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Model projections for household energy use in India

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ABSTRACT

Energy use in developing countries is heterogeneous across households. Present day global energy models are mostly too aggregate to account for this heterogeneity. Here, a bottom-up model for residential energy use that starts from key dynamic concepts on energy use in developing countries is presented and applied to India. Energy use and fuel choice is determined for five end-use functions (cooking, water heating, space heating, lighting and appliances) and for five different income quintiles in rural and urban areas. The paper specifically explores the consequences of different assumptions for income distribution and rural electrification on residential sector energy use and CO_2 emissions, finding that results are clearly sensitive to variations in these parameters. As a result of population and economic growth, total Indian residential energy use is expected to increase by around 65–75% in 2050 compared to 2005, but residential carbon emissions may increase by up to 9–10 times the 2005 level. While a more equal income distribution and rural electrification enhance the transition to commercial fuels and reduce poverty, there is a trade-off in terms of higher CO_2 emissions via increased electricity use.

1. Introduction

Historically, energy consumption in industrialised countries has dominated global energy use. Energy consumption in developing countries, however, is rapidly increasing, with a significant effect on issues like climate change, depletion of energy resources and deforestation (IEA, 2010; IPCC, 2007; UNEP, 2007). Therefore, understanding the trends in energy use in developing countries is important. In developing countries, residential energy use plays a dominant role in energy-related sustainability issues. For instance, access to commercial (liquid) energy sources plays a critical role in development and in reducing the negative implications of indoor air pollution.

In modelling residential energy use it is important to understand and take into account the large differences between developing countries and industrialised regions. First of all, the socio-economic factors that are driving residential energy use, such as income and household size (Narasimha Rao and Reddy, 2007; Pachauri, 2004), are more heterogeneous in developing countries than in industrialised countries. Secondly, different factors and processes play a role in shaping future demand. In developing countries, key factors include the transition from traditional to modern energy use and household electrification. Thirdly, in developing countries the relationship between monetary data and energy data is less obvious as a result of data quality, but also the role of the informal economy. Current energy models rarely take these factors into account (Bhattacharyya and Timilsina, 2010; Shukla et al., 2007; Urban et al., 2007; van Ruijven et al., 2008).

We developed a residential energy use model that simulates the demand for several energy functions, such as heating and cooling, lighting and the use of appliances, and the way in which these functions are provided by final energy carriers. It accounts for differences in income classes and between rural and urban households. It includes an explicit formulation of electrification and subsidy schemes. As such, the model goes beyond many existing (global) energy models. The results are expected to give better insight in the dynamics of residential energy use, certainly in developing regions. In this paper, we present an application of this model for India,[1] discuss the input data, model assumptions

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[1] The model has recently been implemented for other global regions (Daioglou et al., in preparation).

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and structure and analyse future projections. The main questions addressed in the paper are the following:

(1) Does available data allow implementation of a detailed energy model in developing countries (or specifically, India)?
(2) What trends are likely to dominate future residential energy use in India?

These questions are addressed through the development of two scenarios for India that focus specifically on the role of electrification and income distribution in the projection of future energy use.

India is an 'awakening giant' with only slightly lower economic growth rates than China and a rapidly increasing population. Compared to other developing countries, many data are available for India. This makes it a good starting point for testing the ability to implement such a detailed model. Total residential energy use in India increased about linearly since the early 1970s. The main end-use function of residential fuel use in India are cooking and lighting (kerosene lamps). Space heating is not important due to India's (sub-) tropical climate (Pachauri, 2007). Air conditioning increases but is still a luxury (NSSO, 2003). Residential fuel use is dominated by traditional fuels, although the use of commercial fuels increases rapidly (IEA, 2007). Government policies play an important role in the Indian energy system, such as price subsidies on electricity, kerosene and LPG and electrification for rural households. It is, however, hard to assess the impact of these policies in the absence of equivalents for comparison (Dzioubinski and Chipman, 1999).

The outline of this paper is as follows: Section 2 provides an overview of the conceptual model and Section 3 discusses primary drivers of residential energy use distinguished in the model: population, household expenditure, household size and temperature changes. Section 4 describes the modelling of intermediate physical indicators: floor space and electrification. The subsequent sections focus on modelling energy use: Section 5 describes fuel choices for cooking, water-heating and space heating; Section 6 describes electricity use for lighting and appliances. Section 7 explores and discusses the performance of the model and Section 8 analyses the impact and relevance of including the dynamics of developing countries on future projections. Finally, Section 9 discusses and concludes.

2. Conceptual model and overview

The residential energy model follows a causal chain from population and income trends to intermediate physical indicators and to end-use functions and energy use, and uses correlations derived from econometric studies and regression analysis. The model also includes dynamic features such as capital stock turnover (vintage structure). The model is designed to form part of the global energy system model TIMER, where residential energy use is influenced by feedbacks from the larger energy system, in particular via energy prices (Van Vuuren, 2007). An outline of the model is shown in Fig. 1. The different components are discussed in detail in the Sections 3–6.

The demand for residential energy services is related to many factors (Schipper and Meyers, 1992; Schipper et al., 2001). Important primary drivers include population, household size, income and temperature, which are all included as exogenous factors to the model (see Section 3). Residential energy use in developing countries differs widely between rural and urban areas and high and low income groups (van Ruijven et al., 2008). Therefore, other features of this model are income distribution and rural/urban breakdown. This is taken into account by disaggregating most model equations for urban and rural population (index $p=u,r$ in equations) and different income groups (quintiles, indexed as $q=1\ldots5$ in equations, see Section 3.2).

In the model, total Final Energy (FE) demand of households in urban and rural areas (p) and income quintiles (q), for different energy carriers (EC=coal, kerosene, LPG, natural gas, fuelwood and electricity) is the sum of final energy demand for fuels and final energy demand for electricity:

$$FE_{p,q,EC(t)} = FEFuels_{p,q,EC(t)} + FEElec_{p,q,EC(t)} \quad \text{(GJ/yr)} \tag{1}$$

Final energy demand for fuels is determined by end-use functions that can be served by multiple fuels and are subject to fuel switching behaviour: cooking (C), water heating (W) and

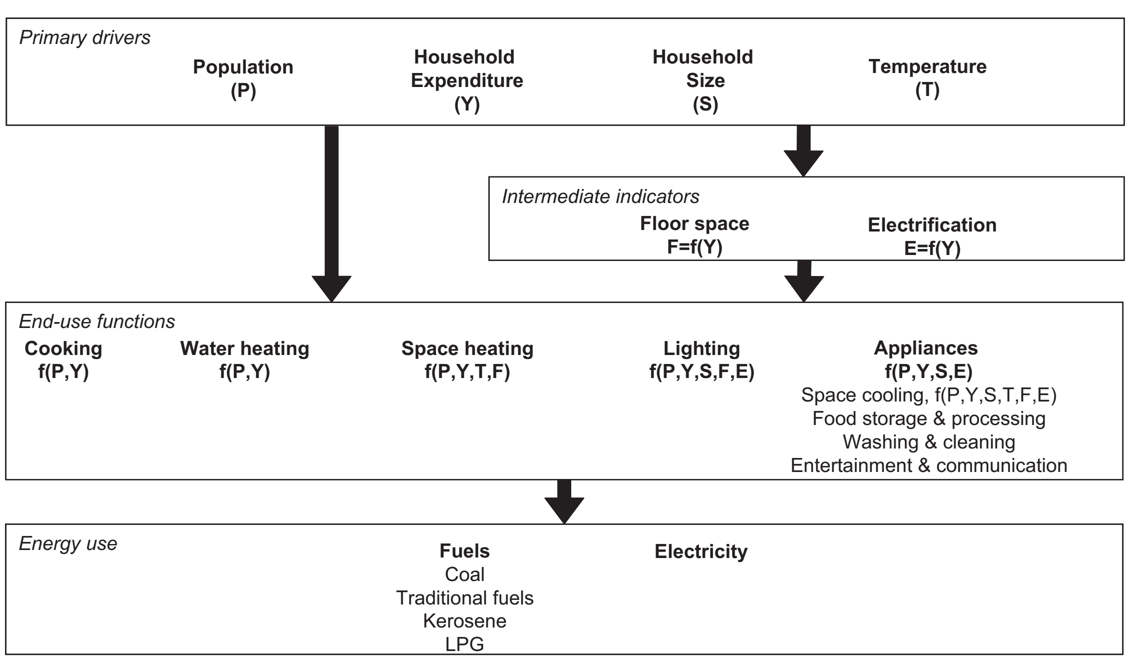

Fig. 1. Outline of the residential energy use model; population and household expenditure have a direct influence on all end-use functions; all variables (except temperature) are distinguished for urban and rural areas and population quintiles.

space heating (H):

$$FEFuels_{p,q,EC(t)} = \frac{UEC_{p,q(t)} \cdot MSC_{p,q,EC(t)}}{EffC_{EC(t)}} + \frac{UEW_{p,q(t)} \cdot MSW_{p,q,EC(t)}}{EffW_{EC(t)}} + \frac{UEH_{p,q(t)} \cdot MSH_{p,q,EC(t)}}{EffH_{EC(t)}} \quad \text{(GJ/yr)} \tag{2}$$

For these end-use functions, the first step is to derive the level of demand, in terms of useful energy (*UE*), i.e. corrected for differences in end-use efficiency of different fuels (*Eff*) (see Section 5.1). This demand is modelled on the basis of physical indicators (see Section 4). For instance, the demand for warm water use is related to the household expenditure level and demand for space heating is determined as a function of floor space. The second step is the allocation of different fuels to meet this demand, determining the Market Share (*MS*, see Section 5.2). This depends on the availability (electrification) and affordability of fuels.

