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Original
A new clustering and visualization method to evaluate urban heat energy planning scenarios / TORABI MOGHADAM, Sara; Coccolo, Silvia; Mutani, Guglielmina; Lombardi, Patrizia; Scartezzini, Jean-Louis; Mauree, Dasaraden. - In: CITIES. - ISSN 0264-2751. - ELETTRONICO. - 88:(2019), pp. 19-36. [10.1016/j.cities.2018.12.007]

Availability:
This version is available at: 11583/2715858 since: 2020-02-25T14:25:49Z

Publisher:
ELSEVIER

Published
DOI:10.1016/j.cities.2018.12.007

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Preprint · February 2018

DOI: 10.31224/osf.io/b9znk

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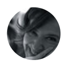

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A new clustering and visualization method to evaluate urban energy planning scenarios

Sara Torabi Moghadam[1,*], **Silvia Coccolo**[2], **Guglielmina Mutani**[3], **Patrizia Lombardi**[1], **Jean-Louis Scartezzini**[2], **and Dasaraden Mauree**[2]

[1]Interuniversity Department of Regional and Urban Studies and Planning, Politecnico di Torino, Viale Mattioli 39, Turin 10125, Italy
[2]Solar Energy and Building Physics Laboratory. Ecole Polytechnique Fédérale de Lausanne, CH-1015 Lausanne, Switzerland
[3]Department of Energy, Politecnico di Torino, C.so Duca degli Abruzzi 24, Turin 10129, Italy
[*]sara.torabi@polito.it

ABSTRACT

The spatial visualization is a very useful tool to help decision-makers in the urban planning process to create future energy transition strategies, implementing energy efficiency and renewable energy technologies in the context of sustainable cities. Statistical methods are often used to understand the driving parameters of energy consumption but rarely used to evaluate future urban renovation scenarios. Simulating whole cities using energy demand softwares can be very extensive in terms of computer resources and data collection. A new methodology, using city archetypes is proposed, here, to simulate the energy consumption of urban areas including urban energy planning scenarios. The objective of this paper is to present an innovative solution for the computation and visualization of energy saving at the city scale.

The energy demand of cities, as well as the micro-climatic conditions, are calculated by using a simplified 3D model designed as function of the city urban geometrical and physical characteristics. Data are extracted from a GIS database that was used in a previous study. In this paper, we showed how the number of buildings to be simulated can be drastically reduced without affecting the accuracy of the results. This model is then used to evaluate the influence of two set of renovation solutions. The energy consumption are then integrated back in the GIS to identify the areas in the city where refurbishment works are needed more rapidly. The city of Settimo Torinese (Italy) is used as a demonstrator for the proposed methodology, which can be applied to all cities worldwide with limited amount of information.

Keywords

Building Energy Consumption; Geographical Information System; Statistical Models; Deterministic Models; Urban Energy Planning.

Highlights

- We use a large building energy 2D-GIS database to predict an energy consumption by statistical methodology.

- A new engineering methodology, using 3D city archetype, is proposed to estimate energy savings for building retrofits.

- We compared the results using monitored data and with energy consumption from a statistical method.
- The proposed spatial decision support system is developed to visualize the refurbishment scenarios for decision-making processes.

1 Introduction

Since 2010, more than 50% of the world population lives in urban areas and this figure is expected to rise to 75% by 2050[1]. Urban development as well as the expansion of cities, through the modification of land uses (from natural to artificial) modify the local energy budget and wind patterns: this causes a phenomenon named Urban Heat Island (UHI)[2]. Furthermore, with the effects of climate change, it is expected that heat waves will become more and more frequent in the near future[3]. The design of more sustainable urban areas is hence crucial to decrease the probability of event such as the heatwave of 2003[4,5] from occurring in the future. Moreover, the Fifth Assessment Report (AR5) issued by the IPCC (Intergovernmental Panel on Climate Change) in 2013, stated that there is clear evidence that this climate change is caused by human activities. There is compelling proof this is due to the release of greenhouse gases (GHG), such as carbon dioxide (CO_2), from the combustion of fossil fuels to produce energy[3]. As energy is one of the main drivers of the world's economy, it can be expected that energy consumption will increase in the future with the rise of the world's human population. The development of tools or methodology for the planning of more sustainable cities is thus necessary if we want to address multiple objectives (mitigation of the energy consumption, increase in energy efficiency of various systems and adaptation of urban areas) at the same time.

