Data-driven urban building energy models for the platform of Toronto

Data-driven urban building energy models for the platform of Toronto

ABSTRACT

Increasing building efficiency is a key topic in territorial policies at different scales, for which new pathways and actions are progressively introduced. However, the evaluation of building consumptions according to energy features, urban and socio-economic variables is crucial to better assess building efficiency measures. This study presents a place-based statistical model for the evaluation of energy demand at the building scale, starting from disaggregating consumption values at the block level. The case study is the central district of Toronto (Ontario, Canada), part of the 2030 Toronto Platform. The existing interactive tool shows energy data only at the block scale, limiting specific evaluations and benchmarking. Therefore, the analysis presents a set of statistical models for assessing residential building consumption by archetypes. The aim to extend the application and visualization of the energy demand of the whole city by GIS software. The statistical models underline more reliable results for electricity use, distinguished by appliances and space cooling. Low-rise apartments are the most challenging category to be assessed for appliances use. The variability of natural gas consumption does not allow to build only one model and values for apartments buildings are more variable for different construction ages.

Keywords: *Data-driven energy model, Statistical model, Top-down model, Buildings, Archetypes, GIS.*

1. INTRODUCTION

Climate change is increasingly affecting life in urban areas, where population and building design are generally denser. For instance, in Canada, the 80% of inhabitants is concentrated in cities, while a two-fold temperature increase (+1.7°C) compared to global values has been registered from 1981 to 2016 [1]. For addressing climate challenges and urban sustainability, multi-level policies have been introduced. The Canadian government structured a 2030 Emissions Reduction Plan to reach Net-Zero Emissions by 2050 [2] in line with the 2016 Pan-Canadian Framework on Clean Growth and Climate Change [3]. To implement these goals, assessing housing demand is crucial because Canada's homes cover the 18% of national greenhouse gases (GHG) emissions, using mainly fossil fuels for heating and electricity [2].

For evaluating building performance, energy models estimate resource consumption and emissions [4]. The scale and character of energy challenges in regions and cities depend on their context, which calls for place-based dimensions for evaluation of demand [5]. The classification of energy models followed by several studies has mainly distinguished top-down or bottom-up approaches [6] [7]. Top-down models use historic aggregate energy and energy-related data at municipal, regional, national scale to estimate average consumption for building stock at city level [8]. To provide long-term projections, top-down models generally rely on past trends, demographic, and macro-economic features rather than on the physical aspects of the single buildings [9]. Any specific data are not required because they estimate building energy consumption from long-term link between energy and some drivers. These drivers are mainly socio-econometric, technical, and physical [10]. They reflect interactions at a large territorial scale, as city or regions: indeed, top-down models are suitable to study spatial variations of energy uses [11] and if the level of detail can be limited. Its related strength is the need for aggregated data for an area only which are mostly available and the simplicity to be developed [12]. However, the dependence on past relations between energy and other aspects might not suit when analysing future trends as climate change issues [9]. According to [6] and [12], top-down approaches favour large-scale preliminary analyses of building consumption, which can reflect long-term changes. Potential improvements by new technologies or integrated energy-supply scenarios can be quantified with bottom-up approaches [13]. Bottom-up models often identify the most cost-effective options to achieve energy or carbon reduction targets, according to the best available technologies and processes. Bottom-up models simulate the energy demand for individual households, single or groups of buildings and then derive the consumption distribution at wider scale, as for a region [8]. Bottom-up models contribute to optimize urban energy systems because their results have higher spatial and temporal resolution compared to top-down techniques [13]. The higher accuracy requires extensive detailed data, as for building components and occupancy schedules, and imply longer elaboration time compared to top-down models [6]. In this study, a top-down model is selected due to the availability of aggregated energy data and the focus on interactions at the larger urban scale [14]. Despite the limited level of detail, a top-down approach manages larger sample of data to build applicable energy models. The large-scale assessment of energy consumption and preliminary evaluation contribute to the suitability of a top-down rather than a more accurate bottom-up approach. In both methods, geo-localising results by Geographic Information System (GIS) allows identification of critical areas and multi-scale decision-making [15]. Starting from an energy platform for a city district, few studies have used a GIS support to disaggregate energy consumption from block or neighbourhood scale and reach the single-dwelling level.

Therefore, this study will focus on the assessment of energy consumption for residential buildings in the city of Toronto, starting from the modelled data at the block level in the Toronto 2030 Platform [16]. This represents one of the most recent tools to report the energy and energy-related features for the city urban core. The Toronto 2030 Platform adopts a bottom-up engineering model, based on the ASHRAE template. However, its assessment stops at the aggregated scale of building blocks due to the limited availability of data. The main challenge faced in this study is the estimation of building demand, having only aggregated modelled data. A top-down statistical model at the building level is based on the Toronto 2030 Platform and the energy model is integrated in GIS environment, subdividing the energy demand for single dwellings. Only the residential stock with energy uses is considered, distinguishing the main housing types. The assessed model aims at its extension to the whole City of Toronto, using building shapefiles in GIS environment. Despite data constraints, results are useful for more specific evaluations on the building stock and can represent a further level of detail of the Toronto 2030 Platform.

2. LITERATURE REVIEW

2.1 Energy platforms: potentials and limits

Energy platforms are interactive dashboards and maps online which can display energy consumption, production, and emissions of the building stock. Energy platforms provide a baseline support for the evaluation and planning of energy policies or interventions. Stakeholders as policy makers, researchers, and citizens can be interested in understanding energy demand-consumption and GHG emissions. They can display mainly two types of information at the city level [7]:

- energy-use data, which can evaluate the distribution of energy-related aspects (as consumption, energy performance certificates, retrofit interventions) or the renewable energy production potential;
- urban features, as morphology, land uses (generally from zoning codes) and socio-economic indicators, which can be complementary to the local energy-use characterisation.

Using GIS, assessments of renewable potentials is spatialised on platforms with a high level of detail due to the easily accessible input requirements [17], as in the case of the Solar Portal for the Metropolitan City of Turin [18]. On the other hand, energy consumption values can be more challenging to obtain.

One of the main constraints for energy urban platforms is the availability, quality, and resolution of data, which can easily result dated and/or not detailed in the scale of definition. Displayed energy results on a platform can be from real acquisitions or estimations derived from models. Temporal resolution characterises non-steady (dynamic simulation), quasi-steady (monthly or daily) and steady models that avoid temporal matters [19] [14]. Annual data are often feasible for mapping and planning purposes due to the focus on energy localisation. High-resolution temporal data estimates the fluctuating nature of demand and renewable resources [17]. However, energy assessments are often based on top-down aggregated estimations on annual basis rather than real acquisition data [17]. As discussed in a recent study for district heating [20], models referred to a city portion tend to cluster buildings for a manageable scale: the more the structures are aggregated and simplified, the less the building heterogeneity will be, as for heating and electricity profiles, and the quality of the final output is likely to decrease. Indeed, energy demand is rarely homogeneous within an urban environment [21].

The GIS visualisation contributes to identify priorities for future interventions in more critical areas [17]. A GIS spatialisation by energy mapping relies mainly on availability of geographic data and suitable energy datasets. Different challenges can limit the elaboration and accuracy: the constrained spatial and temporal resolution for suitable projections as well as socio-economic problems for acquisition and transfer of data (privacy, data ownership, costs) [17]. Some relevant examples for online urban energy platforms are here reported, with main aspects and limits:

- the Southern California and Bay Area Energy Atlases [22], which displays results from counties to neighbourhoods based on disaggregated data, but the temporal frame is only from 2006 to 2016. It combines electricity and natural gas demand with GHG emissions, building age and functions divided by macro areas;

- the New York City Energy and Water Performance Map, which is developed by lots [23] due to privacy and disclosure issues of providers. The platform distinguishes age, floor area, property types for energy use, and GHG emission intensity. The tool does not completely characterise the city (especially in the case of emissions) and data goes from 2011 to 2017;
- the Wien City Map [24], developed at the building level, according to cadastre maps. It localises power generation plants and renewable energy potentials (wind, geothermal, waste, solar), overlapped with natural and historical constraints. Despite the availability of other urban layers (green areas, mobility, climate, etc.), the platform lacks spatialisation of city energy consumption.

In conclusion, main challenge to develop an effective platform is to balance the level of accuracy with rapidity of simulations, according to available data. Mostly aggregated data from platforms can represent a starting point for more detailed evaluations at building scale. As for the following study, top-down energy models begin from energy data at neighbourhood scale to disaggregate and obtain the spatial distribution of energy consumption at building scale.