In the literature, the energy ladder is often mentioned as a generic concept describing trends in the choice of energy carriers as a function of economic development. It postulates that with increasing income, households switch towards cleaner, more efficient and convenient fuels. This implies a shift from dung and fuelwood towards kerosene, LPG and electricity (Hosier and Dowd, 1987; Reddy and Reddy, 1994; van Ruijven et al., 2008). This concept is purely empirical, and it has also been criticised for being an oversimplification, because household commonly use multiple fuels in parallel (Masera et al., 2000) and other factors can influence fuel choice as well (Farsi et al., 2007).

The demand for final energy in the form of electricity is, beside being one of the options in the fuel choice above, determined by end-use functions that are technically limited to electricity: lighting (*L*) and appliances (*A*):

$$FEElec_{p,q(t)} = \sum_{EP=1}^{2} FEL_{p,q,EP(t)} MSL_{p,q,EP(t)} + FEA_{p,q,elec(t)} \quad \text{(GJ/yr)} \tag{3}$$

Here, the level of useful energy demand for lighting (UE_L) is related to floor space, and the model simulates the choice between packages of standard and efficient lighting technologies (*EP*, see Section 6.1). Final energy demand for appliances is the result of ownership and the annual energy consumption per appliance (Section 6.2).

3. Primary drivers of energy use

This section describes model dynamics related to the primary drivers of energy use and the available data sources on historical trends. A consistent set of future projections for these drivers in India is derived from the OECD Environmental Outlook scenario (Bakkes et al., 2008; OECD, 2008).

3.1. Population and households

During the last decades, total Indian population doubled from about 550 million people in 1970 to approximately 1.1 billion people in 2005, but the growth rate is decreasing. While the level of urbanisation increased as well, the vast majority of Indian population still lives in rural areas. Data on household characteristics in India are collected regularly by the National Sample Survey Organisation (NSSO) of the Ministry of Statistics and have been obtained from a variety of sources (IndiaStat.com, 2007; NSSO, 2004; World Bank, 1996). The OECD Environmental Outlook scenario (Bakkes et al., 2008; OECD, 2008) assumes a further increase in the Indian population towards almost 1.6 billion in 2050, of which 47% lives in urban areas.

3.2. Household consumption expenditure

In general, data on household income are hard to obtain for developing countries. Poor households do not pay income tax, many subsistence activities are not monetised and during surveys people often hide part of their income. Therefore, economic activity of households is often presented as expenditure rather than income.[2] Data for India are available from two different sources: household surveys (NSS) and National Account Statistics (NAS). Household survey data are obtained by canvassing a sample of households with standard questionnaires on their expenditures during a certain recall period. Non-monetary purchases, like home-produced food, clothing or other services, are monetised by the National Sample Survey Organisation (NSSO) to the ex-farm or ex-factory rate. Private consumption expenditures in the NAS are residuals, derived from estimated domestic availability of commodities left after deducting non-private consumption uses (Srinivasan, 2001). Generally, household expenditure levels from surveys are lower than NAS data. For India, the ratio of 'NSS to NAS' decreased over the last decades to low values of about 0.5 (Deaton and Kozel, 2005). The differences in income-numbers led to a debate among poverty economists on which method is more reliable (see Deaton, 2001; Deaton and Kozel, 2005; Ravallion, 2001; Srinivasan, 2001; Sundaram and Tendulkar, 2003). Adjustment of the data in both directions has been argued for by different authors, but the debate has been inconclusive. Until 1990, the Indian Planning Commission adjusted the NSS data to the NAS. However, in recent years, the two measures are increasingly used in parallel (Sundaram and Tendulkar, 2003). For use within a modelling framework, however, this is impractical and inconsistent. We decided to use NSS data for distribution between urban/rural and income classes, but adjust the absolute level of expenditures to the NAS.

All monetary variables (e.g. household expenditures, investment costs and prices) were originally available in current Indian Rupees (Rs). We converted them to constant year 2000 values (Rs_{2000}), using consumer price indices[3] as provided by the Reserve Bank of India (RBI, 2007). Data on household expenditures are published in monthly per capita expenditure (MPCE). In the model we use annual values in market exchange rate (MER): USD_{2000} with a conversion rate of 44.9 Rs_{2000}/USD_{2000} (FXhistory, 2008).

The number of income classes and the class-limits changed regularly between survey rounds of the NSSO, complicating comparison over time. We clustered the expenditure classes to quintiles of the population (five groups, each containing 20% of the population). The survey data show that the growth rate of household expenditures per capita in India has been rather low until the economic reforms in 1991, with a roughly constant gap between rural and urban households. After 1991, urban expenditure levels increased rapidly and were in 2002 on average twice the rural expenditure per capita (Fig. 2).

A commonly used measure to express inequality in income distribution is the GINI-coefficient (Cypher and Dietz (1997)). India has GINI values of about 30 for rural and 35 for urban areas, indicating a relatively equal income distribution.[4] We disaggregate

[2] Data on household income are rarely available in developing countries; therefore we use expenditure data as collected by the surveys of the NSSO. At low income levels, household expenditures can be assumed to roughly equal household income; however, at higher income levels households can use part of their income for savings. This is not directly reflected in the expenditure data, although one can argue that capital intensive purchased are the result of household savings.

[3] The Agricultural Labourers index was used for rural data; for urban data we used the average of the index for Industrial Workers and 'Urban Non-manual employees'.

[4] The GINI coefficient is a commonly used measure to express inequality in income distribution. It is a statistical summary for the Lorenz curve and has values between zero and 100, with zero being total equality and 100 total inequality.

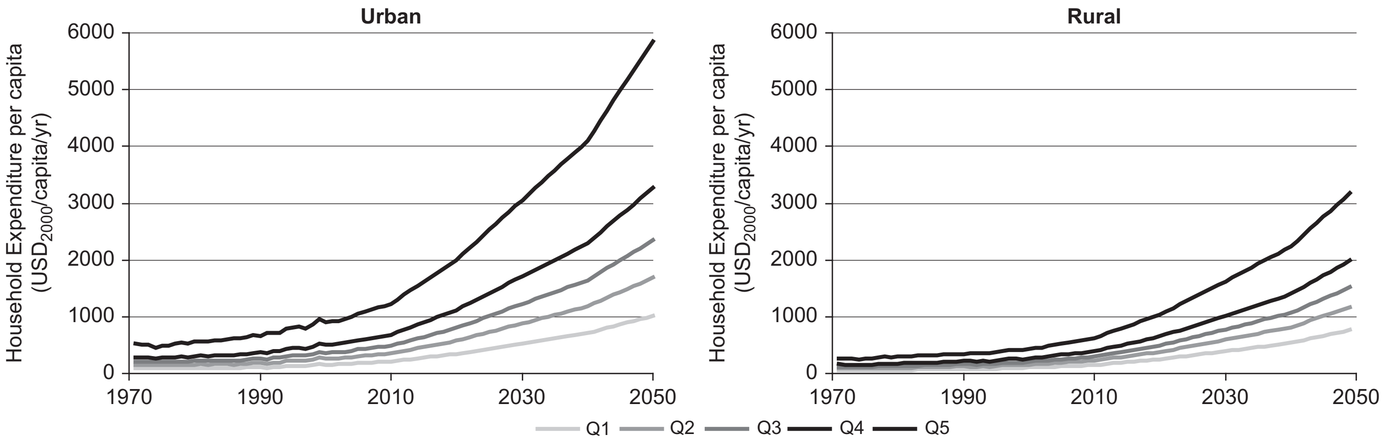

Fig. 2. Historic data (IndiaStat.com, 2007; NSSO, 2004; World Bank, 1996) and future projections (Bakkes et al., 2008) of household expenditure in rural and urban areas, allocated to population quintiles.

the average household expenditure levels to population quintiles using the GINI-coefficient (see Electronic Annex in the online version of this article and Humberto Lopez and Servén, 2006; Rutherford, 1955).

Future projections of household expenditure are derived in three steps:

1. We use the OECD environmental outlook scenario (OECD, 2008) that shows average household expenditures increasing from about 300 USD_{2000}/capita/year in the year 2000 to 2300 USD_{2000}/capita/yr in 2050.
2. Next, this expenditure is allocated to rural and urban areas, based on the ratio of average (per capita) rural and urban expenditure level to the all-Indian average expenditure level. Historically, the urban-to-average ratio decreased from 1.6 in 1970 to 1.45 in 2004. The rural-to-average ratio has historically been rather constant at about 0.82.
3. GINI coefficients are used to allocate expenditures over population quintiles within rural and urban areas.

For future scenarios, both the urban–rural ratio and the GINI coefficients can converge or diverge in line with the scenario storyline (see Section 8).

3.3. *Household size*

For several end-use functions, the number of persons per household (or household size) is an important determinant because decisions are made at the household level. Historic data for household size at different income levels are derived from NSSO survey data (IndiaStat.com, 2007; NSSO, 2004; World Bank, 1996). In general, household size decreases with increasing income levels. We assume that future household size in all population quintiles follows the trend of UN-Habitat (2005) projections for the average household size in India until 2050.

3.4. *Temperature*

Temperature is a determinant of energy use for space heating and space cooling (Schipper et al., 2001). Isaac and Van Vuuren (2008) performed a global analysis on energy use for residential heating and air conditioning for the current and a changing climate. Here, we use their climate data, which include population weighted monthly temperature, historically calibrated against the CRU database (New et al., 2002) and the IMAGE model. To determine both heating and cooling degree days for world regions a base temperature of 18 °C was used. This value is commonly used in studies from Europe and the USA, but might be low in the context of developing countries.

It is clear that, potentially, the demand for space cooling in India is much larger than for space heating; especially because it is projected that climate change considerably decreases the number of heating degree days in the winter months and increases cooling degree days during summer (Fig. 3).