Recently, a comprehensive systematic review is conducted by Torabi Moghadam et al.[6] regarding a vast number of spatial energy modeling approaches in the cities for Urban Energy Planning (UEP) processes. In particular, the calculation of energy consumption at city level has previously been performed by different modeling methods, classified as the top-down and bottom-up approaches[7]. The top-down method has been recognized suitable for a large national scale analysis and not for the identification of the possible improvements at the building at urban and local levels[8].While the bottom-up approach has been identified more appropriate with the aim of evaluating the energy consumption based on a high detailed level of data and the ability to model technological systems[9]. Bottom-up models are divided into two types: deterministic (or engineering) and statistical[7].On the one hand, statistical methods search for correlations, utilizing a sample of information in energy bills as a source of data for energy modeling and analyzing the link between energy consumption and a range of different variables (e.g. building shape, age, and occupant behavior)[10]. They are also able to take into account socioeconomic effects in the equations[11]. They calculate reliable consumption based on the available information on the current status of buildings. However, due to their strong dependency on available historical consumption data, these methods are restricted to predict the impact of new technology options and energy saving potential after applying refurbishment measures[11].

On the other hand, deterministic methods are very detailed models based on thermodynamic relationships and heat transfer calculations[12,13]. The main advantage of an engineering-based method is the capability of predicting energy savings for buildings after the application of renovation measures[14]. Although the historical data can be used for the comparison against measured consumption data, this method is able to assess energy consumption without any historical information. However, these modeling approaches require a high quantity of information about building structure and parametric input to calculate the energy consumption of a set of reference buildings of the stock based on a numerical model. Additionally, the evaluation of urban planning scenarios is computationally very extensive and the availability of construction and geometrical data needed as input for the models is very scarce.

Geographic Information Systems (GIS) along with 3D city models, thus offers the opportunity to characterize the building stocks and to visualize the distribution of data by geo-referencing it[15]. GIS is particularly useful to store and manage a large number of spatial data for urban planning purposes through its representation of multiple layers. While several statistical and engineering building stock models have already been developed at city scale, only a few GIS-statistical-engineering combination models are currently available[10]. The reduction of these time-consuming methods thus still remains to be resolved.

The present study combines both the statistical and deterministic approaches to obtain a more robust prediction of the urban energy consumption. Moreover, the integration of these two methods with

GIS demonstrates the opportunity to identify the high energy use hot-spots and make the better spatial decisions. The novelty of the proposed methodology lies in its simplicity and applicability. The framework is performed in order to reduce time-consuming processes of energy demand simulation, assessment and for designing urban energy saving scenarios.

In the current study, we propose to use a methodology according to Ratti et al.[16] and Salat[17] to define a model, of the medium-sized city of Settimo Torinese, that would be representative of the urban form and characteristics. We then evaluated the energy consumption with a deterministic model based on the period of construction and compared the results using monitored data and with energy consumption from a statistical method. Finally, multiple renovation scenarios were evaluated and the energy consumption was also integrated within the GIS database and used for visualization and decision-making.

The paper is divided as follows. In the Section 2 we will describe how we constructed the archetype district and give a detailed overview of the energy model used for the study case. In Section 3, the results will be discussed in details to demonstrate the robustness of the solution and we will also provide decision-support maps. We finally conclude, giving a few perspectives for the current work.

2 Material and methods

As shown in Fig. 1, the proposed framework consists of four major parts: (1) GIS-database creation (2) a statistical model making use of 2D-GIS and Multiple Linear Regression (MLR) across an entire city (3) an engineering simulation model based on 3D city models performed for an archetype of the city (4) energy saving scenarios visualization using GIS mapping. The geo-coded datasets is expected to make urban planning evaluation processes much easier with data visualization, integration and its distribution. Details of the proposed methodology are introduced below.