2.2 Urban energy modelling: from aggregated values to building-scale results

Disaggregation of energy data has been frequently applied in previous studies at different scales. Recent studies applied methodologies to evaluate building consumptions from aggregated datasets, assuming distinct methodologies and levels of simplification. Disaggregation of energy consumption can be by energy sources [25] [26], by fuel, end-uses services and technologies [27] or by multiple geographical levels [28]. Gonzales et al. [28] analysed the energy consumption of Europe by three decomposition levels, or rather by subgroup, by member state and by regions. The energy intensity was the criteria to aggregate and disaggregate countries to test the factors changing energy consumption. Results suggested that when reducing the fineness of the decomposition scale, the influence of the considered variables is reduced than by single country. Moving to the district scale, in the case of Gran Mendoza (Argentina) [29], a top-down model for space heating was performed starting from the measured energy consumptions. From the obtained average consumptions of the census sections, simplified models for the seven typologies of residential buildings were applied at the urban scale. These archetypes are identified according to typological and socio-economic characteristics. Thanks to a GIS support, an iterative calculation identified the energy demand for each group of buildings until the consumption of all districts matched the measured data. This process started from districts with only one group of buildings, then with mixed ones. With a different approach, Lorimer [30] developed a model for evaluating non-heating energy end uses (appliances and lighting) in England, which can be verified using aggregated data of meters in small zones and housing census data. A bottom-up housing stock was based on number of occupants and of rooms to predict the uses with multilinear regressions and then validated against total electricity demand data. The total modelled and actual energy use resulted close, despite variations for different areas and the model can quickly adapt to new available data. Working on the urban scale, Roth et al. [31] realised a two-step urban building energy model for the city of New York. They estimated the annual energy use for all buildings with supervised machine learning. Values were then extended with physic-based simulations to minimise the difference between the publicly available building data at the borough scale and the calculated hourly electricity demand. A more detailed mathematical method [32] is applied by algorithm to disaggregate energy demand into end-uses and minimising the error with the total measured energy consumption. In this case, a fraction of energy loads was already known, while the remaining part was assessed by algorithm at the household level. Zhuravchak et al. [11] downscaled the analysis from the city-level to 1*1 km^2 grid to create an urban energy map for Trondheim, Norway. A top-down probabilistic approach was applied, with a disaggregation by exogenous factors (mainly, by construction year). The approach contributed to convey the aleatory uncertainties, accommodate the heterogeneity of building features with flexible spatial resolution. Top-down energy models for urban environments implies spatial downscaling from agglomerated energy data for an area to progressively subdivide values into smaller sections, as city, district, or building. This is the opposite to bottom-up reasoning, in which information at finer levels can be aggregated energy consumption. Differently from previous cases, this study downscales energy consumption from block level to the building scale starting from an energy platform, distinguishing the main dwelling archetypes. The procedure is easily applicable to other contexts with a GIS support and with low computational efforts. Disaggregated data are the base to build a statistical model based on regressions, with independent building-related variables. Finer results are meant to be displayed in an energy mapping tool integrating energy and building aspects.

3. METHODOLOGY

This study proposes top-down statistical models to assess the residential building demand. Results distinguish main dwelling types, based on the Canadian context. The methodology workflow is illustrated in Figure 1. To perform regressions, the statistical models require data at the building scale which are not available. Therefore, the methodology disaggregates energy data of the 2030 Toronto Platform from the block scale to the building level for electricity and natural gas uses. Two methods are applied to distinguish values by housing category: the method by subtraction and the method by equation. Results of electricity and natural gas are then compared with provincial data, from which the most satisfying disaggregation method is selected (Table 6).

From the downscaled building consumption, energy uses are estimated for appliances (App) and space cooling (SC) included in electricity and space heating (SH) and domestic hot water (DHW) included in natural gas. From the assessed energy uses by dwelling types, regression analyses (linear and multilinear) are performed to identify which independent variables impact more on building energy demand. Independent variables build equations to calculate energy uses' consumption by housing types and can be extended for the other residential zones of the City of Toronto. Figure 1 shows the territorial levels of input data, steps to downscale data from block to building level on which perform regression analyses, the top-down statistical models to be applied to estimate energy consumption by dwelling types. Regression analyses are applied because they do not require detailed values, relying on census information or consumption bills, and they are able to manage a wide sample of data. In this way, regressions can identify the relations between energy demand and relevant drivers, which affect building energy consumption [12].

3.1 Input data

At territorial and urban scale, the control of GIS data is essential for the development of analyses and models. In this work, the GIS shapefile with building outlines [33] is corrected from non-habitable structures because not relevant in the energy consumption assessment. Specifically, buildings which cannot be identified as heated buildings.

The block data of energy consumption from the Platform is then overlapped with single building shapes to obtain an overview of consumption distribution and neighbourhood profiles [34]. The available data are (Figure 1, Section 3.1):

a. From the 2017 building shapefile [33], height and ground floor area. Using GIS, other geometrical data can be calculated: number of floors, heat loss surfaces, useful floor heated surface (UHS), surface to volume ratio (S/V, m^2/m^3), air volume and gross heated volume;
b. At the block level retrieved from the 2030 Toronto Platform [16], energy consumption for electricity and natural gas based on 2017 (kWh/y), category mix (use and period of construction in percentage of gross floor area, GFA), energy-use intensity (EUI, $kWh/m^2/y$). The block energy modelling followed the ASHRAE 90.1 (2004) framework for residential buildings, using values in Table 1. Evaluations by single building were then grouped by block: indeed, consumption by single building is not available nor displayed by the Platform due to restrictions;
c. From the 2016 neighbourhood profiles [34] for the City of Toronto, socio-economic variables for each neighbourhood, among which number of inhabitants.

The study focuses on residential blocks, with at least 95% residential GFA displayed by the Platform [16]. The residential function relies on the category mix at the block scale and further validated with the Toronto zoning by-law 569-2013 [35].

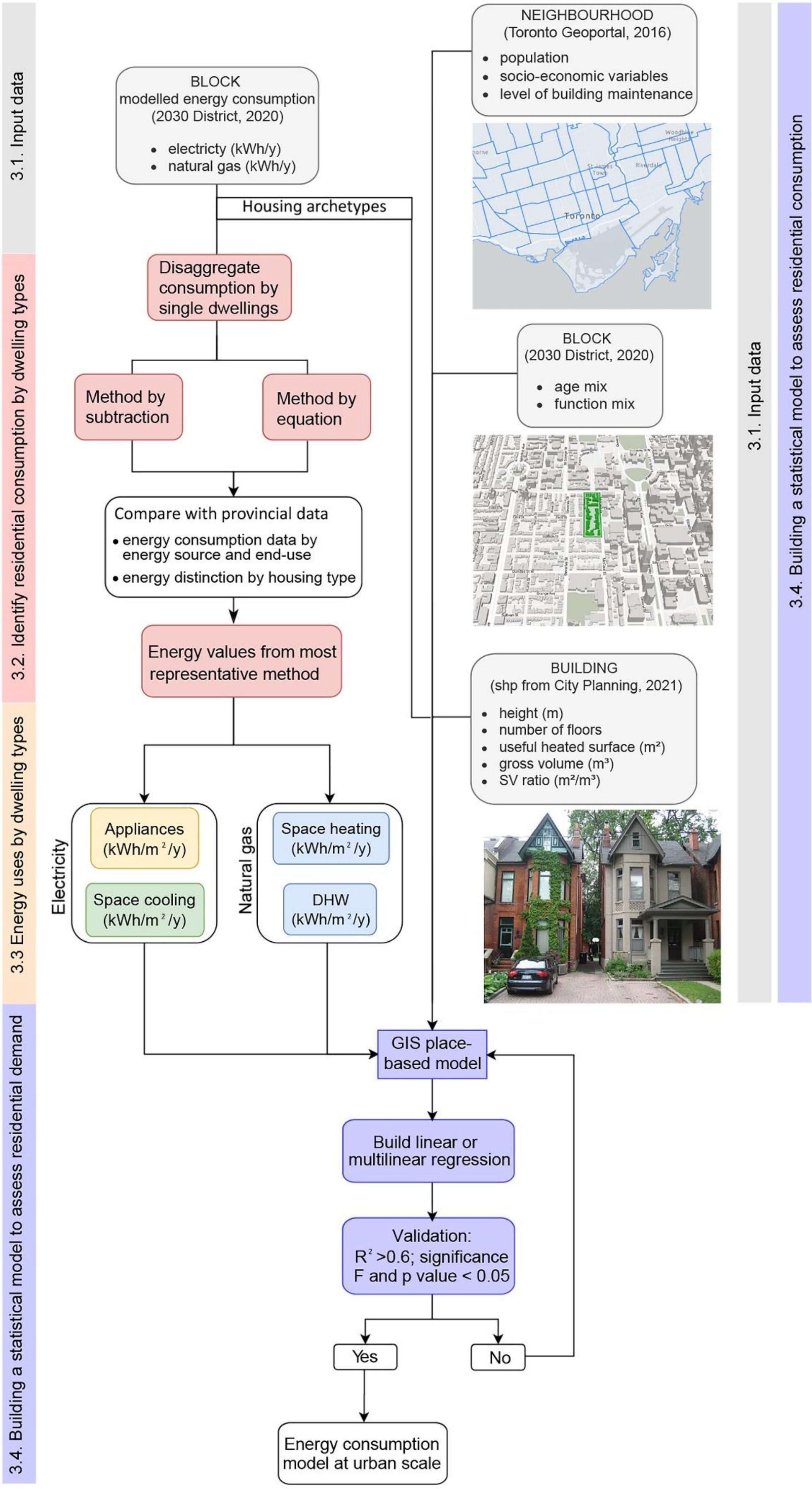


Figure 1. Methodology flowchart with the main steps, from disaggregating energy-use data to top-down statistical model.