3.5. *Energy prices*

An important determinant for fuel switching is the price of commercial alternatives. These are usually kerosene and LPG, both based on oil. We derived historical fuel prices from IndiaStat.com (2007). Kerosene is subsidised for poor households in India, through the public distribution system (PDS; see Section 5.2.1 on how our model captures this). For fuelwood, we used data from the NSSO rounds, as provided by the World Bank India database (World Bank, 1996). For future projections of fossil energy prices, we used the trend of the OECD environmental outlook scenario, leading to an increase of oil prices of about 20% between 2007 and 2050.

4. Physical indicators: floor space and electrification

4.1. *Floor space*

Floor space per capita is a commonly used indicator for household energy use, because end-use functions like lighting and space heating and cooling are closely related to living space (Schipper et al., 2001). Detailed and geographically explicit bottom-up models (e.g. Koomey et al., 1995; MacDonald and Livengood, 2000) include housing stocks with typical characteristics like floor space, but also insulation, retrofit-options and heating equipment. More aggregate models (e.g. Isaac and Van Vuuren, 2008; Kainuma et al., 2003; Price et al., 2006) use data-regressions and assumptions on floor space trends.

Data on residential floor space are available from different sources, mostly for urban situations (Eurostat, 2006; IEA, 2004; NSSO, 2003; Shen, 2006; UN-Habitat, 1998). Most available data are from single countries or cities. A plot of residential floor space vs. average (country or city) income merely indicates that industrialised countries have higher residential floor space levels and that developing countries are rapidly catching up (Fig. 4, upper left graph). IEA (2004) time series for several OECD

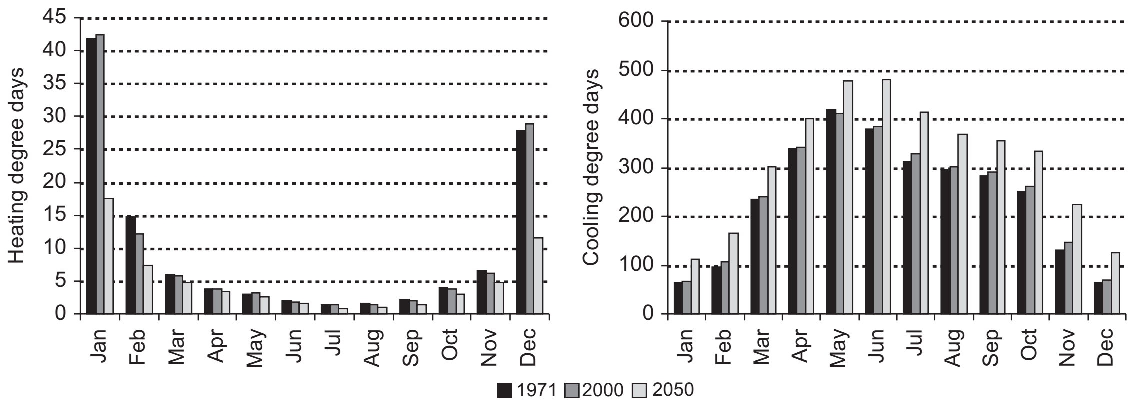

Fig. 3. Population weighted heating and cooling degree days (in °C/yr) for India in 1971, 2000 and 2050 (for the ADAM baseline scenario), with a base temperature of 18 °C (Isaac and Van Vuuren, 2008).

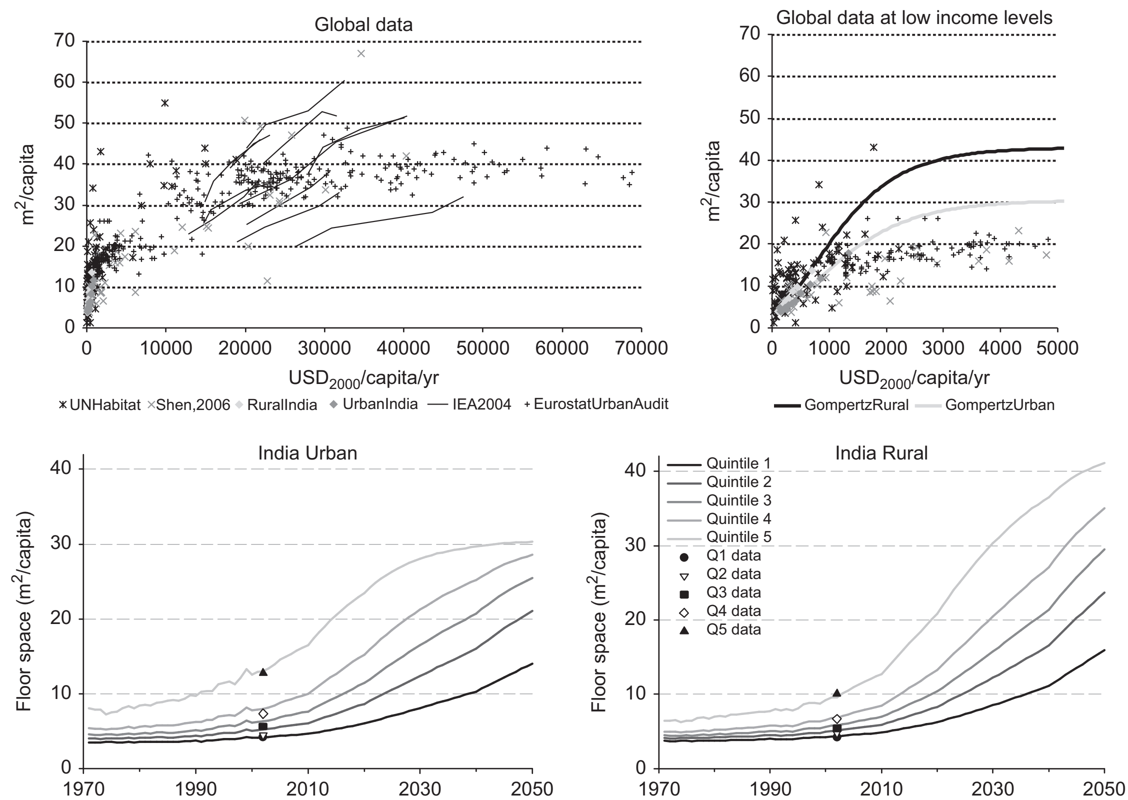

Fig. 4. Historic simulation and future projections of residential floor space for urban and rural India, compared to the observed data in 2002 (NSSO, 2003).

countries for the period 1973–1998 indicate a continuous growth of floor space per capita with increasing income levels (i.e. no signs of stabilisation) and a difference in floor space levels between densely populated countries (Japan), medium dense populated countries (Western Europe) and countries with low population density (USA, Canada and Australia). Data for India (NSSO, 2003) show a steep increase across rising household expenditure levels (Fig. 4, upper right graph), driven also by a decreasing number of household members. At very low incomes, the floor space seems to stabilise around 4 m^2/capita. The quality of these data is uncertain, however, especially for lower income groups, given the large amounts of people living in slum areas.

The general trends in these data can be summarised as increasing floor space with higher income levels, but with a decreasing growth rate and lower floor space levels with higher population density. We performed a regression analysis with a Gompertz[5] curve through the available Indian data. This assumes logistic growth of residential floor space levels as function of household expenditure towards the present day levels for Japan (urban India) and Western Europe (rural India).

Applying this function to Indian historic expenditure data yields a historically rather constant floor space per capita for urban and rural low expenditure quintiles (Fig. 4, lower graphs), which can be explained from both limited expenditure growth and the flat shape of the Gompertz curve at its lower tail. The highest expenditure quintile increased its floor space, in both

[5] We prefered to use a Gompetz curve over the more common exponential curve fitting in this area, because of its behaviour at low income levels. Exponential functions tend to yield negative floorspace for low income households.

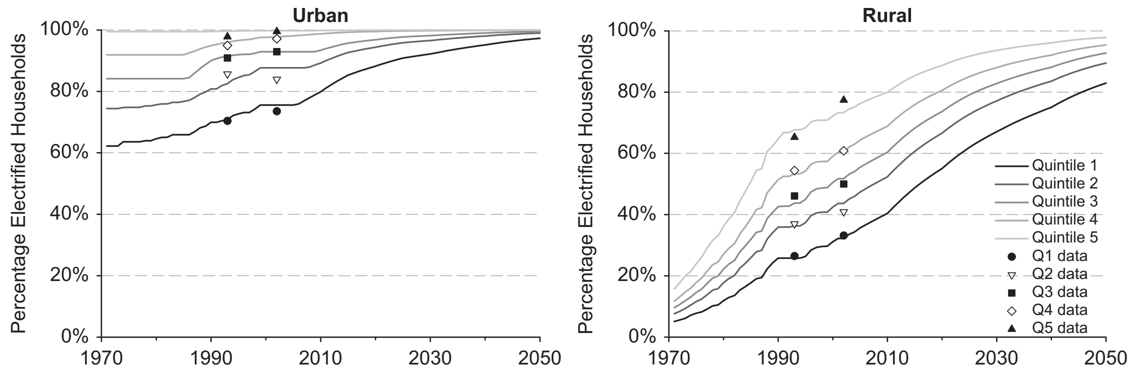

Fig. 5. Historic simulation and future projections for urban and rural household electrification, compared to data in 1993 and 2002 (NSSO, 1997, 2004).

urban and rural areas. Future projections show an increase for all quintiles, driven by rising expenditure levels.

4.2. Electrification

Access to electricity is an essential factor in household energy use. Without electricity, rooms have to be lighted with candles and kerosene lamps and electric appliances cannot be used. However, access to electricity is in most cases not a decision of the household itself but the result of policy-driven electrification schemes. Unfortunately, data on household electrification are scarce. We use the application of electricity for lighting as a proxy for electrification rates of households at different income levels, assuming that once a household has access to electricity, this will be the preferred source lighting.

