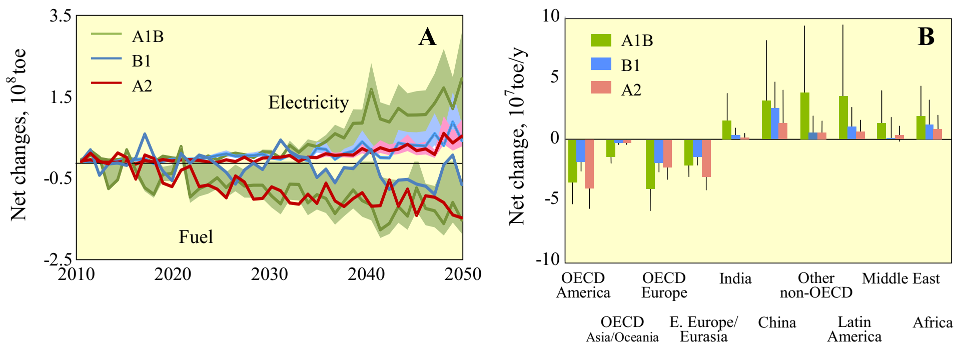


Fig. 4. Net effects of climate warming on global energy consumption. (A) Future trends for A1B, B1, and A2 scenarios. The results are presented as medians (curves) and semi-interquartile ranges (shaded areas, only A1B for fuel) from the Monte Carlo simulation; (B) Predicted net effects of climate warming on energy consumption in various regions for A1B, B1, and A2 scenarios in 2050. Uncertainties from the Monte Carlo simulation are shown as the 25th and 75th percentiles.

Similarly, temporal variations of *F*cap from 1960 to 2011 are shown for 10 countries in Fig. S3B. As with *E*cap, there were slight increasing trends in *F*cap for most countries, reflecting the influence of income. For nine of the countries, the seasonality of *F*cap dominated the temporal variation, causing strong winter peaks. Those peaks were 43.2% (China) to 75.5% (Russia) higher than the values in other months. The only exception was India, where heating is not needed.

Temporal variations in the per capita emissions of air pollutants from 1990 to 2011 were calculated (Fig. 3). The trend in CO_2 emissions is similar to that reported previously [20]. In terms of seasonal and interannual variations, emissions of CO_2, SO_2, Hg, and NOx as fuel compositions or higher-temperature products correlated with electricity consumption, while emissions of incomplete combustion products correlated with fuel consumption. In general, seasonal variations in emissions within a country were strongly temperature dependent, whereas interannual variations were both climate- and socioeconomically driven. The results agree well with the limited data available in the literature. For example, based on the measured CO_2 flux at a residential site in Seoul, Korea, it was found that fluxes in January were 3.7 times higher than those in June [85], which is similar to our result (4.7 times). The BC emissions from the Chinese residential sector in January and July of 2008 contributed 14.5% and 6.2% of the annual total, similar to those calculated (19.25% and 5.75%) [86] based on an assumption proposed in TRACE-P [87].

3.4. Future simulation and net influence of climate change

Based on projected changes in temperature, population, *G*cap, *I*cap, *R*u, *P*e, and *H*, global temporal trends in electricity and fuel consumption were simulated from 2012 to 2050 for the A1B, B1, and A2 IPCC scenarios (Fig. S4A). The results indicate that globally, there will be a sharp increase in *E*cap from 0.06 toe/cap in 2008 to 0.196, 0.146, and 0.10 toe/cap in 2050 for the three scenarios, respectively. The annual increase rates range from 2.0% to 3.4%, which are comparable to the rate of 2.7% predicted by Nezhad [88]. The relative contributions of various factors to the increases in residential energy consumption were quantified by calculating differences with and without changes of individual parameters. Fig. S4B shows the relative contributions of individual factors to total electricity and fuel consumption from 2012 to 2050. Total electricity consumption was most affected by *I*cap followed by population growth, with positive influences from *R*u and climate warming and a negative influence from *P*e accounting for a relatively small fraction of the total change. For A1B, income growth was the most important factor positively driving changes in fuel consumption, followed by income and climate warming (negative effect).