2.1 The demonstrator

Settimo Torinese (45°8' North, 7°46' East, 207 m asl), a small city near the city of Torino, is selected as a case study. The choice of this small city is significantly important since these cities have not been at the center of attention of sustainable developments[18]. The city hosts 47,875 inhabitants, and it occupies an area of 33 km^{-2}, as visible in Fig. 2, showing aerial views of the city of Settimo Torinese. We

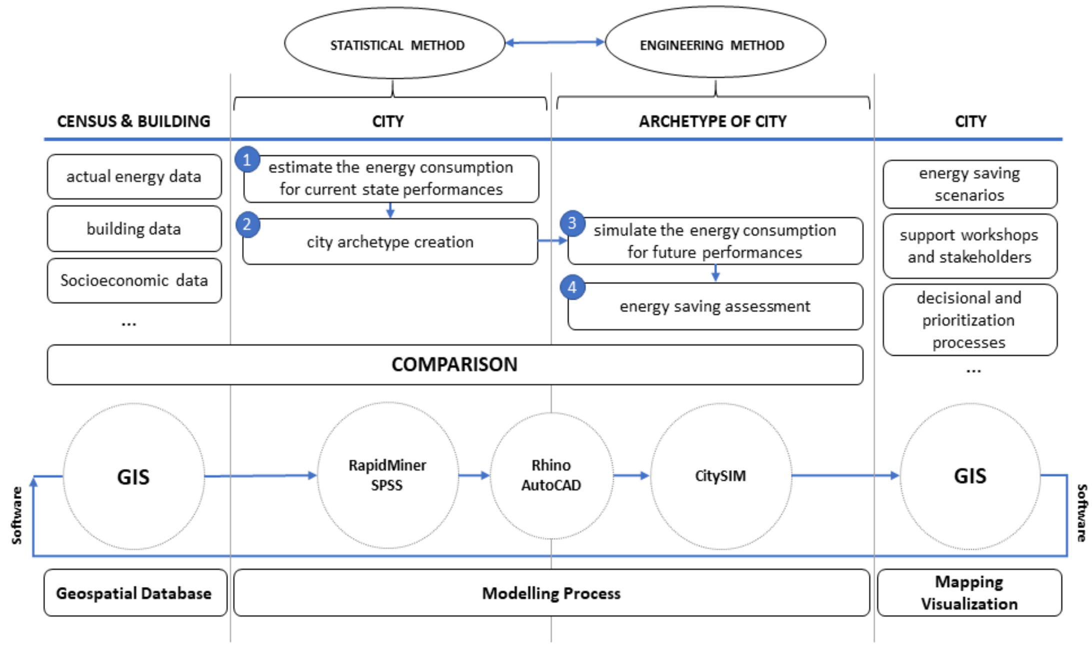


Figure 1. Flow chart of the multi-scale framework to support energy saving scenarios. The statistical method is used at the city scale. Furthermore, the engineering method performs a more detailed energy analysis of retrofit measures for an archetype of city.

divided the city into three main zones based on their geometrical and urban characterizations: Fiat Village (semi-suburban area), Campidoglio Square (transformation area) and Historical Center (consolidate area). As underlined in the next section, the previous urban properties will be used to create the archetype model for the city Fig. 2.

In order to perform our study, a GIS database containing all the actual energy demand data and the geometrical characteristics of the building was setup, and it was combined with the urban energy dynamic model, realized with CitySim[12].