Electrification in this model is based on Kemmler (2007a,b), who used a probit model (see Electronic Annex in the online version of this article) in an econometric analysis of the influence of different variables on residential electricity use in India (expenditure, household size, education, labour, electricity tariffs and geographical information). Kemmler (2007a, b) found household expenditure as the main correlating factor for electricity use by households, and we fitted the following probit equation to the NSSO data on electricity use for lighting in population quintiles (Table 3):

$$E_{p,q(t)} = N(POLICY(\varepsilon 1_p LN(Y_{p,q(t)}) + \varepsilon 2_p))(\text{fraction}) \quad (4)$$

with $E_{u,q(t)}$ the electrification level for urban and rural areas ($p=u,r$) and population quintiles ($q=1\ldots5$) in 1993 and 2002; N is the cumulative normal distribution and Y is household expenditure (in USD_{2000}/cap/yr). Before 1990, rural electrification levels increased faster than household expenditures. Therefore, the rural model is adjusted for the trend of rural village electrification between 1971 and 1990. The value of the *POLICY*-parameter is scenario-dependant, simulating increased or decreased electrification efforts. This parameter is historically (and in Fig. 5) set to 1. Forward calculations with this model lead to rapid electrification in urban areas, towards almost full electrification in 2050. Rural electrification projections proceed more slowly, towards levels above 80% in 2050 (Fig. 5). More recent data suggest an even faster increase of electricity access in urban areas, but we were not able to incorporate those in this paper.

5. Fuel use for cooking, water-heating and space heating

5.1. Energy demand for cooking, water-heating and space heating

In industrialised countries, space heating is usually the largest component of residential final energy use, followed by water-heating and cooking (Schipper et al., 1996). In many developing countries, however, cooking and water-heating are the largest energy consuming activities. Nevertheless, we included space heating in our model, because we aim to implement this model globally in a later stage.

The absolute amount of energy use for cooking, water heating and space heating varies widely between regions, according to estimates in the literature. For cooking, we compared available literature for India at the level of useful energy (*UE*), i.e. corrected for differences in end-use efficiency (Ang, 1986; D'Sa and Murthy, 2004; ESMAP, 2003; Gupta and Ravindranath, 1997; Kumar Bose et al., 1991; Purohit et al., 2002; Reddy and Balachandra, 2006a), and compared these to studies from China (Price et al., 2006; Xiaohua et al., 2002b), Japan (Price et al., 2006), Turkey (Utlu and Hepbasli, 2005) and the Netherlands (EnergieNed, 2004; UCE et al., 2001). We found a wide range of daily useful energy use for cooking (0.5–3.5 MJ_{UE}/capita/day, clustering between 1.7–2.7 MJ_{UE}/capita/day), without any relation to income, geography or household size. One factor here is that energy use for cooking is strongly dependant on cultural food habits, while income dependence might exist in two directions. Higher income may allow for more food (and thus more energy use), but it might also allow use of pre-processed food or increased consumption in restaurants, shifting energy use from households to industry and services. Finally, family size tends to decrease with rising income levels, increasing the per capita use of energy per meal (decreasing scaling advantages). Based on these considerations and data analysis, we assume a constant value of 2 MJ_{UE}/capita/day for cooking in India (so, $UE_{Cp,q}=2$ in Eq. (2)).

Energy use for warm water is currently very low in India, about 0.5 MJ_{UE}/capita/day, but studies from other countries indicate that an increase with income per capita is likely. Based on available data (Foekema et al., 2008; Price et al., 2006; Reddy and Balachandra, 2006a; Utlu and Hepbasli, 2005; Xiaohua et al., 2002a), we derived a stylised curve for useful energy demand for warm water as function of household expenditure (in PPP, $int\$_{2000}$/cap/yr), for population quintiles, $q=1\ldots5$):

$$UEw_{p,q(t)} = 8.5\cdot(1-e^{-(0.1/1000)Y_{p,q(t)}})\ (\text{MJ/capita/day}) \quad (5)$$

Energy use for space heating is derived from Isaac and Van Vuuren (2008) and elaborated for population quintiles, using the function for floor area described in Section 4.1 This model follows the decomposition approach of Schipper et al. (1996) and IEA (2004) and describes useful energy demand for residential space heating per capita as function of floor space (*F*) and heating intensity:

$$UEH_{p,q(t)} = F_{p,q(t)} HDD_{(t)} Intensity_{(t)}\ (\text{kJ/capita/year}) \quad (6)$$

in which floor area (*F*) is in m^2/capita, *HDD* reflects heating degree days (in °C/yr, see Section 3.4) and *Intensity* is useful energy intensity per square metre per degree day ($kJ_{UE}/m^2/°C/yr$). Heating intensity is determined as a residual factor between energy use for cooking and

Table 1
Assumptions on unit energy consumption (UEC) of household appliances in India.

Appliance	UEC (kWh/hh/yr)		Source
	2000	**2030**	
Fan	145	145	Murthy et al. (2001)
Food storage (refrigerator)	500	650	Letschert and McNeil (2007)
Cleaning (washing machine)	190	190	Murthy et al. (2001)
Entertainment (TV)	150	150	Murthy et al. (2001)
Air cooler	$UEC_{AC}*300/2160$		UEC_{AC} adjusted for power use
Air conditioner	$CDD*(0.865*\ln(Y-ppp)-6.04)$		Isaac and Van Vuuren (2008)

lighting and historic total energy use (although this ignores the use of electricity for heating). We found a rather constant average value of 130 $kJ_{UE}/m^2/^{\circ}C/yr$ for the period 1971–2003 (with many short term fluctuations).[6] Space cooling is discussed in Section 6.2 with appliances.

5.2. Fuel choice for cooking, water-heating and space heating

5.2.1. Model description

Fuel choice is not a daily issue for households. Most households have equipment (stoves) for a single fuel-type (wood, kerosene or LPG) and only choose to use another fuel once in a few years, for instance, when a stove is broken, worn out or economically 'depreciated'. Even then, people often choose the similar fuel, due to familiarity or habit (Masera et al., 2000). So, transitions in consumer fuel choice often proceed slowly because of the capital stock dynamics and delays in fuel switching behaviour. In the model, we simulate these processes with a capital vintage model for the stock of stoves. The actual market shares in the stock of stoves are the results of marginal investments and depreciation after the technical lifetime. The actual market shares for marginal investments are derived from the indicated (optimal) market shares with a smoothing delay of 10 years (to simulate the sub-optimal investment behaviour of households). The indicated (optimal) market shares (*MS*) of different energy options (*EC*=coal, kerosene, LPG, natural gas and fuelwood) are derived from the annual perceived costs with a multinomial logit allocation:

$$MS_{p,q,EC(t)} = \frac{e^{-\lambda C_{p,q,EC(t)}}}{\sum_{EC=1}^{NEC} e^{-\lambda C_{p,q,EC(t)}}} \text{(fraction)} \qquad (7)$$

where λ is the logit parameter and C are the perceived annual costs of the cooking options (in USD_{2000}/hh/yr) (see further). The logit parameter (λ) determines how strongly consumers react to changes in perceived cost differences. High values for λ indicate optimising consumer behaviour; while low values for λ indicate a gradual change in consumption patterns and investments in multiple fuels at similar income levels with hardly any influence from costs and prices. Thus, effectively we simulate the choice between fuels for cooking, water-heating and space heating (i.e. wood, coal, kerosene, LPG, natural gas and electricity) on the basis of relative perceived costs Table 1.

Data on energy use for cooking and water heating of households in India are regularly collected during the major NSSO rounds. The data in Table 2 show that energy for cooking and water heating in India generally follows the energy ladder. Energy in rural areas is mainly provided by fuelwood, followed by kerosene and LPG. Even the richest rural quintile relied in 2002 for 70% on traditional fuels. For urban households, the use of fuelwood is still common at low-income levels, but LPG gained market share between 1993 and 2002 in all urban expenditure groups. Coal is almost solely used in low-income urban households and regionally limited to the northern Indian states of Bihar, West Bengal and Jharkhand.

In the model, we distinguish two forces that drive fuel choice. The first factor captures the effect that, although efficient cooking options are generally cheaper on a life-cycle basis, poor households experience a threshold from front-end investment costs of more expensive stoves (Gupta and Ravindranath, 1997). The savings rate of these households is very low, hence, capital availability is limited and capital costs are depreciated over a short time period (often only a few months) or against high discount rates. The real interest rate for low-income households is often higher than 36% (Gupta and Ravindranath, 1997) and the discount rate for fuel switching was found to increase exponentially with decreasing income (Reddy and Reddy, 1994). In the model, we represent this with a dynamic consumer discount rate (CDR), as function of household expenditure levels (Y):

$$CDR_{p,q(t)} = m + e^{\alpha-\beta Y_{p,q(t)}} \quad (\%) \qquad (8)$$

Table 2
Historic shares of fuels for cooking and water heating in household expenditure quintiles; traditional bio-energy (TBIO) includes fuelwood and dung (NSSO, 1997, 2004).