The net effects of climate change on energy consumption were calculated (Fig. 4A). An increase in temperature will promote electricity use and reduce fuel consumption. However, there will be almost no change in electricity consumption until 2030, after which there will be a sharp increase in the A1B scenario because of rapid increases in population and income. Residential fuel consumption will decline almost constantly over the entire period, with slight differences among the scenarios, which differ in temperature. Climate change-induced shifts in residential energy consumption will not be evenly distributed in space. Fig. 4B shows net changes in 2050 for 10 regions. Although energy consumption will increase under the A1B and B1 scenarios and decrease under the A2 scenario globally, there will be negative changes in the OECD and eastern European countries in all three scenarios, owing to decreasing heating demands in the future. For almost all developing countries, climate warming will lead to substantial increases in cooling electricity use. It was estimated that climate warming-induced changes in residential energy consumption in Canada, the United States, Russia, and India would range from −4.7 to −2.7, −33 to −9, −23 to −9.7, and 1.1 to 14 Mtoe, respectively, in 2050, which are comparable with estimates reported in the literature (−3.58, −11.9, −10.8, and 5.1 Mtoe) [32]. Similar results for the effects of climate change on household energy consumption have been previously reported on regional scales. By assessing climate warming-induced changes in heating and cooling energy consumption in Finland, it was found that total energy consumption would be reduced by −11.2%, −11.7%, and −13.6% under A1B, B1, and A2 scenarios in 2050, respectively (our predictions were −12.9, −4.5 and −10.8%, respectively) [89]. It was also reported that climate warming would lead to a 45% rise in cooling energy use in Miami under the medium emission scenario (A2), which is similar to our estimation of 35% [90].

As shown in Fig. S5, the increase in temperature and cooling demand under all three scenarios will increase residential CO_2 emissions in developing countries, which would be countered by a decrease in emissions from developed countries prior to 2035 (A1B); thereafter, emissions will increase globally. The net increase in CO_2 emissions will be 367, 125, and 167 Mt in 2050 according to the A1B, B1, and A2 scenarios, respectively. These trends are similar to those projected by Isaac and van Vuuren [32]. Emissions of incomplete combustion products are often dominated by solid fuel combustion in the residential sector [9–11]. As a result, future climate warming will reduce fuel consumption and associated emissions of BC and other incomplete combustion products. For example, BC emissions will have decreased by 83, 135, and 25 kt in 2050 under the A1B, B1, and A2 scenarios, respectively.

Again, these changes will vary by region. Taking the A1B scenario as an example (Fig. S6), the most prominent reductions of CO_2 emissions will occur in Russia (−40.2 Mt) and the United States (−37.6 Mt), while emissions will increase in China (143.8 Mt), India (67.7 Mt), and other developing countries; these estimates agree well with other values reported in the literature [32,91]. For incomplete combustion products, climate warming-driven reductions of emissions will occur in almost all countries, except those in tropical and subtropical regions where heating is not currently required.

4. Conclusion

The space-for-time substitution approach was successfully applied at the global scale to simulate both seasonal and inter-annual temporal trends in residential fuel and electricity consumption based on data collected from different countries and regions. The important factors affecting temporal trends in electricity and fuel consumption were identified. As a result of climate warming, residential electricity consumption for cooling will increase, while residential fuel consumption for heating will decrease, resulting in a net increase in CO_2 emissions and a net decrease in BC, PAHs, and $PM_{2.5}$ emissions. The models may also be used to quantify the dependence of fuel consumption and pollutant emissions on socioeconomic factors, which is important to policymakers interested in formulating abatement strategies.

Since the residential energy consumption related pollutant emission contributes significantly to the total emission, abatement strategy in this sector should be formulated. This is particularly true for developing countries. According to the results of this study, the emission depends strongly on both temperature and socioeconomic factors. Although economic development and urbanization will help the residents in developing countries to climb the energy ladder, leading to a reduction in air pollutant emission, policy and regulatory efforts can also promote the replacement of solid fuels with clean energy. Since future climate change will also affect the residential energy use and emissions, more study on adaptation in this aspect should be carried out.