2.2 Statistical heating energy consumption modeling

A statistical methodology was previously developed to estimate the heating space energy consumption of residential stocks over an entire city[11]. The model was based on a MLR method and it has been validated through cross-validation approach for the entire city. The model was applied for the housing stock of the city. A deeper detailed description of data inputs and applied methodology are described in Torabi Moghadam et al.[11]. In this previous study, we updated the GIS energy-database with real measured district

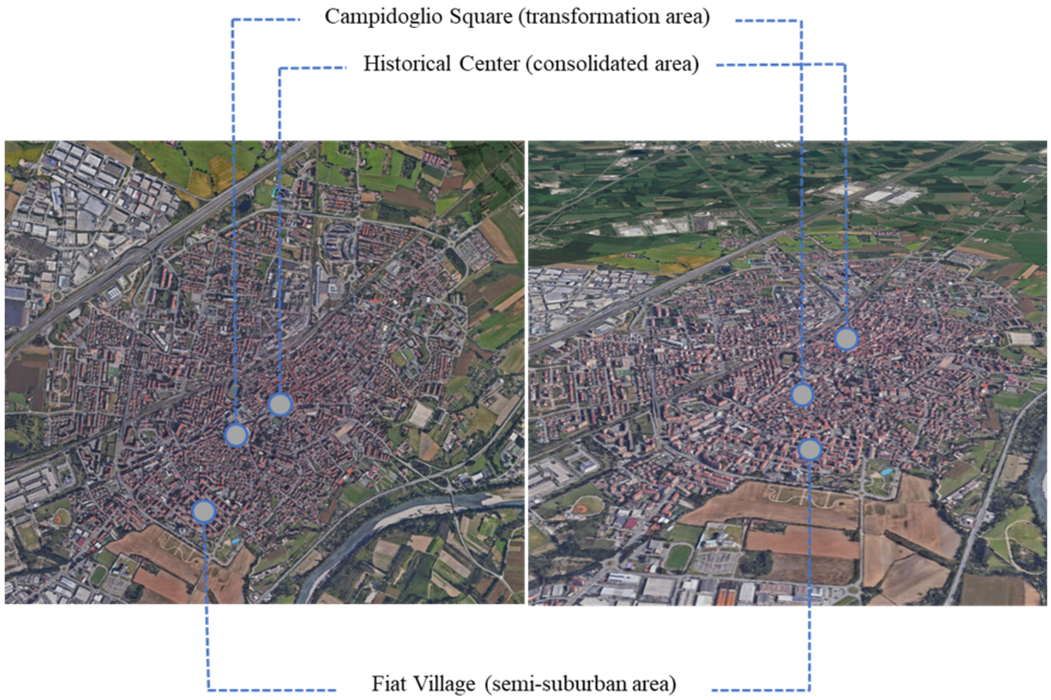


Figure 2. Aerial and 3D view of the city of Settimo Torinese, Source Google maps.

heating data and estimated heating data to create an energy consumption map and to understand the current status of the whole city.

2.2.1 Input data

The GIS database of the case study was the main source of information for the description of the existing residential building stock and input for analysis, as presented in Fig. 3. While it should be noted that this information strongly depends on the availability of data for each country / cities, it can however be highlighted that the procedure is generalizable. The proposed methodology integrates GIS as a supportive data collection tool, which can overlap different type of information by using location as a common feature. The collected data consists of the following geo-referenced data:

- A GIS database characterizing the residential building stock with some energy-relevant building and household information: (i) Geometrical features such as eave's height (m), dispersing surface (m^2), perimeter (m), number of floors, heated volume (m^3), and net floor area (m^2). (ii) Prevailing period of construction of buildings, which represents the buildings envelope and energy systems efficiencies.

According to the Italian national classification[19], the period of construction is divided into seven classes: C1= 1900-1918; C2= 1919-1945; C3= 1946-1960; C4= 1961-1970; C5= 1971-1990; C6= 1991-2005; C7= 2006-ongoing (see Fig. 4). (iii) The building's occupation factor, which is the percentage of occupied building. (iv) Ground-floor typology (v) The surface to volume ratio of the buildings (S/V, dispersing surface/heated volume) that determines the compactness of the buildings and is classified as Detached House (DH): $S/V > 0.8\ m^{-1}$; Terrace House (TH): $0.6 < S/v <= 0.8\ m^{-1}$; Multi-Family House (MFH): $0.4 < S/V <= 0.6\ m^{-1}$; Apartment Block (AB): $S/V <= 0.4\ m^{-1}$[19]. The aforementioned data and information are derived from the digital cartographic technical map of the municipality[20] and ISTAT national census database[21].