	Coal (%)	TBIO (%)	Kerosene (%)	Biogas (%)	LPG (%)
Urban 1993					
Q1	8.1	59.8	21.7	0.0	10.4
Q2	8.0	36.3	29.6	0.1	26.0
Q3	5.8	22.5	31.6	0.1	40.0
Q4	4.4	12.2	27.3	0.2	55.9
Q5	2.2	5.9	23.5	0.1	68.2
Urban 2002					
Q1	8.0	65.6	9.9	0.0	16.5
Q2	5.6	46.5	16.7	0.1	31.0
Q3	4.3	27.9	20.1	0.0	47.7
Q4	2.5	11.1	21.3	0.2	64.9
Q5	0.8	3.5	8.2	0.0	87.4
Rural 1993					
Q1	1.0	98.0	0.7	0.1	0.3
Q2	1.6	96.2%	1.2	0.3	0.8
Q3	1.8	94.2	2.3	0.4	1.3
Q4	1.8	90.7	3.8	0.7	3.0
Q5	2.1	80.7	7.2	1.1	8.9
Rural 2002					
Q1	0.6	98.3	0.1	0.0	1.0
Q2	0.8	96.8	0.5	0.1	1.8
Q3	1.1	94.8	0.8	0.1	3.2
Q4	0.9	91.5	1.2	0.3	6.1
Q5	0.9	72.8	3.0	0.7	22.6

[6] For reference, useful heating intensity in Canada, USA and Western Europe decreased between 1971 and 2000 from about 150–180 to the range of 90–130 $kJ_{UE}/m^2/^{\circ}C/yr$.

The parameters α and β in this function were estimated after the literature (Goett, 1978; Hausman, 1979; Reddy, 1996; Train, 1985; Winer, 1997) in such a way that the model simulates historic fuel switching behaviour, with urban CDR starting around 60% at low income levels, and decreasing to the minimum level (m) of 10% around 1000 USD/capita/year, and rural CDR starting around 150% at low income levels and decreasing towards 10% at 2500 USD/capita/year.

The second factor captures the effect that households prefer to use the most convenient fuels at higher incomes even if they are more expensive than the alternative. In the model, the preference for convenience fuels is incorporated by a fuel-specific penalty, which we assume a function of household expenditure levels. Richer households have generally more options to use more expensive fuels, more education and access to information and perceive the disadvantages of cheaper fuels as more important than poor households. The penalty (P) of each fuel is defined as

$$P_{p,q,EC(t)} = PU_{EC}\cdot(1-e^{-\beta_p\cdot Y_{p,q(t)}}) \quad (\$/\mathrm{GJ}) \qquad (9)$$

with P_U the penalty at high income levels and β a factor to determine the sensitivity to changes in household expenditure (Y). These two parameters are used to calibrate the model results to historic data. The penalty is modelled additive to the other costs (capital, O&M and fuel) and related to total annual fuel use for each option.

Hence, the total annual costs of each energy option (or the perceived costs (C) in Eq. (7)) are the sum of annualised capital costs (CC), fuel costs ($price$) and fuel-specific penalties (P):

$$C_{p,q,EC(t)} = \frac{CDR_{p,q(t)}}{1-(1+CDR_{p,q(t)})^{LT_{EC}}}\cdot CC_{EC} + \frac{UE_{p,q(t)}}{Eff_{EC}}\cdot(price_{p,q,EC(t)} + P_{p,q,EC(t)})(\$/\mathrm{hh/yr}) \qquad (10)$$

Three issues require discussion, when implementing this conceptual model for India. First, the use of electricity for water heating and space heating. Data show that at low income levels, people use their cooking equipment for water heating and space heating, but at higher income levels, the ownership of electric water heaters (emersion heaters, boilers or geysers) and space heaters increases and households use LPG for both cooking and water heating (Murthy et al., 2001). Therefore, we have modelled electricity for water heating and space heating separately as function of the ownership of water heaters and space heaters (see Section 6) and subtracted from the total energy use for water heating and space heating. Second, almost all kerosene in India is distributed to through the public distribution system (PDS) (Gangopadhyay et al., 2005; Rehman et al., 2005). This means that almost all rural and 50% of urban households have access to subsidised kerosene. In the model, we simulate this effect by forcing households with access to the PDS to use kerosene first, before using the market share from the multinomial logit (Eq. (7)). Non-electrified households use this kerosene first for lighting, while electrified households use it for cooking. The distributed kerosene is not enough to fulfil the full energy demand of these households, so the above described dynamics still largely drive the results. Third, we currently do not include efficient renewable cooking options, like improved stoves and biogas. Although the Indian government developed programs for the distribution of improved stoves over the last decades, we lack adequate data for model calibration. The use of biogas is monitored by the NSSO, but according to the survey data it is hardly used for cooking in India.

5.2.2. *Model calibration*

Data to calibrate the fuel choice model were available for 1993 and 2002 across the different income levels (NSSO, 1997, 2004).

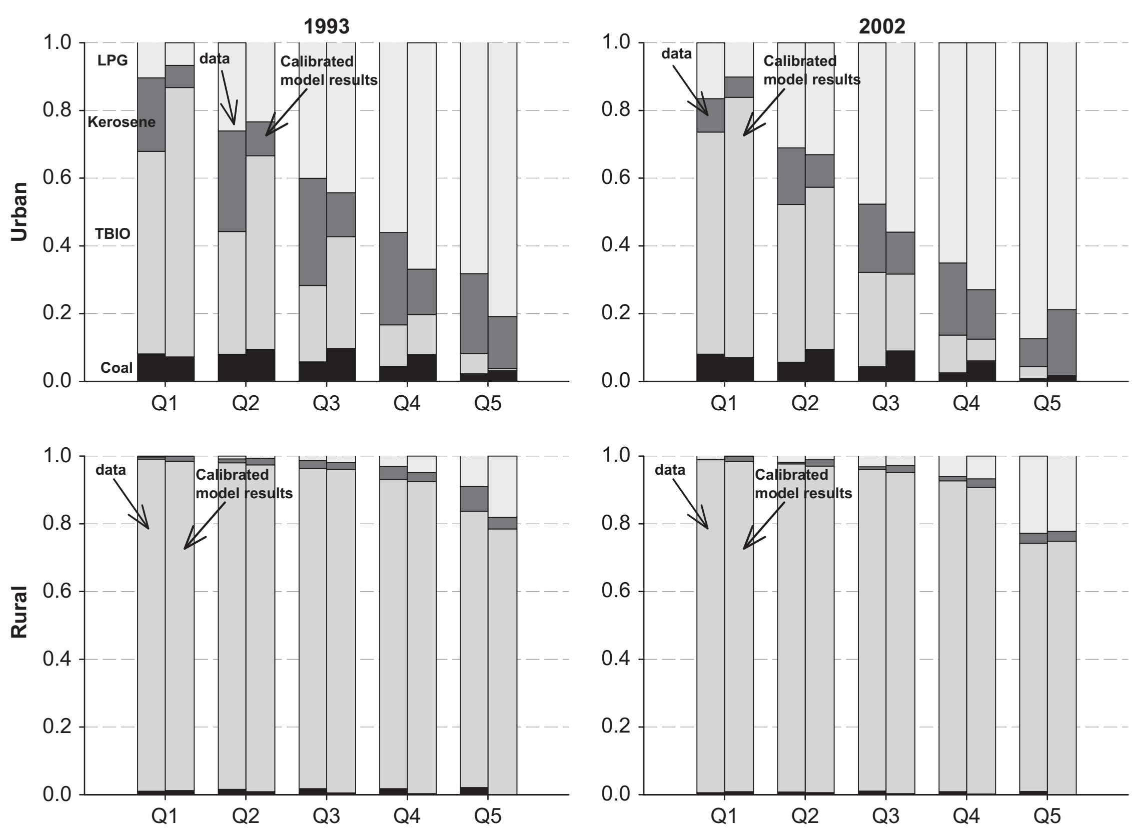

Fig. 6. Historic data (left bars, equal to Table 2) and calibrated model results of household fuel choice for cooking and water heating.

Using the change in consumer discount date (*CDR*), the rate of change in fuel-specific penalties (β) and the maximum value of these penalties (P_U) as calibration parameters (see Eqs. (8) and (9)) the shares of the different energy options were calibrated against historic data. With three calibration-parameters, four energy options, five urban and rural population quintiles and data for two years, this calibration process has many degrees of freedom. We applied an automated model calibration procedure, that repeatedly starts at different random locations in the parameter space and minimises the error between model results and observations (van Ruijven et al., 2009; van Ruijven et al., 2010). The best calibrated sets of parameter values have Root Mean Square Error values of 9% for urban and 2% for rural areas across all fuels and quintiles. Comparison of these calibrated model results and data learns that the model simulates the generic trends, but that it allocates too little market share to kerosene in urban areas (Fig. 6). The main conclusion of the calibrated parameter values is that urban households apply capital intensive energy options at lower income levels than rural households.

6. Electricity use for lighting and appliances

6.1. Lighting

The lighting technologies follow a clear preference ladder (Table 3). At low incomes and without electrification, candles and kerosene are the only available options. Once electricity is available, electric lighting is preferred. The barrier of front-end investment costs causes less efficient incandescent bulbs to come first, before fluorescent tubes and bulbs are applied (Reddy and Balachandra, 2006b).

In modelling terms, we assume that demand for lighting services is mainly driven by residential floor area (see Section 4.1). Reddy and Balachandra (2006a) identified a series of standard and energy-efficient lighting packages that vary with respect to the number of bulbs and tubes and the usage pattern. The energy efficient lighting packages have higher capital costs, but lower energy use than the standard lighting packages. Originally, these packages were associated with different income levels. However, the demand for lighting services is not expected to increase endlessly with income. Therefore, we linked these lighting-packages to floor space per capita as physical driver. Annual energy use (in kWh/hh/yr) for different energy packages (*EP*=standard or energy-efficient) is defined as

$$FEL_{q,EP(t)} = (\gamma_{p,EP}F_{p,q(t)} + \delta_{p,EP})MS_{p,q,EP(t)}\ (\text{kWh/hh/yr}) \quad (11)$$

with floor space (*F*) in m^2/capita and the parameters γ and δ distinguished for rural and urban areas. Minimum electricity use for standard and efficient lighting are, respectively, a single 40 and 10 W bulb. The use of kerosene for lighting is modelled as function of electrification: all non-electrified households are assumed to use kerosene for lighting: 4 litres per household per month (ESMAP, 2003). Sales of compact fluorescent lights (CFL) in India started to increase in 1997, but from very low levels (Kumar et al., 2003). Therefore, we assumed the efficient lighting packages to be only available since 1995 (though at higher cost than standard lighting). Total capital costs are depreciated using the CDR (see Section 5.2). The actual market shares of the energy packages are determined from a multinomial logit distribution on marginal investments and a vintage capital stock (see Section 5).