Although the hypothesis and the models were satisfactorily validated, the limitation of the approach and the models developed should not be overlooked, leaving room for future improvement. The limitations are mainly due to (1) the trial-and-error approach could be too simplified, (2) the models used may not accurately reflect the dependence of energy consumption on the parameters and some parameters may not even be included, and (3) Nonorthogonality of some socioeconomic variables are inevitable and the exogeneity of them cannot be totally ensured, (4) data available for model validation are rather limited, and (5) the uncertainty associated with fuel consumption, consequently pollutant emissions, in residential sector is among the highest and more first-hand data are needed to further improve the models.

Acknowledgment

Funding for this study was provided by the National Natural Science Foundation of China (41390240 and 41130754).

Appendix A. Supplementary material

Tables of an abbreviate list, a list of countries included in various models, and results of preliminary correlation analysis and Figures including comparisons between predicted and recorded residential per capita electricity and fuel consumptions, temporal trends of *E*cap and *F*cap of 10 countries, seasonal maps of per capita emissions of CO_2 and BC, predicted future trends of fuel and electricity consumptions, and predicted net effects of climate warming on global residential CO_2 emission. Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2015.10.185.

References

[1] ECE (Economic Commission for Europe). Residential heating with wood and coal: health impacts and policy options in Europe and North America. Working group of the joint task force on the health aspects of air pollution. Economic and Social Council, United Nations; 2014.
[2] Kannan R, Strachan N. Modelling the UK residential energy sector under long-term decarbonisation scenarios: comparison between energy systems and sectoral modelling approaches. Appl Energy 2009;86:416–28.
[3] Fikru MG, Gautier L. The impact of weather variation on energy consumption in residential houses. Appl Energy 2015;144:19–30.
[4] Zhu D, Tao S, Wang R, Shen HZ, Huang Y, Shen GF, et al. Temporal and spatial trends of residential energy consumption and air pollutant emissions in China. Appl Energy 2013;106:17–24.
[5] IEA (International Energy Agency). World Energy Statistics and Balances (2014 edition) <http://data.iea.org/ieastore/product.asp?dept_id=101&pf_id=205> [accessed on 13.02.14].
[6] DECC (Department of Energy & Climate Change). Energy Consumption in the UK (2014), chapter 3: Domestic energy consumption in the UK between 1970 and 2013. London, United Kingdom; 2014.
[7] EIA (U.S. Energy Information Administration). State Energy Data System (SEDS), 1960-2012 (Complete). <http://www.eia.gov/state/seds/seds-data-complete.cfm?sid=US> [accessed on 15.03.14].
[8] Lin WB, Chen B, Luo SC, Liang L. Factor analysis of residential energy consumption at the provincial level in china. Sustainability 2014;6:7710–24.
[9] Wang R, Tao S, Shen HZ, Huang Y, Chen H, Balkanski Y, et al. Trend in global black carbon emissions from 1960 to 2007. Environ Sci Technol 2014;48:6780–7.
[10] Shen HZ, Huang Y, Wang R, Zhu D, Li W, Shen GF, et al. Global atmospheric emissions of polycyclic aromatic hydrocarbons from 1960 to 2008 and future predictions. Environ Sci Technol 2013;47:6415–24.
[11] Huang Y, Shen HZ, Chen H, Wang R, Zhang YY, Su S, et al. Quantification of global primary emissions of PM2.5, PM10, and TSP from combustion and industrial process sources. Environ Sci Technol 2014;48:13834–43.
[12] IPCC (International Panel on Climate Change). In: Expert Meeting on Uncertainty and Validation of Emission Inventories. Utrecht, the Netherlands; March 23–25, 2010.
[13] Andres RJ, Gregg JS, Losey L, Marland G, Boden TA. Monthly, global emissions of carbon dioxide from fossil fuel consumption. Tellus 2011;63B:309–27.
[14] EIA (U.S. Energy Information Administration). International Energy Statistics. <http://www.eia.gov/cfapps/ipdbproject/IEDIndex3.cfm> [accessed on 04.03.15].
[15] UN data. MBS (Monthly Bulletin of Statistics Online). <http://unstats.un.org/unsd/mbs/app/DataSearchTable.aspx> [accessed on 04.03.15].
[16] IEA (International Energy Agency). Monthly Oil/Electricity/Gas Data Service; 2015 <http://www.iea.org/statistics/mods/> [accessed on 05.07.14].
[17] Clark ML, Peel JL, Balakrishnan K, Breysse PN, Chillrud SN, Naeher LP, et al. Health and household air pollution from solid fuel use: the need for improved exposure assessment. Environ Health Perspect 2013;121:1120–8.
[18] Gurney KR, Mendoza DL, Zhou YY, Fischer ML, Miller CC, Geethakumar S, et al. High resolution fossil fuel combustion CO_2 emission fluxes for the United States. Environ Sci Technol 2009;43:5535–41.
[19] Blasing TJ, Broniak CT, Marland G. Estimates of annual fossil-fuel CO2 emitted for each state in the U.S.A. and the district of Columbia for each year from 1960 through 2001. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, TN, U.S.A. 2004. http://dx.doi.org/10.3334/CDIAC/00003.
[20] Erickson III DJ, Mills RT, Gregg J, Blasing TJ, Hoffman FM, Andres RJ, et al. An estimate of monthly global emissions of anthropogenic CO_2: impact on the seasonal cycle of atmospheric CO_2. J Geophys Res 2008;113:G01023. http://dx.doi.org/10.1029/2007JG000435.
[21] Petrick S, Rehdanz K, Richard SJT. The impact of temperature changes on residential energy consumption. Kiel Working Paper No. 1618. Kiel Institute for the World Economy, Germany; 2010.
[22] Labanderia X, Labeaga JM, Rodriguez M. A residential energy demand system for Spain. The MIT Center for Energy and Environmental Policy Research (CEEPR), Massachusetts, USA. Energy J (IAEE) 2006;27:87–111.
[23] Alberini A, Gans W, Velez-Lopez D. Residential consumption of gas and electricity in the U.S.: The role of prices and income. Energy Econ 2011;33:870–81.
[24] Wangpattarapong k, Maneewan S, Ketjoy N, Rakwichian W. The impacts of climatic and economic factors on residential electricity consumption of Bangkok Metropolis. Energy Buildings 2008;40:1419–25.
[25] Kialashaki A, Reisel JR. Modeling of the energy demand of the residential sector in the United States using regression models and artificial neural networks. Appl Energy 2013;108:271–80.