- A set of geo-referenced monthly and yearly measured gas consumption records is included. The measured energy consumption data available consist of monthly records of district heating energy consumption (from energy provider) and yearly gas consumption (from Consortium for the Information System, CSI, of Piedmont region) for the heating season of 2014-2015 with 2342 HDD at 20°C. In some cases, the fuel type and the boiler age were also available. Where the real measured data was not available, the estimated data has been inserted in order to complete the GIS-database (See Section 2.3)[1].

Finally, all the available data were integrated into GIS in order to create a strong and supportive geo-spatial database. In this stage, the stakeholders' involvement should be also integrated in order to obtain the data and determine a shared vision of sustainable objectives for future urban energy planning.

2.2.2 Model of consumption prediction at the city scale

The statistical methodology based on a geo-spatial-MLR model is applied at the city scale. Using regressions helps in easing the usage and interpretation of the parameters introduced in the analysis[22]. Specifically, many researchers have used the MLR method with the aim at estimating energy consumption using a range of different predictors. These techniques determine the strength of the relationship between one dependent variable used for numerical prediction[23]. The heating space energy consumption of

[1] In this step, these kinds of data should be geo-referenced and associated to each building polygon using Google maps and in-situ analyses. This procedure can be also performed automatically by geo-coding process.

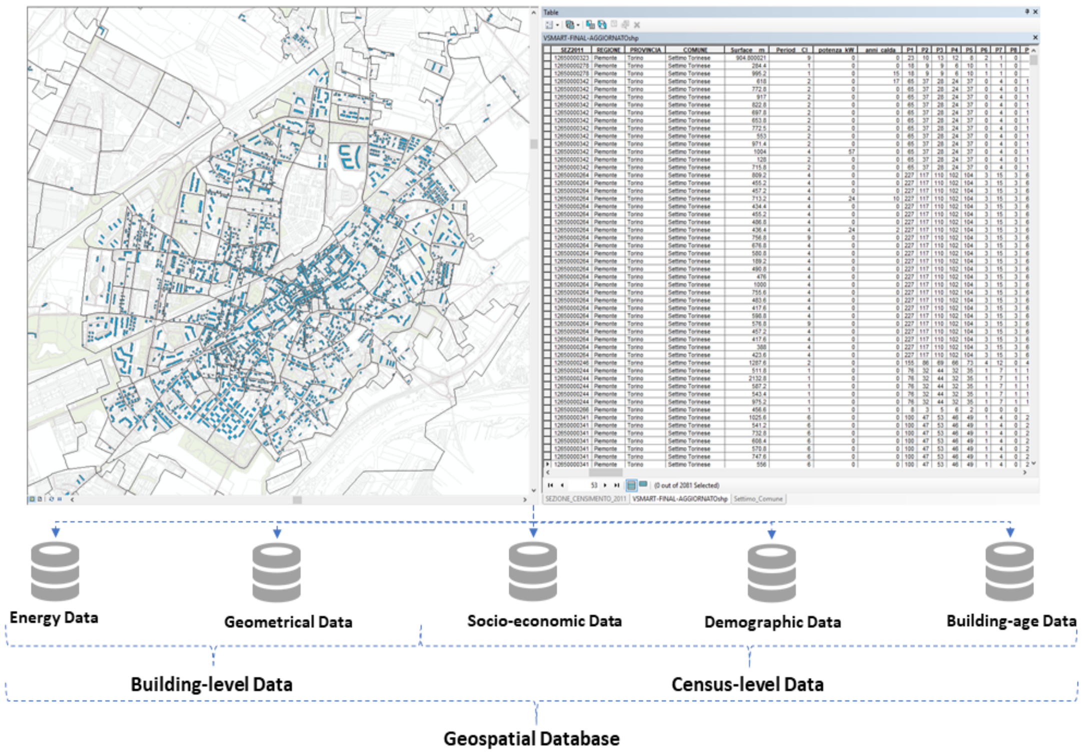


Figure 3. GIS-Database.