3.2 Residential consumptions at building block scale

For each residential block, the dwelling type is identified for each building according to their S/V ratio (i.e., the compactness of buildings' form). The S/V (m^2/m^3) is calculated from the 2017 building shapefile [33] as the ratio between heat loss surfaces and gross heated volume. From previous elaborations for Canada [36] [37], the four considered archetypes are: detached and semi-detached houses, low-rise and high-rise apartments.

Two approaches are applied to disaggregate data from block to building scale. In case of 95% residential GFA for the block, the remaining 5% consumption is derived from homogeneous blocks of that function by the Platform [16] and then subtracted from the total energy-use. The results from the two methods are then compared with measured data from provincial surveys [37] [38], to identify the most reliable ones on which statistical analyses are based.

3.2.1 Method by subtraction

Based on the category mix at the block level and the distribution of housing types within it, blocks can be: residentially homogeneous, with 80% of GFA covered by that category and 100% same block vintage mix; housing mix, with more than one dwelling archetype. From homogeneous residential blocks, electricity and natural gas consumption are calculated in kWh/m^2/y, dividing the total block consumption by the UHS from the building shapefile on GIS. The averages of the energy intensities by dwelling type are then applied to the blocks with housing mix. The share (kWh/m^2/y*UHS) from known archetypes is subtracted by the whole block consumption. The remaining consumption is divided by UHS of the investigated housing type. In this way, an energy characterisation can be obtained for residential areas, divided by housing category.

Main typological and geometrical features are required by archetype to be calculated on GIS. The Toronto Platform and the building shapefile provide data to perform calculations. The method by subtraction is easily applicable to disaggregate consumption data from the block scale, for which it can be applied in case of scarce data.

3.2.2 Method by equation

This method applies the relations of energy consumption among dwellings, based on data by the Survey of Household Energy Use (SHEU) [38] for Canada. The SHEU distinguishes values by the previous four dwelling types and construction age. According to the block of buildings and building data, the energy consumptions are:

$$Block\ consumption = UHS_{DTC} \cdot x + UHS_{SMDTC} \cdot (x \cdot a) + UHS_{LR} \cdot (x \cdot b) + UHS_{HR} \cdot (x \cdot c) \qquad (1)$$

where:

- UHS_{DTC}, UHS_{SMDTC}, UHS_{LR}, UHS_{HR} are the useful heated surfaces respectively of detached houses/semi-detached houses/low-rise apartments/high-rise apartments for the selected block, distinguished by S/V ratio on GIS;

- x is the consumption of detached houses before 1980 given by [38] calibrated to the modelled block energy-use;
- *a/b/c* are the multiplicative coefficients respectively given by the different share between the calibrated consumption of detached houses before 1980 and of semi-detached houses/ low-rise apartments/ high-rise apartments for the considered age [38].

The multiplicative coefficients are calculated as:

$$a = 1 - (C_{DTC} - C')/C_{DTC} \tag{2}$$

where:

- C_{DTC} is the consumption of detached houses before 1980 by the survey [38];
- C' is the consumption to assess.

The equation (1) firstly needs to identify the detached house consumption x of the block, for electricity and natural gas.

In case some blocks do not count any detached dwelling, semi-detached houses will represent the demand x in the equation (1). Then, the multiplication between the consumption value x and the considered coefficient will identify the kWh/m^2/year for the selected dwelling type by energy source. The reference year for each block is selected by the higher share of GFA in the vintage mix of the Platform [16] because data for single building are not available.

The equation may be more complex than the subtraction method. However, once the equation is step up, results are faster to obtain on an Excel spreadsheet, having the UHS of each dwelling type for each block. The potential of the equation for Toronto relies on the availability of data for single dwelling types, distinguished by age, at the provincial level. In case a residential survey is unavailable for the case study, the method by equation is not suggested because relations of energy consumption among dwelling types cannot be performed.

3.3 Energy uses by dwelling types

The steps followed so far are:

- overlap of input data at the three scales;
- identification of main residential archetypes for each block;
- based on residential composition of each block, disaggregation of energy consumption from block to single dwelling scale with the two methods.

The identified electricity and natural gas consumptions for the single residential building include energy uses in the residential profile. Each energy use is assumed to be satisfied by electricity or natural gas based on data from the provincial survey [37]. The database provides a characterisation of fuels and energy end-uses from 2000 to 2018, distinguished by detached, semidetached and apartments for Ontario. Domestic hot water (DHW) and space heating (SH) are mainly covered by natural gas, while space cooling (SC) and appliances (App) by electricity. Considering the Canadian climate, SC is not a major component even if it is likely to increase with rising temperature trends. According to Ontario data for 2017 [37], SC is assessed as 14% of electricity demand for detached houses, 9.4% for semi-detached and 5.1% for apartments. Appliances cover the remaining part of electrical consumption for the residential sector.

The mean daily DHW per person is 75 l for washing, cleaning, showering, bathing [39]. Downscaling the number of inhabitants per buildings from neighbourhood data, the DHW consumption per building and per m^2 have been calculated. Then, the share of natural gas used is identified from the block values, through the following equation:

$$Q_{u,d} = V \cdot \rho \cdot c_p \cdot \Delta\mathrm{T} \,/\, \eta_{\mathrm{DHW}} \tag{3}$$

where:

- $Q_{u,d}$ is the daily natural gas consumption for DHW;
- V is the daily volume of water per person, as 75 l/d;
- ρ is the water density (about 1 kg/l);
- c_p is the water specific heat (1.163 Wh/Kg/K);
- ΔT is the temperature difference between the outlet (assumed as 49°C) and the inlet (water supplied to the heater, assumed as 11°C) temperature, according to [40];
- η_{DHW} is the efficiency of heat exchanger, considering 0.9 for DHW systems with natural gas boiler.

The result (kWh) from (3) is multiplied by number of days in a year, then inhabitants in one building and divided by the UHS (m^2) to obtain the DHW consumption by m^2. The remaining share of natural gas consumptions is assumed to cover SH for each building.

3.4 Statistical model to assess residential consumption

Starting from the energy use data, a statistical analysis builds models to estimate building energy demand of the TOcore area and then applicable to the whole Toronto. As reported in literature [15] [41], the main aspect is the identification of independent variables which influence energy consumption: in case of satisfying correlations, linear or multiple linear regressions can be performed to obtain energy profiles for single buildings.

Variables influencing the four energy uses and their relationships are identified by:

- the Pearson's correlation that is used to measures how a variable is linearly correlated to the energy-use;
- the coefficient of determination (R^2), which shows that the variation of the dependent variable can be explained by changes of independent variables;
- the significance F, which confirms that the regression is statistically significant, and the p-value <5%, which means how each variable is statistically significant.

The independent variables are obtained from the building shapefile, block characterisation by the Platform, and neighbourhood profiles. Correlations are performed for the disaggregated energy data of the four housing types. To be consistent, the R^2 must be higher or equal to 0.6, even if it could be higher in other cases. The lack of functions and age by single buildings has limited the development of more specific evaluations and higher correlations. The regressions performed for the TOcore area by energy uses can be then extended to other areas to assess residential consumption. The building shapefile identifies typological data, while the 147 Neighbourhood Profiles [34] distinguish the share of housing by age of construction (before 1960, 1961-1980, 1981-2000, 2001-2005, after 2005). The statistical model can be applied only on residential zones by zoning [35].

4. THE CASE STUDY OF TORONTO, CANADA

The starting point of the analysis is the area of the 2030 Toronto Platform, which is structured at the block scale for the city central core. This is an online tool developed by the Canadian Urban Institute to report building performance and improvements. For the existing buildings, the aim is to reduce GHG emissions in line with Canadian perspectives [42], while for new constructions pursuing net-zero structures by 2030. Along with the Platform, the 2030 District is developing research and engagement activities to define pathways for a zero-carbon district by 2050 [43].

The considered area (called Toronto Core – TOcore) covers the city centre, extends for 16.44 km^2, with 7,216 structures and more than 31 million m^2 ground floor area. TOcore involves eleven neighbourhoods, further subdivided in sixteen by the TOcore profile [44], with a population of around 200,000 in 2011 (7.6% of the City of Toronto) an increase by 19% from 2005. Mostly residential zones within the area of the Toronto 2030 Platform date back to 1980 or earlier. Expansions along the waterfront and financial blocks are more recent (1981-2000 or 2001-2010) where buildings with more than 30 floors are concentrated. These neighbourhoods are identified as most affected by estimations of population growth along pipelines [44].

The online platform displays information only at the block scale, based on energy data for 2017:

- Block profile: function and vintage mix (by GFA %).

  Building functions are distinguished in: Office (small, street-level office units up to large multi-storey office towers), Retail & Hospitality (all retail, restaurants, hotel, and entertainment establishments), Multi-Unit Residential (MUR, all buildings with seven or more residential units), Residential (RES, all buildings with six or fewer residential units), Institutional (schools, post-secondary campuses, long-term care facilities, and hospitals) and Industrial (warehouses and manufacturing). The vintage mix has three ranges: pre-1980 (which is the prevalent category, especially for residential), 1980-2004 and post 2004.
- Energy performance, with minimum and maximum values: GHG from buildings and from transportation (t_{CO2eq}/y), energy use intensity (EUI, kWh/m^2/y), electricity (E, MWh/y), natural gas (NG, eMWh/y) and water (eMWh/y) and, if used, steam and deep lake cooling (eMWh/y).