[26] ABS (Australian Bureau of Statistics). Household Energy Consumption Survey, Australia: Summary of Results, 2012; 2013. <http://www.abs.gov.au/ausstats/abs@.nsf/mf/4670.0> [accessed on 08.03.15].

[27] Hosgör E, Fischbeck PS. Predicting residential energy and water demand using publicly available data. Energy Convers Manage 2015;10:106–17.

[28] Shimoda Y, Yamaguchi Y, Okamura T, Taniguchi A, Yamaguchi Y. Prediction of greenhouse gas reduction potential in Japanese residential sector by residential energy end-use model. Appl Energy 2010;87:1944–52.

[29] Olofsson T, Mahlia TMI. Modeling and simulation of the energy use in an occupied residential building in cold climate. Appl Energy 2012;91:432–8.

[30] Bigano A, Bosello F, Marano G. Energy demand and temperature: a dynamic panel analysis. Fondazione ENI Enrico Mattei Working Paper No. 112.06. Italy; 2006.

[31] De Cian E, Lanzi E, Roson R. The impact of temperature change on energy demand: a dynamic panel analysis. FEEM Working Paper No. 46.2007. Italy; April 2007.

[32] Isaac M, van Vuuren DP. Modeling global residential sector energy demand for heating and air conditioning in the context of climate change. Energy Policy 2009;37:507–21.

[33] MNP (Netherlands Environmental Assessment Agency). D-S.1 Preliminary ADAM scenarios (deliverable for the ADAM project); 2007.

[34] National Bureau of Statistics and National Energy Administration. China Energy Statistical Yearbook, 1996–2009; China Statistics Press: Beijing; 1997–2010.