Figure 4. Buildings age map.

dwellings city level was modeled using the the following equation[11]:

$$y = \beta_0 + \beta_{pc}.x_{pc} + \beta_{gf}.x_{gf} + \beta_p.x_p + \beta_{nf}.x_{nf} + \beta_v.x_v + \beta_t.x_t + \beta_{of}.x_{of} + \varepsilon \quad (1)$$

Where y variable represents a daily measured gas consumption of residential buildings and x stands for the input variables of dwellings, which influence significantly the heating space energy consumption y. In the case of Settimo Torinese housing stock[11], the main influencing parameters were defined as: the period of construction (x_{pc}), the type of ground floor(x_{gf}), the perimeter (x_p), the number of floors (x_{nf}), the heated volume (x_v), and the occupied buildings factor (x_{of}). The terms β refers to the regression coefficients estimated by using the Ordinary Least Squares (OLS) method and ε is a remaining errors. Assumptions on which the regression model is based, should be carefully chosen to ensure the accuracy in the prediction. The feature selection procedure and regression were validated with a cross-validation approach in order to achieve more robust results and to avoid high risk of over-fitting[11]. Once the statistical analysis using building function was performed, mapping of the results across the city was done. The database information quality and, accordingly, the geo-referenced model can be continuously improved[24]. This methodology is flexible enough to add variables according to the data availability and purpose of the analysis, such as occupants' behavior or buildings renovation ratio information. ArcGIS, Excel spreadsheets, Rapidminer and SPSS softwares were employed for performing the statistical method. The application of the energy regression model to the entire building stock area in Settimo Torinese, through the GIS framework, provided data for the spatial representation of the energy consumption and to create a visual map of its distribution. Moreover, the results of this study helped to identify in which zones the energy consumption was mostly concentrated. The results showed[11] that the buildings located in the historical city center are one of the largest annual energy consumers, consuming about 171.71 (kWh/m^2). Those constructed after 2005 show a relative decrease in the heating energy consumption of 10%. However, if refurbishment data is not available, the statistical model is not able to predict the energy savings potential for building stock[25]. Therefore, in the next section, we introduce a new methodology to simulate the future energy savings potential using an archetype of city.