Due to licensing restrictions, measured consumption data were available only for the whole district. Having measured values at the district level, building energy simulations were modelled for single blocks and using information on building size, age, occupancy. Consequently, they are not directly measured at block and building scales. The ASHRAE 90.1 (2004) Standard for climate zone 5A was used for low-rise and high-rise apartments (Table 1). The prototypes are pre-1980, 1980-2004, and post 2004. ASHRAE has only a more recent version of template (IECC 2015) for single family dwellings (detached and attached) for new residential constructions: therefore, distinctions by construction period were not available by ASHRAE and are not performed in the Platform. A set of four heating systems and four foundation types were matched to create the single-family prototypes.

Table 1. ASHRAE Standards and main requirements, assumed in this study.

	Single-family	**Mid-rise apartment**	**High-rise apartment**
ASHRAE version	2015 IECC	DOE pre-1980; DOE 1980-2004; 90.1 2004	
Wall type	Wood frame	Steel frame	
Wall R-value	2.75 m^2K/W	Pre 1980: 1.13 m^2K/W 1980-2004: 2.15 m^2K/W Post 2004: 3.23 m^2K/W	
Roof type	Gable roof	Built-up flat roof, insulation entirely above deck	
Roof R-value	2.4 m^2K/W	Pre 1980: 2.50 m^2K/W 1980-2004: 3.38 m^2K/W Post 2004: 5.56 m^2K/W	
Floor-to-ceiling height (m)	2.5	3.05	
Window U-value	0.32 $W/m^2/K$	Pre-1980: 3.53 $W/m^2/K$ 1980-2004: 3.35 $W/m^2/K$ Post 2004: 2.33 $W/m^2/K$	
Window SHGC	0.34	Pre-1980: 0.41 1980-2004: 0.39 Post-2004: 0.39	
Window-to-wall ratio	0.13	Pre-1980: 0.15 1980-2004: 0.15 Post-2004: 0.30	
Foundation U-value	Slab: U = 0.15 $W/m^2/K$, crawlspace: U = 0.31, heated space: U= 0.37, unheated space: U=0.53	Pre-1980 and 1980-2004: 0.54 Post 2004: R-2.6 ci	
HVAC system	Electric resistance, gas furnace, oil boiler or heat pump	Gas furnace, split AC system DX, gas water heater (η = 80% pre-1980, η = 78% 1980-2004)	
Electricity plugs and process (W/m^2)	14.05	Pre-1980: 5.38 1980-2004: 5.38 Post-2004: 6.67	
Infiltration (ACH)	0.11	Pre-1980: 0.7 1980-2004: 0.7 Post-2004: 0.14	

* ci = continuous insulation, defined by ASHRAE standard 90.1.

The full characterisation of the 2030 Platform distinguished for functions is reported in Table 2, distinguished by function. Data by energy end-uses are not available for the TOcore area.

Table 2. Characterisation of building stock by use and energy-service according to the Toronto 2030 Platform, data taken and elaborated from [16].

	RES	**MUR**	**Office**	**Industrial**	**Institutional**	**Retail & Hospitality**
Energy use intensity (ekWh/m^2/y*)	179	234	268	N.A.	440	491
Number of structures	N.A.	3,034	2,603	26	561	4,690
Gross floor area (1,000 m^2)	2,848	10,711	8,671	61	3,495	5,544
Gross floor area (%)	9	34.1	27.6	0.1	11.1	17.6
Electricity demand (GWh/y)	140	950	1,010	20	810	740
Electricity intensity (kWh/m^2/y)	49.2	88.7	116.5	327.9	231.8	133.5
Natural Gas demand (eGWh/y)	360	1,300	730	410	400	1,630
Natural gas intensity (kWh/m^2/y)	126.4	121.4	84.2	6,721.3	114.5	294
Total energy intensity (kWh/m^2/y)	175.6	210.1	200.7	7,049.2	346.3	427.5
Steam (eGWh/y*)	0	140	300	0	270	180
Deep lake water cooling (eGWh/y*)	0	90	260	0	40	160
Water (eGWh/y*)	6	22.5	18.2	0	7.3	11.6

* data not available for some building functions.

Natural gas is the main fuel source used in Toronto due to its lower costs compared to electricity. It significantly contributes to greenhouse gas (GHG) emissions, while a lower share is from electricity.

District heating and deep lake cooling interest only some areas of the district (i.e., the closest to the waterfront) and, therefore, count for a minimum share in the overall energy panel. Energy demanding and emitting sectors are offices and commercial: they cover a remarkable GFA share and number of structures, mostly distributed along the main streets (designated as financial-commercial areas by zoning). MUR prevails on the residential one due to the diffused presence of apartments in the central area, while dwelling with less than seven units are more limited and spread around the outer suburbs. MURs have also higher energy intensity, impacting more on the energy balance of the district. Industrial sector represents a minor contribution due to its limited presence in the downtown area, leaving room for more-tertiary oriented function as offices.

5. RESULTS

5.1 Elaboration of input data

The shapefile of the whole building stock contains the main typological data for buildings (height, footprint area), from which other variables (heated gross volume, number of floors, heat loss surfaces, S/V ratio) are derived [33]. On the other hand, building functions from Open Street Maps are not sufficiently complete and accurate (6,129 out of 12,211, equal to 50.2%). As mentioned in paragraph

3.1, prior to the analyses, the shapefile is cleaned from polygons representing not habitable structures (garages, canopies, etc.), following these rules (Table 3).

Table 3. Criteria and results from the cleaning of shapefile polygons for the TOcore area [33].

Type of geometry	**Number of deleted elements**	**Number of deleted elements out of overall buildings (out of 14,279)**
Area less than 50 m^2	2,397	16.7%
Height less than 4 m	369	2.6%
Overlapped polygons	976	6.8%

Having building and block outlines in GIS, the housing demand is calculated for 75 residential blocks (21% of total blocks). Residential blocks have at least 95% GFA covered by RES and/or MUR (according to the Platform), due to the highly variable demand of other functions. In case of blocks with 95% GFA residential, the remaining 5% consumption is derived from homogeneous blocks of that category (mainly retail or office) and then subtracted from the overall block demand. Assuming 95% GFA as threshold, all the eleven neighbourhoods of the TOcore area are represented, expect for the financial district of Bay Street Corridor. The functions of residential blocks have been further checked with the zoning by-law 569-2013 [35], completed in 2022.

5.2 Disaggregated residential consumption by dwelling archetypes and energy end-uses

For these residential blocks, the housing configuration are distinguished in four archetypes (Table 4), according to their S/V ratio, and following previous Canadian classifications [38] [37]: detached (S/V ≥ 0.6 m^2/m^3), semi-detached houses (0.6 > S/V ≥ 0.4 m^2/m^3), low-rise (less than 5 storeys, 0.4 > S/V ≥ 0.3 m^2/m^3), and high-rise apartments (S/V < 0.3 m^2/m^3). Then, the two methods (ref. paragraphs 3.2.1 and 3.2.2) are applied to identify the electricity and natural gas consumption distinguished by dwelling types. The method by subtraction considers the following division between homogenous and housing mix blocks (

Table 5), based on to the share of housing types by the Platform.

Table 4. Classification of residential building stock by main characteristics and S/V ratio (m^2/m^3) ranges [33].

Classification of dwelling types	**S/V_{avg}**	**S/V_{median}**	**Number of residential buildings (TOcore)**
Detached houses	0.71	0.67	780
Semi-detached houses	0.53	0.55	1,204
Low-rise apartments	0.34	0.35	91
High-rise apartments	0.26	0.25	374

Table 5. Classification of residential blocks (RES+MUR ≥ 95% GFA) by main dwelling type and age [16] [33].

Classification by types	Number of blocks	Classification by age	Number of blocks
Mainly detached	18	pre-1980	66
Mainly semi-detached	20	1980-2004	2
Mainly low-rise	2	post-2004	6
Mainly high-rise	9	mixed	2
Housing mix	26		

Table 6. Comparison between calculated data from the two models and data from for electricity (E) and natural gas (NG) energy intensity [37,38].