[35] Bureau of Resources and Energy Economics. Australian Energy Statistics Data. <http://www.agriculture.gov.au/abares/publications/display?url=http://143.188.17.20/anrdl/DAFFService/display.php?fid=pe_abares99010610_12c.xml> [accessed on 13.02.15].

[36] Natural Resources Canada. Comprehensive Energy Use Database, 1990-2011. <http://oee.nrcan.gc.ca/corporate/statistics/neud/dpa/menus/trends/comprehensive_tables/list.cfm> [accessed on 13.02.15].

[37] EEA (European Environment Agency). Heating Degree Days. <http://www.eea.europa.eu/data-and-maps/indicators/heating-degree-days-1> [accessed on 13.02.15].

[38] Blazquez L, Boogen N, Filippini M. Residential electricity demand for Spain: new empirical evidence using aggregated data; CEPE Working Paper No. 82. Center for Energy Policy and Economics, Zürichbergstrasse, Switzerland; 2012.

[39] Kalnay E, Kanamitsu M, Kistler R, Collins W, Deaven D, Gandin L, et al. The NCEP/NCAR 40-Year reanalysis project. Bull Amer Meteor Soc 1996;77:437–71.

[40] ORNL (Oak Ridge National Laboratory). LandScan Global Population Database. <http://www.ornl.gov/sci/landscan/> [accessed on 13.02.15].

[41] The World Bank. World Development Indicators; 2014. <http://data.worldbank.org/data-catalog/world-development-indicators> [accessed on 13.02.15].

[42] BEA (U. S. Bureau of Economic Analysis). Per Capita Personal Income by State, 1990–2011. <http://www.bea.gov/regional/index.htm> [accessed on 13.02.15].

[43] National Bureau of Statistics of China. China statistical yearbook 1994–2008. China Statistics Press: Beijing, 1995–2009.

[44] Australian Bureau of Statistics. Australian National Accounts: State Accounts. <http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/5220.02010-11> (released at November 23, 2011). [accessed on 23.03.15].

[45] Statistics Canada. Provincial and Territorial Economic Accounts; Data Tables, catalogue number 13-018-X. <http://www.statcan.gc.ca/pub/13-018-x/2011001/t/tab1801-eng.htm> [accessed on 23.03.15].

[46] IEA (International Energy Agency). IEA Energy Prices and Taxes Statistics; 2014. <http://www.oecd-ilibrary.org/energy/data/end-use-prices/energy-prices-in-us-dollars_data-00442-en?isPartOf=/content/datacollection/ene-pric-data-en/> [accessed on 23.03.15].

[47] Eurostat. Gas and electricity prices, 1985-2012. <http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_pc_204&lang=en> [accessed on 23.03.15].

[48] U. S. Census Bureau. National and State Housing Unit Estimates, 2010-2012. <https://www.census.gov/popest/data/housing/totals/2012/index.html> [accessed on 23.03.15].

[49] DECC (Department of Energy & Climate Change). Sub-national electricity sales and numbers of customers 2005-2011. <https://www.gov.uk/government/collections/sub-national-electricity-consumption-data> [accessed on 11.04.15].

[50] Tsuji K, Saeki O, Suzuhigashi A, Sano F, Ueno T. An end-use energy demand monitoring project for estimating the potential of energy savings in the residential sector. ACEEE (American Council for an Energy-Efficient Economy), Washington, D.C.; 1998. <http://www.eceee.org/library/conference_proceedings/ACEEE_buildings/2000/Panel_2/p2_2> [accessed on 26.03.15].

[51] Proof of Concept Residential Energy Monitoring Program: Final Report. A whole house metering 'proof of concept' project. Melbourne, Australia; March 2012.

[52] RTE (Réseau de Transport d'Electricité). Electrical Energy Statistics for France 2009; 2010. <http://www.rte-france.com/uploads/Mediatheque_docs/vie_systeme/annuelles/Statistiques_energie_electrique/an/statistiques_annuelles_2010_an.pdf> [accessed on 26.03.15].