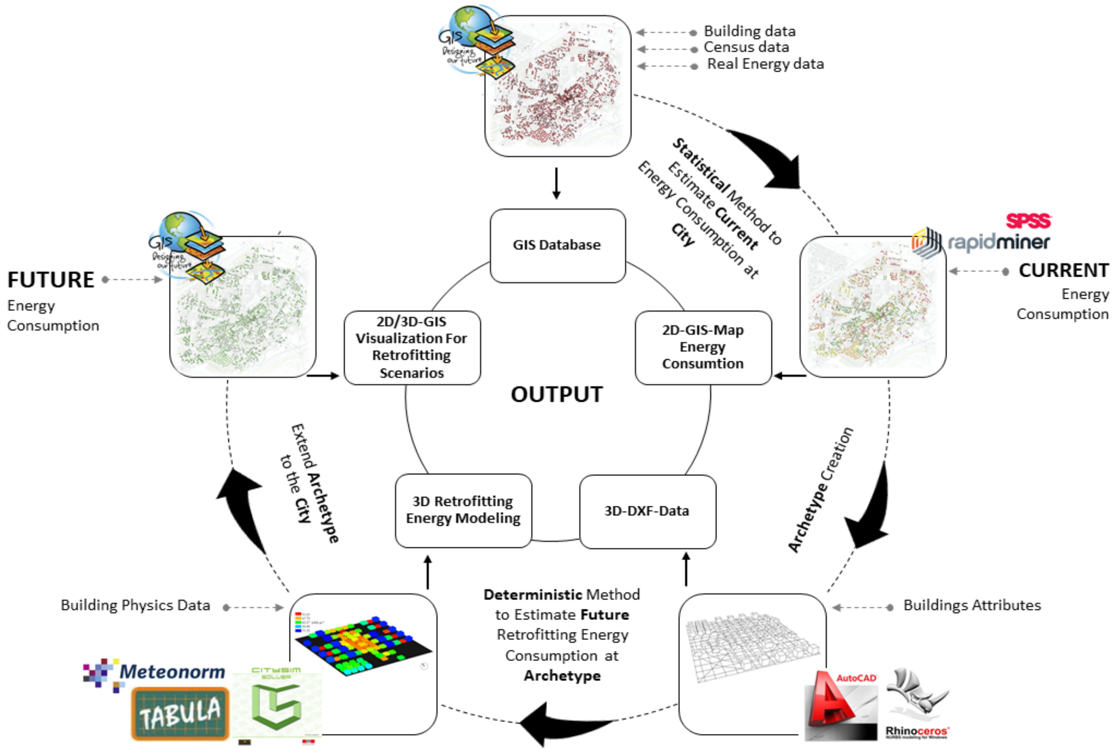


Figure 5. Flowchart describing the methodology used to create and use the archetype for energy demand simulation.

2.3 Deterministic heating energy consumption modeling

The methodology illustrated in the Section 2.2 provides the current energy performance of the whole built environment at the city level; however, the methodology should also be able to support decision making about future energy planning[26]. In this context, a further effort was made to perform an analysis of different future scenarios using a deterministic method. Fig. 5 pictures the methodology that will be used to determine the energy consumption and how we will used them to evaluate renovation scenarios. The heating energy consumption modeling method presented in this paper is based on 3D-city models. The urban energy modeling tool CitySim was employed to simulate the energy consumption of the proposed archetype, representing the city of Settimo Torinese. Further, we used the archetype of city to predict the energy saving potential of buildings at the city scale, by applying several refurbishment scenarios, as it is explained in the following sections.

2.3.1 Input data

A 3D-city model is extracted from the 2D-ArcGIS database. Afterwards, the file is imported in Rhinoceros to make the 3D model with all associated buildings attributes. Finally, the Rhinoceros model is imported in CitySim. All thermostatic characteristic of the building envelope system are from Tabula[19], which is an exhaustive dataset of building physics parameters, energy systems and building use. This helps to refine the urban thermal model and improve the result accuracy. Nevertheless, it is possible to create a model based on a minimum set of building attribute data: building usage and building year (or age class). These characteristics are necessary to pick up realistic building physics parameters from the building libraries. Although the renovation ratio is not necessary to start the energy analysis, they are valuable data that will be used consequently. These information impact significantly the precision of the heat demand and energy saving scenarios[25].

2.3.2 Modeling an archetype city

Defining an archetype urban area representative of a full city is quite a tedious task. To do this, one has to consider the geometrical characteristics of the buildings, the age of the buildings and also their physical properties. In order to create a 3D geometrical model, able to scale and fully describe the energy and micro-climatic behavior of the city of Settimo Torinese, we started from the analyses of the available archetype, as presented by Ratti[27]. As a first step, we tried to correlate the archetypes to the city of Settimo Torinese, looking for the "typical" urban form, according to the existing tissue. The second step considers the real city: indeed, the use of archetype was not completely representing the city, as the city is characterized by several urban typologies (e.g. the city center and the Fiat district). In order to overcome this problem, we decided to create the typical urban typology for the city of Settimo Torinese. By analyzing the geometrical characteristics of the city, we provided a new methodology to "prototype" the entire city. In order to do so, we subdivided the city into 22 concentric sections (each 400 m), starting from the city center (see Fig. 6). Each section is then analyzed, defining the average height of buildings, their length as well as the width of the street. Based on the data previously calculated, we defined the new urban archetype of the city, as visible in Fig. 7.

The obtained archetype is composed of 87 buildings (see Fig. 7) with their height corresponding to the

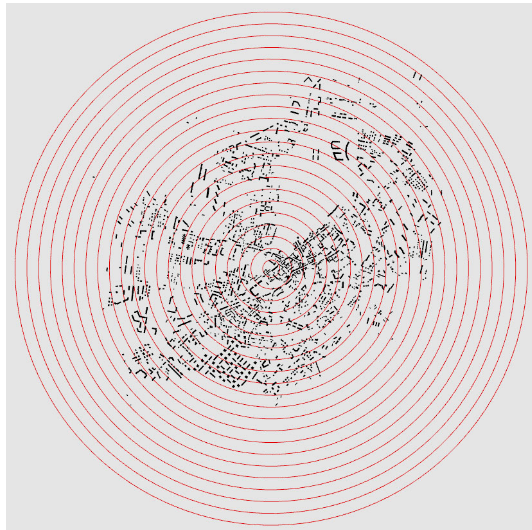


Figure 6. Superposition of the concentric circles, starting from the city center.