Table 3
Historic data on urban and rural shares of kerosene and electricity as main energy source for lighting in 1993 and 2002 per population quintile (NSSO, 1997, 2004).

	Kerosene (%)	Electricity (%)
Urban 1993		
Q1	30	70
Q2	14	86
Q3	9	91
Q4	5	95
Q5	2	98
Urban 2002		
Q1	26	74
Q2	16	84
Q3	7	93
Q4	3	97
Q5	1	99
Rural 1993		
Q1	74	26
Q2	63	37
Q3	54	46
Q4	46	54
Q5	35	65
Rural 2002		
Q1	67	33
Q2	59	41
Q3	50	50
Q4	39	61
Q5	23	77

6.2. Household appliances

At higher income levels an increasing share of electricity is used for other end-use functions and appliances. Similar to other end-use functions discussed so-far, also here clear income-related preferences can be observed: first a fan is bought, second a TV and third a refrigerator, followed by more energy-intensive appliances, like air coolers, air conditioners and washing machines (Fig. 7). We clustered the use of household appliances in four end-use functions and use one major energy consuming technology as representative item for its cluster. The end-use clusters are as follows:

1. Space cooling:
   Represented by fans, air coolers and air conditioners.
2. Food storage and processing:
   Represented by refrigerator (includes immersion water-heaters, mixer and hot plate).
3. Washing and cleaning:
   Represented by washing machine (includes vacuum cleaner and iron).
4. Entertainment and communication:
   Represented by TV (includes radio, PC and mobile phone).

For space cooling, we modelled all three appliances explicitly, because of their diverging characteristics. Fans are the first appliance that many poor households buy (Fig. 7) and consume little energy (Table 1). At high income levels, air conditioners are preferred with higher energy consumption. An alternative that uses less energy is the air cooler (or evaporative cooler), but its potential is limited, as it depends on specific climatic conditions.

Electricity use for household appliances depends primarily on two indicators: the ownership of appliances (as fraction of total electrified households) and energy use per appliance (unit energy consumption, *UEC* in kWh/hh/yr or kWh/unit/yr). Therefore, the formulation of annual electricity use of appliances is

$$FEA_{p,q,(t)} = ownership_{p,q(t)} \frac{UEC_{p,q(t)}}{EfficiencyImprovement_{(t)}} (\text{kWh/yr}) \quad (12)$$

Ownership of household appliances generally shows a logistic (or S-shaped) form over income. We followed Letschert and McNeil (2007) in using a Gompertz-curve as the simplest representation of such form, and used non-linear regression to

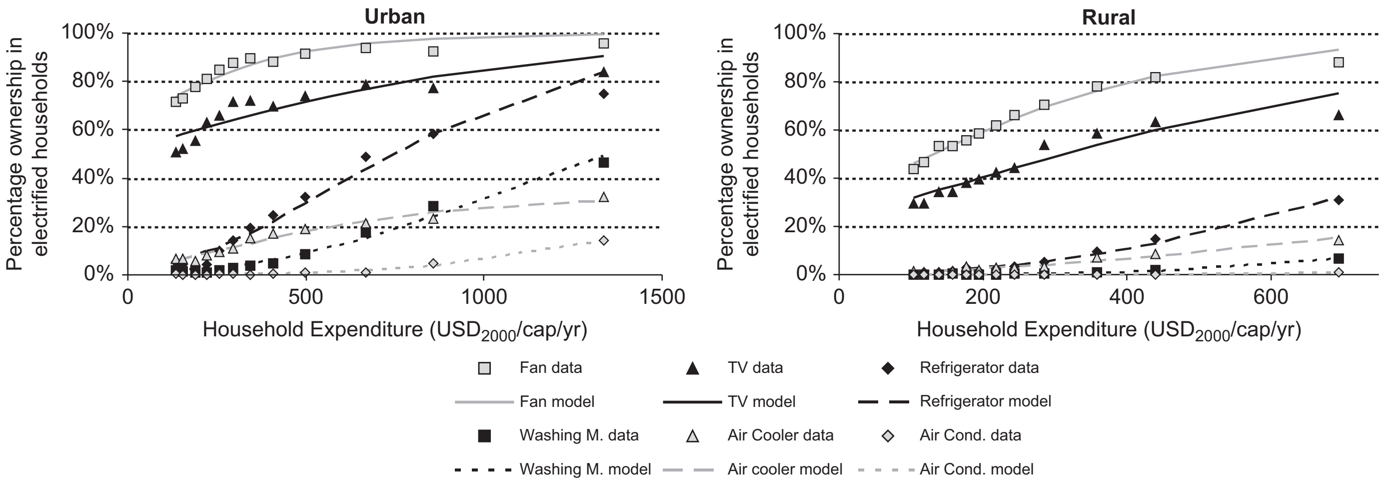

Fig. 7. Data and results of regression model for appliance ownership in rural and urban electrified households in 2002.

estimate parameter values per appliances cluster and urban/rural area (Fig. 7). We adjusted the historic ownership data (used in the regression analysis) for electrification levels, price decrease of appliances and the option of multiple ownership. Electrification levels are a natural upper limit for appliance ownership; the historic saturation level of many appliances increased over time, which can (among others) be explained from decreasing prices. Finally, several appliances are likely to be available in multiple units in households. We included this explicitly in the ownership curve for fans; for air coolers and air conditioners this is implicitly included in the unit energy consumption (Table 1). It should be noted that the regression is mainly based on a one-time measurement across different expenditure levels (because of limited data availability), the development of appliance ownership within a certain expenditure group over time might have a different shape.

The second step is unit energy consumption (*UEC*) of the different appliances. Following Letschert and McNeil (2007), we distinguish between appliances with a rather constant *UEC* (fan, TV and washing machine), appliances with a time-dependant *UEC* (refrigerator, driven by expected increasing market share of larger models) and appliances with an income-dependant UEC (air cooler and air conditioner, driven by the use of multiple units, increasing unit cooling capacity and increase in hours of use). For fans, we explicitly account for ownership of multiple units as a function of household floor space. UEC of air conditioners is assumed to be a logarithmic function of household expenditure, with an upper level based on cooling degree-days (Section 3.4) and a minimum energy consumption of 400 kWh/hh/yr (Akpinar-Ferrand and Singh, 2010; Isaac and Van Vuuren, 2008; Letschert and McNeil, 2007; Murthy et al., 2001). For air coolers, we assume a similar pattern with household expenditure, adjusted for the difference in annual power consumption (McNeil and Iyer, 2008; Murthy et al., 2001).

The final step is the improvement of appliance energy efficiency. Two processes are distinguished here. First, efficiency improves (autonomously, i.e. without extra costs) over time as result of technology development and increased efficiency standards. Second, more efficient appliances are often available against higher costs. In this model version, we have included the first process of autonomous efficiency improvement on the basis of literature estimates (Letschert and McNeil, 2007; McNeil et al., 2008; Rong et al., 2007). An alternative option, to include both autonomous and price-induced efficiency improvement, is to define a cost-supply curve of energy-saving measures. However, this requires extensive data collection and, hence, might be useful for future further model development.

7. Model performance

We have first run the residential energy model for the historic period of 1971–2003. The model results for this period show that residential energy use in India is dominated heavily by traditional bio-energy (TBIO), followed by oil, coal and electricity (Fig. 8). With respect to end-use functions, cooking is clearly dominant in Indian households (Fig. 9), but a considerable amount of kerosene is applied for lighting in households without access to electricity. For electricity use, lighting has been the major electricity end-use function up till 1990; after that, fans became more important and currently, electricity use for televisions and refrigerators is rapidly increasing.

We compare the simulation results of the residential energy model to the historic data of the IEA energy balances (IEA, 2005). As the IEA energy balances only specify the amount of fuels used by the residential sector as a whole, comparison needs to be done at an aggregated level (the IEA data should be treated carefully because India does not submit official energy balances to the IEA and fuelwood data are inherently uncertain; recently, the IEA improved the quality of its Indian energy data with bottom-up statistics from the NSSO[7] (IEA, 2007)). As we did not calibrate our model to the IEA data, the comparison presented here involves two independent data sources.

The model results on fuel use (the sum of cooking, water heating, space heating and kerosene for lighting) in (Fig. 8) show that they comply reasonably well to the IEA energy balance data. Expressed as the Normalised Root Mean Square Error, the error between data and model results over the whole period 1971–2003 is 2.7%. The best fit for residential fuel use in India of the existing top-down energy demand module of TIMER was found to be 6% (van Ruijven et al., 2009).

For individual fuels, the model simulates a lower market share for coal and higher market share for oil during the 1970s than the IEA data suggests. The latter is mainly related to kerosene use for rural lighting and cooking. Historical energy use for lighting might be overestimated, because we assume that people always light their houses, whereas in reality many families might use some candles and go asleep early.

Although the simulations of households depending on coal as main cooking fuel are calibrated to the NSSO data (Section 5.2), the use of coal in the model is less than in IEA data. Because we used NSSO data on the main fuel of households, it might be that

[7] These improvements are not included in Fig. 8.