[53] Houri A, Korfali SI. Residential energy consumption patterns: the case of Lebanon. Int J Energy Res 2005;29:755–66.

[54] Kucukbahar D. Modeling monthly electricity demand in Turkey for 1990–2006. A thesis submitted to Graduate School of Natural and Applied Sciences of Middle East Technical University. (Supervisor: Prof. Dr. Gülser Köksal); 2008.

[55] Nahata B, Izyumov A, Busygin V, Mishura A. Application of Ramsey model in transition economy: a Russia case study. Energy Econ 2005;29:105–25.

[56] Davaki M. Analysis of energy use in typical Greek residential buildings and proposed retrofit strategies. A thesis presented to high performance building in the School of Architecture in Georgia Institute of Technology. (Advisor: Dr Gentry TR); 2011.

[57] Qin F, Liu HY, Jing L, Liu W, Yin J, Wei XD. The investigation of energy consumption in the village of Jilin province. J Jilin Architect Civil Eng Ins 2007;24:37–40 [in Chinese].

[58] U.S. Energy Information Administration. Monthly Energy Review. <http://www.eia.gov/totalenergy/data/monthly/previous.cfm> [accessed on 26.03.15].

[59] Nakicenovic N, Alcamo J, Davis G, de Vries B, Fenhann J, Gaffin S, et al. IPCC (International Panel on Climate Change) Special report on emission scenarios; Nakicenovic N, Swart R Eds.; Cambridge University Press: Cambridge, 2000; 608.

[60] CIESIN (Center for International Earth Science Information Network). Country level GDP and downscaled projections based on the SRES A1, A2, B1, and B2 scenarios 1990–2100. CIESIN, New York, USA; 2002. <http://www.ciesin.columbia.edu/datasets/downscaled/> [accessed on 26.03.15].

[61] Geophysical Fluid Dynamics Laboratory. IPCC DDC AR4 (IPCC Data Distribution Centre: Assessment Report Four data sets) GFDL-CM2.1; 2005. <http://www.ipcc-data.org/sim/gcm_monthly/SRES_AR4/index.html> [accessed on 26.03.15].

[62] European Commission. Energy roadmap 2050; 2011. <http://ec.europa.eu/energy/energy2050/roadmap/index_en.htm> [accessed on 26.03.15].

[63] Alfsen KH, Bjart H. PPP correction of the IPCC emission scenarios: does it matter? Climatic Change 2005;68:11–9.

[64] van der Werf GR, Randerson JT, Giglio L, Collatz GJ, Mu M, Kasibhatla PS, et al. Global fire emissions and the contribution of deforestation, savanna, forest, agricultural, and peat fires (1997–2009). Atmos Chem Phys 2010;10:11707–35.

[65] CIESIN (Center for International Earth Science Information Network). Intergovernmental Panel on Climate Change Scenarios 1992 (IS92); A to F, Digital Version 1.1; William JP, Xing XS, Robert S, Richard HM Eds. New York, USA; 2005. <http://sedac.ciesin.columbia.edu/ddc> [accessed on 26.03.15].

[66] Eom JL, Clarke LE, Kim SH. China's building energy use: a long-term perspective based on a detailed assessment; PNNL (Pacific Northwest National Laboratory) Richland: Washington D.C.; 2012.

[67] Bhattacharyya SC. Influence of India's transformation on residential energy demand. Appl Energy 2015;1434:228–37.

[68] Dzioubinski O, Chipman R. Trends in consumption and production: household energy consumption. New York: USA: DESA (United Nations Department of Economic and Social Affairs); 1999.

[69] Lin B, Jiang Z. Estimating of energy subsidies in China and impact of energy subsidy reform. Energy Econ 2010;33:273–83.

[70] Grubler AX, Bai T, Buettner S, Dhakal DJ, Fisk T, Ichinose JE, et al. Chapter 18—Urban Energy Systems. In Global Energy Assessment – Toward a Sustainable Future, 1307–1400; Cambridge University Press: Cambridge, UK and New York. IIASA (International Institute for Applied Systems Analysis), Luxemburg, Austria, 2012.