	E/m² detached	E/m² semi-detached	E/m² low-rise	E/m² high-rise
Method by subtraction (I), not normalised	83.68	68.07	181.07	44.73
Method by equation (II), not normalised	68.11	74.42	87.88	43.35
Method I, normalised[1]	87.98	70.37	184.39	45.55
Method II, normalised[1]	71.61	76.94	89.49	44.15
SHEU, 2015[2]	39.74	41.89	88.33	49.69
NRCan, 2017[3]	56.06	51.43	N. A.	47.96

	NG/m² detached	NG/m² semi-detached	NG/m² low-rise	NG/m² high-rise
Method by subtraction (I), not normalised	76.21	38.71	122.04	97.40
Method by equation (II), not normalised	52.62	43.29	107.96	88.58
Method I, normalised[1]	76.06	38.71	122.04	97.40
Method II, normalised[1]	52.51	40.92	107.96	88.58
SHEU, 2015[2]	101.79	105.04	166.78	185.31
NRCan, 2017[3]	114	104.23	N. A.	96.41

[1]*Results are normalised by share of consumption from* [37] *for 2017 for Ontario by energy source and applying CDDs (26.3) and HDDs (3518) values for 2017 on a 30-year range with CDDs = 35.8 and HDDs = 3498.*

[2]*The SHEU provides data measured for 2015* [38], *distinguished by Canada provinces and by typology of buildings.*

[3]*The Comprehensive Energy Use Database* [37] *provides data from 2000 to 2018, distinguished by Canada provinces; in this case, the 2017 values have been considered. It classifies detached, semi-detached, apartments (without dividing high rise and low rise) and mobile homes (not considered).*

The comparison between the two models for disaggregated block data confirms that the lack of function and age at the building scale limits accuracy and completeness. Indeed, values for post-1980 housing are scarcer for detached and semi-detached: more recent high-rise developments prevail in downtown, whereas low-density ones are more common in the suburbs.

Compared to Ontario data (Table 6), electricity consumption is higher, while lower natural gas for detached and semi-detached. The most aligned results appear for high-rise, while a difficult demand to assess is from low-rise, both from the models and from the datasets. Overall, it must be underlined that Ontario data were assessed on a wide region (with different climate zones) and this significantly influences variations on energy-use compared to the results on Toronto.

Except for low rise consumptions, the two methods show similar results while discrepancies with Ontario data are recurrent. The most effective is the method by subtraction rather than by equation. In the former, values depend only on Toronto characterisation (based on the block data from the 2030 Platform) rather than on external datasets. However, block with housing mix can have a more limited accuracy because a part of consumption derives from an average of other blocks. On the other hand, the approach by equation follows the relation among dwelling types of another survey, being dependent from it, even if it is still quicker with available block demand and reliable surveys.

From the values of natural gas and electricity, energy end-uses are derived for each building, following the steps of Paragraph 3.3.

Table 7 shows results for each dwelling type. SC is assumed as part of electricity-use, while the remaining share for App. According to Ontario data [37] for 2017, SC is assessed as 14% of electricity demand for detached houses, 9.4% for semi-detached and 5.1% for apartments. DHW is calculated with Eq. 3 as included in natural gas, while the remaining part is covered by SH.

Table 7. Assessed energy-end uses for each dwelling type, using natural gas (NG) and electricity (E) values obtained from the method by subtraction.

	SH (kWh/m^2)	**DHW (kWh/m^2)**	**App (kWh/m^2)**	**SC (kWh/m^2)**
Detached	76.2	8.1	71.7	9.3
Semidetached	38.7	7.9	61.7	7.2
Low-rise	122	7.3	116	3.5
High-rise	97.4	7.5	42.4	1.8

5.3 Statistical model to assess the residential consumption

As following step, regression analyses are performed between independent and dependent variables (

Table 8). Dependent variables are the energy uses previously assessed. Independent variables are calculated from the building, block and neighbourhood scales.

Table 8. Pearson's correlations of energy-related variables with energy-use intensities.

	Vol (m^3)	**S/V (m^2/m^3)**	**UHS (m^2)**	**Number of floors**	**Inh/ m^2**	**% pre-1980**	**DHW /m^2**	**SC/ m^2**	**App/ m^2**
SH_{NG}/m^2	0.06	0.04	0.06	0.14	0.04	0.12	0.06	0.18	0.11
DHW_{NG}/m^2	0.003	0.01	0.02	0.01	**0.80**	0.11	1	0.06	0.05
$(SH+DHW)_{NG}/m^2$	0.09	**0.31**	0.07	0.14	0.18	0.07	**0.23**	0.03	0.03
SC_{E}/m^2	0.15	**0.40**	0.15	**0.25**	0.02	0.15	0.04	1	**0.35**
App_{E}/m^2	0.15	**0.30**	0.14	**0.23**	0.15	**0.41**	0.05	**0.36**	1

**NG=natural gas; E=electricity*

Correlations for SC and App energy intensities can build MLR models, both having quite high correlations with S/V ratio. DHW intensity shows higher values with residential density (inh/m^2) because it is calculated from it, whereas the remaining natural gas share for SH is not unsatisfying. Therefore, DWH and SH intensities are summed to have only one natural gas consumption model. Considering the low results obtained by linear correlations (

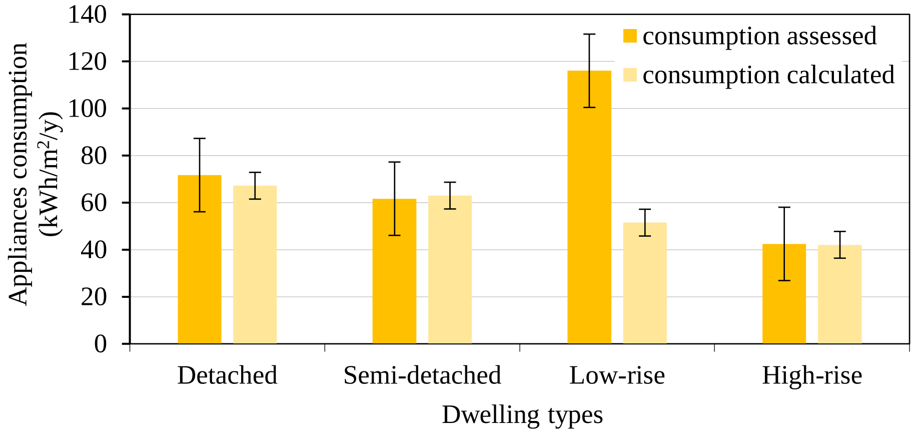
Table 8), multiple linear regressions (MLR) are applied for the different uses to obtain more satisfying values.

Regression results may also reflect the different materials of construction of each class and their impacts on energy demand: for instance, more recent high-rise can be realised in glass/steel with high glazing ratio, while older ones mainly in concrete/bricks [45]. However, the heterogeneity of consumptions of each housing type by age will not be fully represented because of assumptions made for modelling the Platform (ref. Paragraph 4). The statistical models attempt to distinguish by age only natural gas, while SC and App will include pre-1980 as a variable in MLR. Low- and high-rise apartments are the most likely to vary demand due to the different values of building components for the ASHRAE models.

5.3.1 *Electricity: SC and App consumption*

Considering the low values for a linear regression, MLRs are applied for housing consumption.

The MLR model for App shows a quite good coefficient of determination and low significance p-value respectively equal to $R^2 = 0.596$ and F = 1.36E-199, while for space cooling $R^2 = 0.631$ and F = 2.6E-223. As it is possible to observe (Table 9 and



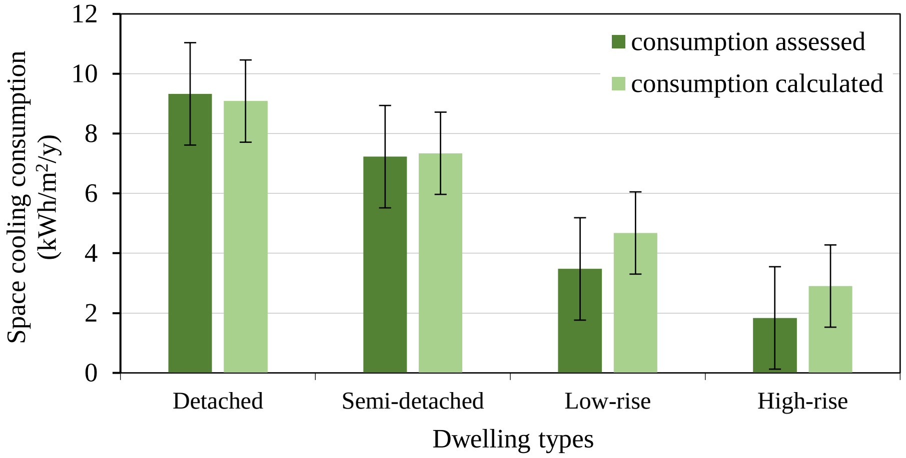


Figure 2), less satisfying results are for low-rise apartments which is the most variable category. For the others, the average values are in line with the consumption assessed from the aggregated values (Paragraph 5.2). As seen before (Table 6), electricity confirms a decreasing trend with lower S/V ratio, having minimum results for high-rise buildings. Additional analyses with material properties and operating systems may underline further differences, especially in the SC outputs. For instance, apartments can have central cooling or larger fenestration area and/or higher glazing thermal transmittance (U-value) can increase SC and SH loads due to higher solar gains and heat losses by transmission (mainly for high-rise buildings) [46].

Table 9. Variables selected to build MLR models for appliances (App) and space cooling (SC).