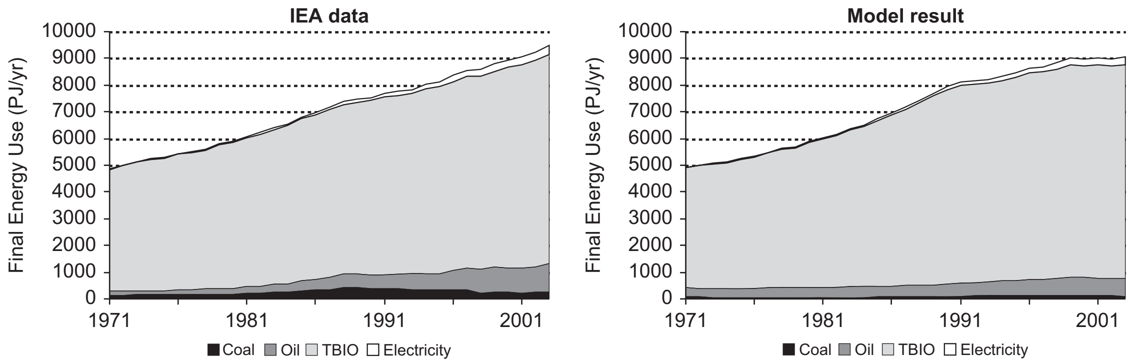

Fig. 8. Historic data (IEA, 2005) and model simulation results for historic total fuel use in the Indian residential sector.

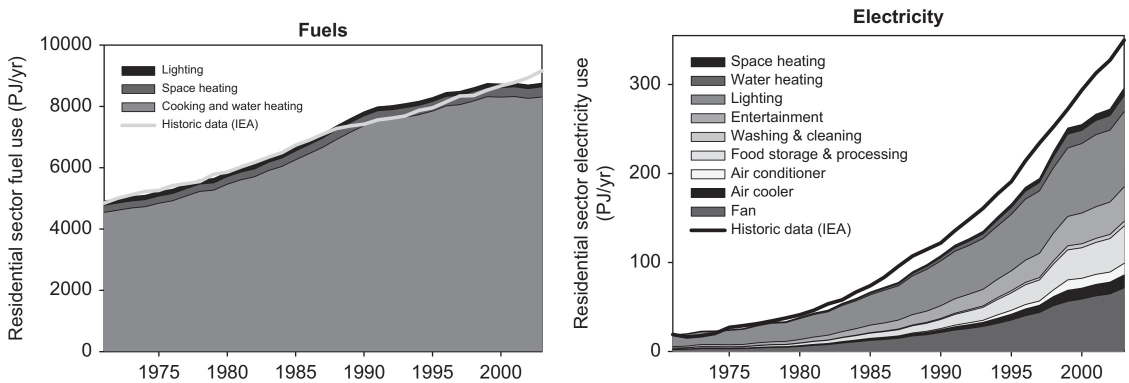

Fig. 9. Historic residential sector fuel and electricity use (IEA, 2005) and model simulation results of energy use for several end-use functions.

coal is usually applied as secondary fuel. The results for electricity use are generally in line with historical data as well (Fig. 9), but the model underestimates the increasing electricity use in later years. Therefore, the NRMSE for the simulation of total electricity use the period 1971–2003 is 13.8%. The best fit for residential electricity use in India of the existing top-down energy demand module of TIMER was found to be 31% (van Ruijven et al., 2009).

8. Scenario analysis: the impact of electrification and income distribution

We use the model to analyse the impact of electrification and income distribution on future energy use and CO_2 emissions. Changes in electrification have an effect on household energy use through changes in the use of electricity for lighting, appliances and water heating. Changes in the distribution of income over households (i.e. change in the GINI coefficient) influence the choice between traditional and modern fuels for different income groups.

For this, we use the baseline scenario of the 2007 OECD Environmental Outlook (OECD-EO) (Bakkes et al., 2008; OECD, 2008). In this scenario, the Indian population increases towards 1.6 billion in 2050 with an urbanisation rate of 47%. The all-India average household expenditures increase from 300 USD_{2000}/cap/yr in 2000 to 2350 USD_{2000}/cap/yr in 2050 (comparable to Turkey, South Africa or the Slovak Republic in 2005). Income distribution is assumed to remain constant under this scenario. Indian residential fuel prices in this scenario increase slightly with 20% towards 2050. Electricity is mainly produced in the baseline scenarios from coal, although natural gas, nuclear and hydropower are increasingly applied, slowly decreasing the carbon emission factor of electricity.

Based on this baseline scenario, we constructed two variants that have an emphasis on equity (OECD-B) versus market-efficiency (OECD-A), consistent with the IPCC/SRES storylines (IPCC, 2000; Shukla et al., 2003). The efficiency-oriented scenario (OECD-A) follows the development strategy of loosening economic policy to stimulate richer groups, while aiming at a trickle down of economic development. This scenario leads to an increasing gap between rural and urban expenditure levels, the GINI coefficients increase to values that are currently observed for China, the USA and Mexico and policy attention fades away from rural electrification. In the equity oriented scenario (OECD-B) policies are effective in enhancing income levels of the poorest groups, the gap between rural and urban expenditure levels decreases and the GINI coefficient decreases towards values that are currently found for Italy and Scandinavia (World Bank, 2007). Extra effort is made for (rural) electrification, aimed at decreasing the dependency on kerosene for lighting. The assumptions of these scenarios are shown in Table 4. For comparison, we also present the results of the original TIMER OECD-EO scenario, which are derived from the existing TIMER energy demand model.[8]

Between 1971 and 2005, the average household expenditure per capita increased on average with 2.3% per year. In both scenarios, the average per capita growth rate is increased to 4.2% per year for the period 2005–2050. Varying the income distribution assumptions (see Table 4) leads in the efficiency-oriented OECD-A scenario to an increase in urban annual per capita household expenditures for the different quintiles with

[8] Several energy scenario studies have been published for India (e.g. Planning Commission, 2006; Shukla et al., 2003). However, because none of these studies published results at the sectoral level, we cannot compare our results of these studies without making heroic assumptions.

3.2–4.6% per year towards 740–8100 USD_{2000} for, respectively, Q1 and Q5 (Fig. 10, upper graphs). In the equity-oriented OECD-B scenario this range is 1290–4800 USD_{2000}/cap/yr in 2050, or 4.4% annual growth for Q1 to 3.4% for Q5. For quintiles in rural areas, the OECD-A scenario projects 490–2990 USD_{2000} (or growth rates of 3.0–3.9%/yr for, respectively, Q1 and Q5), while the OECD-B leads to a range of 1080–2950 USD_{2000} (or growth rates of 4.9–3.9%/yr for, respectively, Q1 and Q5). So, for the rural rich, the situation is comparable in both scenarios, while the urban rich earn almost twice as much in the OECD-A scenario. The difference between the scenarios is most prominent in the low-income quintiles: in rural areas their expenditures in OECD-A are half the value of OECD-B, for the urban poor the difference is about one-third.

Table 4
Scenario assumptions for OECD-B and OECD-A scenarios on Indian residential energy use.

Variable	2005		OECD-B (2050)		OECD-A (2050)	
	Urban	Rural	Urban	Rural	Urban	Rural
Ratio to average expenditure	1.46	0.82	1.3	0.9	1.6	0.7
GINI coefficient	34	28	26	20	45	35
Electrification effort	1.0	1.0	1.1	1.1	0.9	0.9

Electrification increases in both scenarios to considerably higher levels than in 2005. The difference between the scenarios (Table 4) is especially important in rural areas (Fig. 10, middle graphs). Electrification rates for rural poor households in 2050 are 70–80% in the OECD-A scenario and over 90% in the OECD-B scenario. The growth rate of electrification slows down in the future, in line with the nature of the logistic growth curve. In the period 1971–2005 the average annual increase of electricity access was 1.3%-point per year, which in the period 2005–2050 slows down to 0.5% and 0.6% in, respectively, the OECD-A and OECD-B scenarios.

The development of incomes has a clear influence on fuel choice. Historically, the percentage of people using solid fuels decreased with an average 0.2%-point per year in the period 1971–2005. In future projections, this increases to 0.8% and 1%-point per year in, respectively, the OECD-A and OECD-B scenarios, driven by the increased growth rate of household expenditures. Still, rural areas are projected to rely mainly on traditional fuels for the next decades. In the OECD-B scenario, the use of traditional (solid) fuels in 2050 is limited to about 20% of