[71] Holtedahl P, Joutz FL. Residential electricity demand in Taiwan. Energy Econ 2003;26:201–24.

[72] Fell H, Li S, Paul A. A new look at residential electricity demand using household expenditure data; Working Paper 2012-04; Division of Economics and Business, Colorado School of Mines, Golden, Colorado; July 2012.

[73] Dergiades T, Tsoulfidis L. Estimating residential demand for electricity in the United States, 1965–2006. Energy Econ 2008;30:2722–30.

[74] Fumo N, Biswas Rafe MA. Regression analysis for prediction of residential energy consumption. Renew Sust Energy Rev 2015;47:332–43.

[75] Dawit Diriba Guta. Application of an almost ideal demand system (AIDS) to Ethiopian rural residential energy use: panel data evidence. Energy Policy 2012;50:528–39.

[76] Baland J, Das SB, Mookherjee D, Sarkar R. The environmental impact of poverty: evidence from firewood collection in rural Nepal. Delhi: Indian Statistical Institute; 2007.

[77] Sivak M. Air conditioning versus heating: climate control is more energy demanding in Minneapolis than in Miami. Environ Res Lett 2013;8:014050.

[78] Craig J. Australia homes are biggest in the world. Economic insights. CommSec, New South Wales; 2009. <http://images.comsec.com.au/ipo/UploadedImages/craigjames3f6189175551497fada1a4769f74d09c.pdf> [accessed on 18.04.15].

[79] Statistics Canada. Households and the Environment Survey: Energy Use Supplement; 2007. <http://www.statcan.gc.ca/pub/11-526-s/2010001/ct001-eng.htm> [accessed on 18.06.15].

[80] Sidorenko A. Chapter 16 Electricity in Russia. In: APEC Policy Support Unit, the impacts and benefits of structural reforms in transport, energy and telecommunications sectors, APEC; 2011.<http://publications.apec.org/publication-detail.php?pub_id=1113> [accessed on 18.08.13].

[81] Lapillonne B, Pollier K, Samci N. Energy efficiency trends for households in the EU. Report of Enerdata, Odyssey Energy; 2014.

[82] Nekrasov AS, Voronina SA, Semikashev VV. Problems of residential heat supply in Russia. Stud Russ Econ Dev 2012;23:128–34.

[83] Lam JC, Tang HL, Li DHW. Seasonal variations in residential and commercial sector electricity consumption in Hong Kong. Energy 2008;33:513–23.

[84] Hadke A, Abhyankar N, Shah N. Avoiding 100 new power plants by increasing efficiency of room air conditioners in India: opportunities and challenges (LBNL-6674). Ernest Orlando Lawrence Berkeley National Laboratory, Berkeley, California; 2014.
[85] Park MS, Joo JS, Park SU. Carbon dioxide concentration and flux in an urban residential area in Seoul. Korea. Adv Atmos Sci 2014;31:1101–12.
[86] Lu Z, Zhang Q, Streets DG. Sulfur dioxide and primary carbonaceous aerosol emissions in China and India, 1996–2010. Atmos Chem Phys 2011;11:9839–64.
[87] Streets DG, Bond TC, Carmichael GR, Fernandes SD, Fu Q, He D. An in ventory of gaseous and primary aerosol emissions in Asia in the year 2000. J Geophys Res 2003;108. http://dx.doi.org/10.1029/2002JD00309. D21, 8809.
[88] Nezhad H. World energy scenarios to 2050: Issues and options. State University of Minneapolis, Minnesota, USA; 2009.
[89] Jylhä K, Jokisalo J, Ruosteenoja K, Pilli-Sihvola K, Kalamees T, Seitola T. Energy demand for the heating and cooling of residential houses in Finland in a changing climate. Energy Buildings 2015;99:104–16.
[90] Wang HJ, Chen QY. Impact of climate change heating and cooling energy use in buildings in the United States. Energy Buildings 2014;82:428–36.
[91] Wilbanks T, Leiby P, Perlack R, Ensminger JT, Wright SB. Toward an integrated analysis of mitigation and adaptation: some preliminary findings. Mitig Adapt Strat Glob Change 2007;12:713–25.