	App EUI		SC energy intensity	
Variables	**Coefficients**	**P values**	**Coefficients**	**P-values**
Intercept	26.6283	3.741E-68	-3.1531	2.4E-28
Number of floors	-0.6543	1.212E-20	-	-
S/V ratio	22.7825	7.198E-35	8.6972	1E-101
% Pre-1980	27.8844	1.77E-103	1.7955	4.2E-11
App/m^2	-	-	0.065	3.6E-92

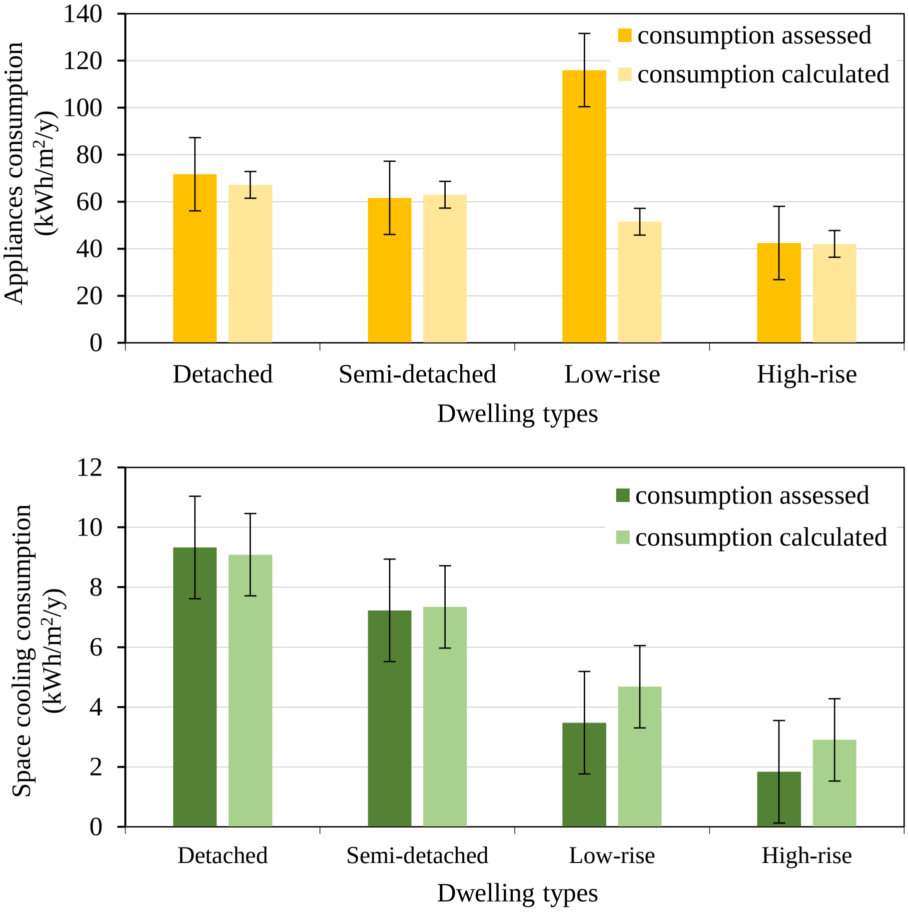


Figure 2. EUI data (dark) and calculated values (light) for appliances (up) and space cooling (down) by dwelling types, with error bars.

5.3.2 Natural gas: SH and DHW consumption

The analysis of natural gas consumption was more complicated because correlations with independent variables are lower and disaggregated data by dwelling types have significant variations for multi-family dwellings. The DHW energy intensity has higher correlation (R^2=0.803) with inhabitant density (inh/m^2) because it is directly assumed from the number of inhabitants. On the other hand, SH (remaining share of NG) shows unsatisfying correlations. Therefore, DHW and SH are joined as total amount of natural gas consumption (ref.

Table 8). The analysis was then performed considering S/V ratio and period of construction, distinguishing low-density and multi-family buildings.

The correlation used for EUI for detached and semi-detached houses depend only by S/V ratio and not by the period of construction. Similar mean values (assessed) are for natural gas EUI before and after 1980 for detached and semi-detached houses, respectively 76.22 and 75.95 (4% difference) kWh/m^2/y and 38.70 and 39.10 (8% difference) kWh/m^2/y. Limits emerge in the model due to few blocks of these categories built after 1980. Only 3 blocks present detached or semi-detached buildings after 1980, while 40 in before 1980: in the downtown, high-rise construction prevailed in the last 40 years. Consequently, the scarcity of post-1980 contributes to have similar values for different construction periods. The linear regression for detached and semidetached can be applied for dwellings realised after 1980, while cautions is needed for more recent stock.

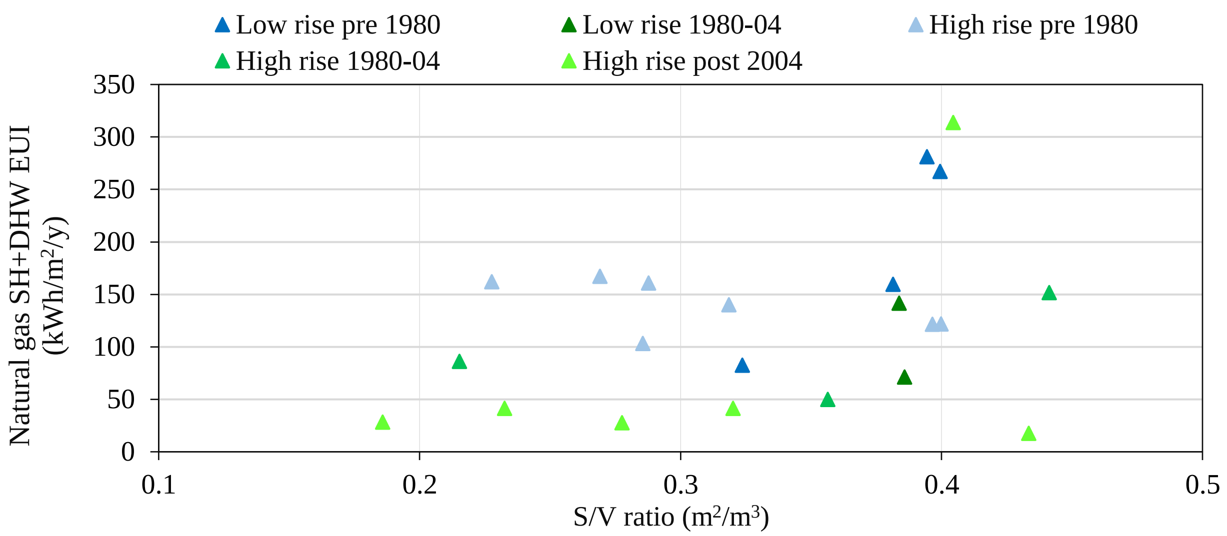


Figure 3. Natural gas EUI for low- and high-rise buildings.

Table 10. Average NG energy-use intensity (kWh/m^2/y) for low-rise and high-rise apartments by period of construction.

Period of construction	Low-rise NG intensity (kWh/m^2/y)	Number of blocks considered	High-rise NG intensity (kWh/m^2/y)	Number of blocks considered
Pre 1980	184.54	6	134.23	10
1980 - 2004	106.45	2	92.11	5
Post 2004	n. a.	0	78.46	6

As already highlighted by [45], EUI data for low-rises and high-rises are highly variable, especially for SH and DHW, and this implies lower correlations than expected. Construction materials (e.g., reinforced concrete-bricks, glass, and steel buildings), technological systems, maintenance level, type of use can characterise the EUI. An additional factor could be the mix of systems especially in more recent buildings, with both electricity and gas-based system. For low- and high-rise buildings, natural gas EUI shows typical trends (in Figure 3 and Table 10):

- Higher EUI for older buildings, lower EUI for 1980-2004 and lowest EUI for after-2004 blocks with more insulated envelope and more efficient technological systems.
- Low-rise apartments present higher EUIs and S/V_{avg} (0.35 m^2/m^3) compared to high-rise with S/V_{avg}=0.25 m^2/m^3; only a limited number of buildings have much higher EUIs.

For low- and high-rise apartments, the average EUI values reported in Table 10 are used considering the three main periods of construction and S/V ratios. The variability of natural gas consumption did not allow to build more solid models.

5.3.3 *Place-based assessment*

The EUI models are then applied to the residential buildings stock of the Platform area using GIS. This approach allows to evaluate and calculate all typological and geometric information of dwellings and population that can influence energy consumptions. The analysis can be extended to the whole city of Toronto using the buildings' shapefile and the 147 Neighbourhood Profile data for the construction period on residential zones reported by zoning.