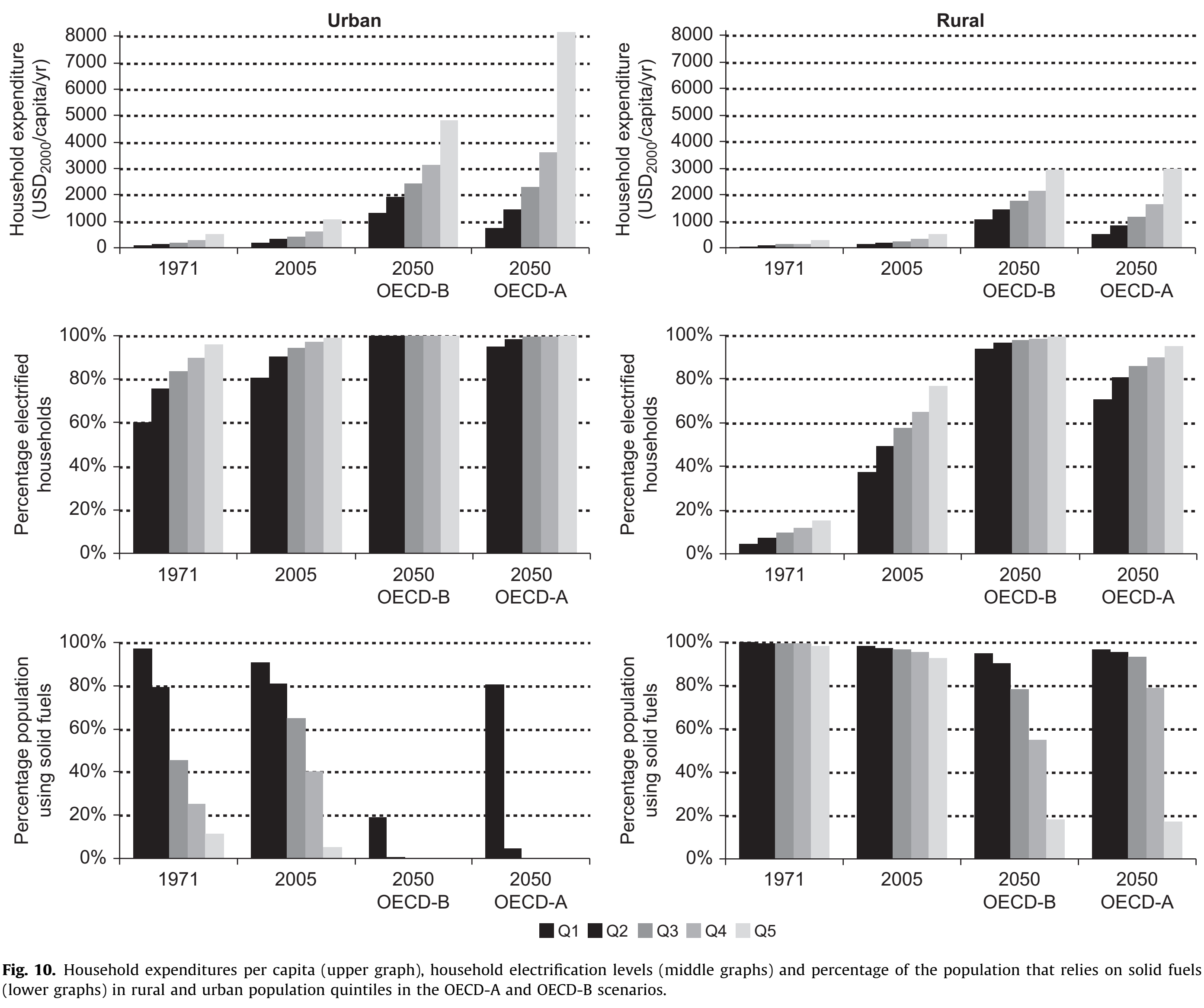

Fig. 10. Household expenditures per capita (upper graph), household electrification levels (middle graphs) and percentage of the population that relies on solid fuels (lower graphs) in rural and urban population quintiles in the OECD-A and OECD-B scenarios.

Table 5
Total final residential energy use in the OECD-A and OECD-B scenarios and the TIMER OECD-EO scenario. Note that the OECD-EO scenario has not been calculated with this model but is taken from another study (Bakkes et al., 2008; OECD, 2008) and presented here for comparison.

PJ/yr	Coal	Oil	Natural Gas	MBIO	Trad.Bio	Electricity	Total
1971	87	328	0	0	4499	19	4932
2005	82	630	0	0	8312	352	9376
2050 OECD-B	0	2527	0	0	5213	7752	15492
2050 OECD-A	0	2460	0	0	7486	6557	16502
2050 OECD-EO	79	4451	0	42	6622	2832	14026

Table 6
Total residential sector carbon emissions in the OECD-B and OECD-A scenarios, including and excluding emissions from fuelwood. Note that the OECD-EO scenario has not been calculated with this model but is taken from another study (Bakkes et al., 2008; OECD, 2008) and presented here for comparison.

MtC/yr	Residential carbon emissions (incl. electricity production)	Residential carbon emissions (including fuelwood)
1971	9.7	79.9
2005	36.9	166.6
2050 OECD-B	376.4	457.7
2050 OECD-A	324.6	441.3
2050 OECD-EO	208.7	312.0

the lowest urban and rural households. In the OECD-A scenario, however, the urban poorest quintile still relies for 80% on traditional fuels in 2050 being most common in the four poorest rural quintiles (Fig. 10, lower graphs).

What is the impact of these developments on total energy use of the residential sector? The total absolute amount of residential energy use increases considerably in both scenarios: from 9.5 EJ in 2005 towards 15.5 EJ/yr in OECD-B and 16.5 EJ/yr in OECD-A in 2050 (Table 5). However, as a result of the different income projections and electrification efforts, the energy mix is different. In 2050, traditional biomass counts for 34% of final energy use in the OECD-B scenario, while it counts for about 45% of final energy use in the OECD-A scenario. Oil use is higher in the OECD-B scenario, because it is the primary substitute traditional fuels. Electricity use is 1.2 EJ/yr higher in the OECD-B scenario, where more households have access to electricity and ownership of fans and televisions is significantly higher. Compared to the original TIMER OECD-EO scenario, this new model projects higher consumption of electricity (about half of which is for air conditioning). The transition from traditional fuels to oil is in the same order of magnitude as the original OECD-EO scenario.

While residential final energy use increases by 65–75% between 2005 and 2050, carbon emissions from fossil fuels in 2050 are projected to increase to 9–10 times of the 2005 level (Table 6). The CO_2 emissions from traditional fuels are uncertain: if one assumes that traditional fuels are produced from sustainable sources they should be counted as carbon-neutral. However, some studies indicate that only 60% of fuelwood is sustainably harvested (Reddy and Balachandra, 2006a). In that case, the present day emissions are much higher and the increase in total emissions (modern and traditional) in 2050 is 'only' a factor 3 higher than today. Another aspect are non-CO_2 greenhouse gas emissions from incomplete combustion of fuelwood. We do not account for these emissions, but if one would take these emissions into account, the greenhouse-gas emissions of fuelwood would be magnified.

The structure of carbon emissions is the main difference between the OECD-A and OECD-B scenario. In the OECD-B scenario, traditional biomass use causes minor carbon emissions in 2050, whereas it counts for 26% of the emissions in the OECD-A scenario. Another major difference between the scenarios originates in the relatively high carbon emission factor of electricity in India, due to the reliance of the electricity system on coal. The projected growth in electricity use, especially in the OECD-B scenario, leads to a strong increase in carbon emissions, whereas lower electrification levels in OECD-A limit carbon emissions from electricity. The total carbon emissions from fossil fuel are considerably higher than the projection of the TIMER OECD-EO scenario. This difference is mainly driven by the higher demand for (carbon intensive) electricity (see Table 5).

9. Discussion and conclusion

In this paper, we described a bottom-up model for residential energy use in India, starting from the dynamics of development and energy use. In this model, urbanisation and heterogeneous income distribution are treated explicitly and urban and rural energy systems are modelled separately. We also included the development processes of decreasing household size and electrification. The model determined residential energy use for five end-use functions: cooking, water heating, space heating, lighting and appliances (including space cooling). For fuel use, also the choice between different fuels is included, following the same type of behaviour as in the empirically observed energy ladder: cleaner, more convenient, but also more expensive energy options are preferred at higher income levels. Also other factors follow income-related trends such as appliance ownership. This detailed model provides a more insightful picture of present and future energy use than aggregated top-down approaches. The nature of the model allows for bottom-up estimations of future efficiency improvements.

Lack of detailed data on the use of energy for different end-use function limits understanding of energy use trends in developing countries. Model development for developing regions is hampered by a lack of data. Although it is known that several issues are important for energy use, there are hardly any data available on these issues to identify model relations. For instance, data on household electrification are scarce, since the government officially measures electrification of villages; also, electricity use in countries like India suffers from many black-outs and brownouts, but information on duration (and location) of these outages is not available. Further, the quality of the data is questionable. Survey data rely heavily on the education and consistency of the interviewers and on the honesty of answers. For India, relatively detailed information is available, which enabled modellers to develop detailed fuel switching models (Ekholm et al., 2010; Mestl and Eskeland, 2009) and provided us enough information to develop the model described in this paper. Nevertheless, we had to make some 'heroic' assumptions during the development of this model. Most of these assumptions (for instance electrification levels, unit energy consumption of appliances and heating energy intensity) were based on information that is available for recent years, and we 'extrapolated' this historically towards 1971. In recent years, more information became available for other world regions as well, enabling us to implement this model globally (Daioglou et al., in preparation).

The bottom-up residential energy model is able to reproduce aggregated energy data relate well. We found that this model, developed from many locally available sources and survey data, simulates historic residential fuel use reasonably well with an NRMSE value of 2.7%. The simulation of historic electricity use is not as good, with an NRMSE of 14%. However, on both fuel and electricity use, this model performs better than the existing top-down TIMER energy demand model, which had minimum error values of, respectively, 6% and 31% for the Indian residential sector.

The new energy model allows addressing important factors for energy use trends in developing countries. We explored the consequences of different development trajectories for income distribution and electrification on total energy use and CO_2 emissions. We used two scenarios, based on the TIMER OECD Environmental Outlook scenario focussing on equity and efficiency. We found in these scenarios that total Indian residential energy use may increase by 65–75% in 2050 compared to 2005. At the same time, total carbon emissions may increase to 9–10 times the 2005 level. The variation in income distribution and electrification significantly influences these future projections. More equal income distribution mainly increases income-levels of the poor and leads to a more rapidly phase-out of traditional fuels and related decreasing indoor air pollution and related health impacts. So, while equal income distribution and rural electrification are good for decreasing poverty and enhancing the use of clean fuels, there is a trade-off in terms of higher CO_2 emissions due to increase electricity use.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.enpol.2011.09.021.

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