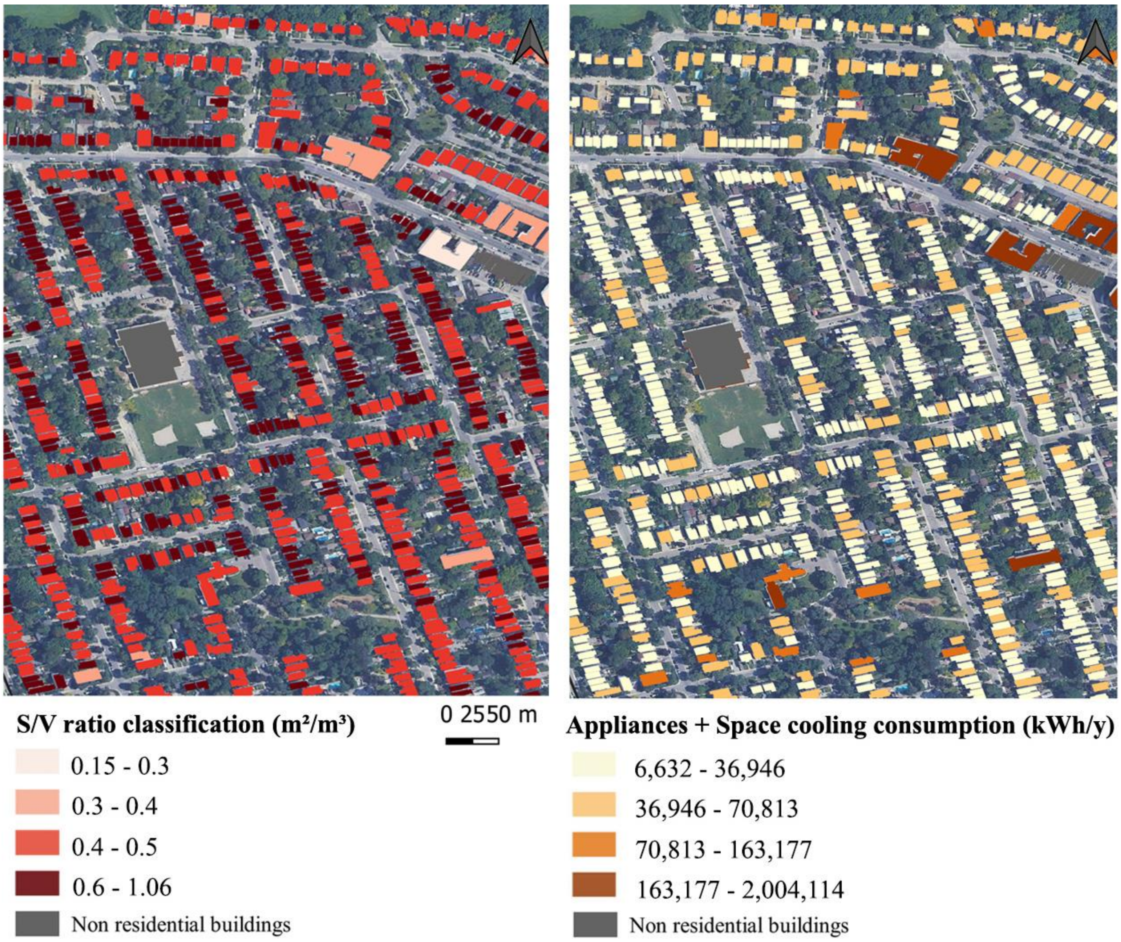


Figure 4. Buildings' S/V classes (left) and App + SC electrical consumption based on linear regressions (right) for the southern part of Humewood-Cedarvale neighbourhood.

The most demanding areas are easily visualised in GIS [35]. An example is provided in Fig. 4 for the Humewood-Cedarvale neighbourhood (North from downtown Toronto), mainly low-density residential zone and with 91% houses built before 1980.

The GIS-based mapping distinguishes and spatialises energy consumption variations for the different building types (Figure 4). In the example, higher intensity values (kWh/m^2/y) characterise buildings with higher S/V ratio, which cover most of dwellings. On the other hand, the overall annual consumption is concentrated for high rise apartments along the main neighbourhood roads. The residential stock covers most of the areas around Toronto downtown, alternating more sprawl-based zones with denser centres with high-rise prevalence.

6. DISCUSSION

The assessment of residential energy consumption by dwelling shows potentials and limits. The identification of single-building energy-use from block data can lead to inaccuracies, especially for housing mix blocks. Between the two approaches, the method by subtraction is more coherent and specific for the case study. It is also easily flexible and adaptable to other contexts if aggregated energy data and typological features are available. On the other hand, the approach by equation must be based on reliable and comprehensive energy data for housing types, which might not be accessible. A further simplification in this study is the use of ASHRAE templates for building models of different structures, materials, and ages of construction. The most simplified housing archetypes are detached and semidetached house, for which the IECC 2015 assumption had been homogeneously applied.

Based on the disaggregated values, the MLRs for electricity uses highlight decreasing intensities with lower S/V ratio, or rather for high-rise dwellings. The natural gas assessment is distinguished for detached and apartments buildings. Regression models are built considering the S/V ratio and the period of construction. Detached and semi-detached count only few blocks built after 1980 and the evaluation is predominantly based on older building stock. A sufficiently reliable model is not found for high- and low-rise apartments due to the high variability of measured results for the same age ranges. The demanding character of older high-rise MURBs (multi-unit residential buildings) in Canada and for Toronto emerged already in other studies, especially if constructed between 1945 and 1980 and if gas heated [46] [47]. The diffused poor maintenance contributes to their low performance and high energy losses, while tenants and owners are reluctant to invest in retrofit measures. To address similar issues, the City of Toronto launched the Tower Renewal Program in 2004 to improve energy savings [46] [47]. According to GIS mapping, high-rise consumption is mainly concentrated in the city centre and in infrastructural nodes (i.e., subway and railway stops), while single-family houses are in more decentralised zones. The GIS support can support and spatialise further evaluations, as the solar potential on building rooftops and the coverable share of electricity demand. Despite providing an initial characterisation of residential consumption, the statistical models are affected by not specific assumptions in modelling and lack of measured data at the building scale, mainly for function and age. The natural gas assessment requires further data for more structured results. Instead of relying on blocks and buildings categories retrieved from the 2030 Platform, a dataset on single buildings would have supported stronger statistical regressions. Privacy limitations, constraints on data accessibility and spatial resolution are obstacles to, as discussed by [17].

7. CONCLUSIONS

The top-down statistical models attempt to assess the energy demand for residential buildings, starting from aggregated block energy consumption. The case study was the central area of Toronto, on which the 2030 Platform is based on, focusing on residential areas. The energy demand at the block level from the Platform was disaggregated at the dwelling scale for electricity and natural gas. Two methods were applied, and more satisfying results were obtained with the techniques by subtraction. The statistical analysis then highlighted relationships between energy uses and independent building variables. The MLRs allow to realise a model for housing electricity demand for space cooling and appliances. The electricity consumption for low-rise resulted more variable for appliances and not returned from the equation. Due to linear regressions below R^2=0.6, DHW and SH were joint in one model for natural gas and distinguished for low-density and multi-family housing. The presence of only three blocks of detached and semidetached houses built after 1980 contributes to have similar values before and after 1980. Low-rise and high-rise showed variable natural gas consumption by construction age. Rather than regressions, average intensities can be considered by apartment archetypes and period.

However, the scarcity of accurate data and variability have significantly impacted on results, especially for natural gas consumption. Future studies require a detailed validation with measured data mainly for SH or process-driven approach to provide a more accurate energy model and understand limitations of the 2030 Platform. In this way, the model could be extended with more accuracy to the city and provide more accurate evaluation for policy framing. In future studies, an extended PV assessment could identify potential residential consumption satisfied by solar technologies to extend decentralised energy systems and to improve the self-sufficiency for the entire City of Toronto.

REFERENCES

[1] Environment and Climate Change Canada - ECCC (2021). Temperature Change. https://www.canada.ca/en/environment-climate-change/services/environmental-indicators/temperature-change, accessed on Nov 24th, 2022.

[2] Environment and Climate Change Canada - ECCC (2022). 2030 Emissions Reduction Plan. https://www.canada.ca/en/environment-climate-change/news/2022/03/2030-emissions-reduction-plan--canadas-next-steps-for-clean-air-and-a-strong-economy.html, accessed on Nov 24th, 2022.

[3] Government of Canada (2016). Pan-Canadian framework on clean growth and climate change. https://www.canada.ca/en/services/ environment/weather/climatechange/pan-canadian-framework.html, accessed on Nov 24th, 2022.

[4] Mutani, G. and Todeschi, V. (2020). Building energy modelling at neighbourhood scale. Energy Efficiency, 13 (2): 1353-1386. https://doi.org/10.1007/s12053-020-09882-4

[5] OECD (2020). Managing environmental and energy transitions: A place-based approach. https://www.oecd-ilibrary.org/sites/f3f8e305en/index.html?itemId=/content/component/f3f8e305-en, accessed on Nov 24th, 2022.

[6] Torabi, S.M., Delmastro, C., Corgnati, S.P., Lombardi, P. (2017). Urban energy planning procedure for sustainable development in the built environment: A review of available spatial approaches. Journal of Cleaner Production, 165 (1): 811-827. http://dx.doi.org/10.1016/j.jclepro.2017.07.142

[7] Mutani, G. and Todeschi, V. (2019). An Urban Energy Atlas and Engineering Model for Resilient Cities. International Journal of Heat and Technology, 32 (4), pp. 936-947. https://doi.org/10.18280/ijht.370402

[8] Todeschi, V., Boghetti, R., Kampf, J., Mutani, G. (2021). Evaluation of urban-scale building energy-use models and tools - Application for the city of Fribourg, Switzerland. Sustainability, 13 (4): 1595-1617. https://doi.org/10.3390/su13041595

[9] Kavgic, M., Mavrogianni, A., Mumovic, D., Summerfield, A., Djurovic-Petrovic, M. (2010). A review of bottom-up building stock models for energy consumption in the residential sector. Building and Environment, 45 (7): 1683-1697. https://doi.org/10.1016/j.buildenv.2010.01.021

[10] Ferrando, M., Causone, F., Hong, T., Chen, Y. (2020). Urban building energy modelling (UBEM) tools: A state-of-the art review of bottom-up physic-based approaches. Sustainable Cities and Society, vol. 62, n. 32. https://doi.org/10.48550/arXiv.2103.01761

[11] Zhuravchak, R. Pedrero, R., Crespo del Granado, P., Nord, N., Brattebo, H. (2021). Top-down spatially-explicit probabilistic estimation of building energy performance at a scale. Energy and Buildings, vol. 238, n. 5, p. 110786. https://doi.org/10.1016/j.enbuild.2021.110786

[12] Swan, L., Ugursal, V. (2009). Modelling of end-use energy consumption in the residential sector: A review of modelling techniques. Renewable and Sustainable Energy Reviews, 13 (8): 1819-1835. https://doi.org/10.1016/j.rser.2008.09.033

[13] Reinhart, C, Cerezo Davila, C. (2016). Urban building energy modeling – A review of a nascent field. Building and Environment, vol. 97, n. 15, pp. 196-202. https://doi.org/10.1016/j.buildenv.2015.12.001

[14] Hong, T., Chen, Y., Luo, X., Luo, N., Hoon Lee, S. (2020). Ten Questions on Urban Building Energy Modelling. Urban Integrated System, vol. 168, n. 5. https://doi.org/10.1016/j.buildenv.2019.106508

[15] Torabi, S.M., Mutani, G. and Lombardi, P.L. (2016). GIS-based energy consumption model at the urban scale for the building stock. 9th IEECB&SC'16, Frankfurt, Germany, pp. 1-8. https://doi.org/10.2790/290244

[16] 2030 District (2020). Toronto 2030 Platform. https://www.toronto2030platform.ca/, accessed on Nov 24th, 2022.

[17] Fremouw, M., Bagaini A., DePascali P. (2020). Energy Potential Mapping: Open Data in support of Urban transition planning. Energies, 13 (5): 1264. https://doi.org/10.3390/en13051264

[18] Città Metropolitana di Torino, Portale Solare. http://www.cittametropolitana.torino.it/cms/ambiente/risorse-energetiche/osservatorio-energia/portale-solare, accessed on Nov 24th, 2022.

[19] Mutani, G, Todeschi, V. (2021). GIS-based urban energy modelling and energy efficiency scenarios using the energy performance certificate database. Energy Efficiency, vol. 14, n. 47, pp. 1-28. https://doi.org/10.1007/s12053-021-09962-z

[20] Steingrube, A., Bao, K., Wieland, S., Lalama, A., Kabiro, P., Coors, V., Schröter, B. (2021). A method for optimizing and spatially distributing heating systems by coupling an urban energy simulation platform and a energy system model. Resources, 10 (5): 52. https://doi.org/10.3390/resources10050052

[21] Pereira, I., Sad de Assis, E. (2013). Urban energy consumption mapping for energy management. Energy Policy, 59 (8): 257-269. https://doi.org/ 10.3390/en13051264

[22] UCLA, California Centre for Sustainable Communities Energy Atlas. https://energyatlas.ucla.edu/, accessed on Nov 24th, 2022.

[23] NYU, NYC Energy & Water Performance Map. https://energy.cusp.nyu.edu/#/, accessed on Nov 24th, 2022.

[24] City of Wien, Energy Map. https://www.wien.gv.at/ english/environment/energy/maps.html, accessed on Nov 24th, 2022.

[25] Sari, R., Soytas, U. (2004). Disaggregate energy consumption, employment and income in Turkey. Energy Economics, vol. 26, n. 3, pp. 335-344, 2004. https://doi.org/10.1016/j.eneco.2004.04.014

[26] Fan, J., Zhang, Y., Wang, B. (2017). The impact of urbanization on residential energy consumption in China: An aggregated and disaggregated analysis. Renewable and Sustainable Energy Reviews, vol. 75, n. 8, pp. 220-233. https://doi.org/10.1016/j.rser.2016.10.066

[27] Chaturvedi, V., Eom, J., Clarke, L., Shukla, P. (2014). Long term building energy demand for India: Disaggregating end use energy services in an integrated assessment modeling framework. Energy Policy, vol. 64, n. 1, pp. 226-242. https://doi.org/10.1016/j.enpol.2012.11.021

[28] Gonzales, P., Landajo, M., Presno, M. (2014). Multilevel LMDI decomposition of changes in aggregate energy consumption. A cross country analysis in the EU-27. Energy Policy, vol. 68, n. 5, pp. 576-584. https://doi.org/10.1016/j.enpol.2013.12.065

[29] Mutani, G., Fontanive, M, Arboit, E. (2018). Energy-use modelling for residential buildings in the metropolitan area of Gran Mendoza (AR). Italian Journal of Engineering Science, vol. 61, n. 2, pp. 74-82. https://doi.org/10.18280/ti-ijes.620204

[30] Lorimer, S. (2012). A housing stock model of non-heating end-use energy in England verified by aggregated energy use data. Energy Policy, vol. 50, pp. 419-427. https://doi.org/10.1016/j.enpol.2012.07.037

[31] Roth, J., Martin, A., Miller, C., Jain, R. (2020). SynCity: Using open data to create a synthetic city of hourly building energy estimates by integrating data-driven and physics-based methods. Applied Energy, vol. 280, n. 12, p. 115981.

[32] Rottondi, C., Derboni, M., Piga, D., Rizzoli, A. E. (2019). An optimisation-based energy disaggregation algorithm for low frequency smart meter data. Energy Informatics, vol. 13, n. 2, pp. 1-11. https://doi.org/10.1186/s42162-019-0089-8

[33] City Planning, 3D Massing. https://open.toronto.ca/dataset/3d-massing/, accessed on Nov 24th, 2022.

[34] Social Development, Finance & Administration, Neighbourhood Profiles. https://open.toronto.ca/dataset/neighbourhood-profiles/, accessed on Nov 24th, 2022.

[35] City of Toronto, Planning & Development, Zoning By-law 569-2013. https://www.toronto.ca/city-government/planning-development/zoning-by-law-preliminary-zoning-reviews/zoning-by-law-569-2013-2/, accessed on Nov 24th, 2022.

[36] Farahbakhsh, H., Ugursal, V., Fung, A.S. (1998). A residential end-use energy consumption model for Canada. International Journal of Energy Research, 22 (13): 1133-1143. https://doi.org/10.1002/(SICI)1099-114X(19981025)22:13<1133::AID-ER434>3.0.CO;2-E

[37] Energy Efficiency at NRCan, Comprehensive Energy Use Database 2020. https://oee.nrcan.gc.ca/corporate/statistics/ neud/dpa/home.cfm, accessed on May 28th, 2022.

[38] NRCan, 2017 Survey of Household Energy Use. https://www150.statcan.gc.ca/n1/daily-quotidien/171201/dq171201f-cansim-eng.htm, accessed on Nov 24th, 2022.

[39] Government of Canada, Energy Efficient Product Information - Water Heaters. https://www.nrcan.gc.ca/energy-efficiency/products/product-information/water-heaters/13735, accessed on Nov 24th, 2022.

[40] Aguilar, C., White, D.J., Ryan, D.L. (2005). Domestic Water heating and water heater energy consumption in Canada. In: Canadian Building Energy End-Use Data and Analysis Centre, CBEEDAC.

[41] Mutani, G., Fabiano, E., Garcia, D.A., Mancini, F. (2021). Spatial energy modelling for the metropolitan city of Rome. 2021 IEEE 4th IEEE CANDO Conference, Budapest, pp. 43-48. https://doi.org/10.1109/CANDO-EPE54223.2021.9667932

[42] Canadian Commission on Building and Fire Codes, National Energy Code of Canada for Buildings 2017. https://nrc.canada.ca/en/certifications-evaluations-standards/codes-canada/codes-canada-publications/national-energy-code-canada-buildings-2017, accessed on Nov 24th, 2022.

[43] Toronto 2030 District (2021). Building Energy Supply Decarbonization – Pathways Project Progress Update. https://www.2030districts.org/toronto/about, accessed on Nov 24th, 2022.

[44] CUI (2016). TOcore Neighbourhood Population Profiles. https://www.toronto.ca/city-government/data-research-maps/neighbourhoods-communities/neighbourhood-profiles/, accessed on Nov 24th, 2022.

[45] Touchie, M.F., Binkley, C., Pressnail, K.D. (2013). Correlating energy consumption with multi-unit residential building characteristics in the city of Toronto. Energy and Buildings, 66 (11): 648-656. https://doi.org/10.1016/j.enbuild.2013.07.068

[46] Alsaadani, S., Roque, M., Trinh, K., Fung, A., Straka, V (2016). An overview of research projects investigating energy consumption in Multi-Unit Residential Buildings in Toronto. The 6th ACSEE Conference, Kobe, Japan, pp. 419-441.

[47] United Way Toronto (2011). Vertical Poverty. http://www.unitedwaytoronto.com/verticalpoverty/, accessed on Nov 24th, 2022.