average height of each concentric layer, as well as the distance between the buildings. With the use of the proposed methodology, we were able to reduce the number of buildings from 3600 to 87, considerably impacting the time required for the simulations.

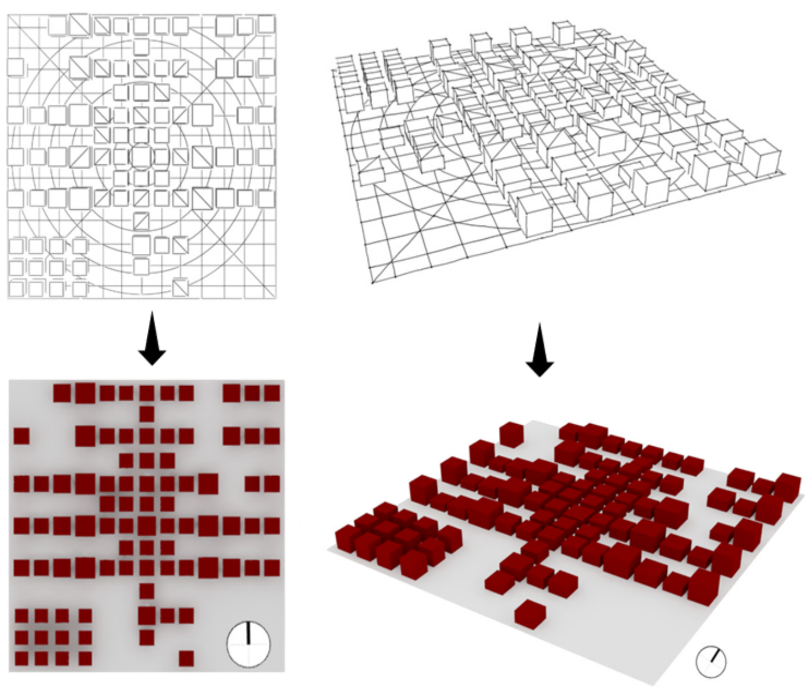


Figure 7. The proposed archetype composed of representative buildings. Plan (left) and 3D view (right).

2.3.3 Urban energy simulations: the energy model.

The energy simulations were performed with the CitySim software[12], an urban energy modeling tool able to quantify the energy demand and the urban climatic conditions, from the building to the city scale. Seven models were designed, as function of the building's period of construction, as presented in Table 1. All the physical properties of the buildings are based on the Tabula project[19], assuming a typical construction typology for each period of construction (single family house, terraced house, multifamily house and apartment block). Based on the typology, the physical properties are retrieved from the web Tabula tool and the envelopes are then calculated with Lesosai[28] based on the available materials and the final U-value of the elements. Table 2 shows, as an example, the physical properties of the walls built during the first phase of construction, as calculated with Lesosai. Each composite of the envelope is defined, assuming its physical properties: thickness (m), conductivity (W m^{-1} K^{-1}), density (kg m^{-3}) and specific heat (J $kg^{-1}K^{-1}$).

Table 1. Physical characteristics (U-value) of buildings per each period of construction.

Period of construction from TABULA	**Type**	**Wall** (W $m^{-2}K^{-1}$)	**Roof** (W $m^{-2}K^{-1}$)	**Floor** (W $m^{-2}K^{-1}$)	**Windows** (W $m^{-2}K^{-1}$)
Before 1919	Terraced House (TH)	1.61	1.80	2.00	4.90
1919 -1945	Single Family House (SF)	1.48	1.80	2.00	4.90
1946-1960	Single Family House (SF)	1.48	2.20	2.00	4.90
1961-1970	Multi Family House (MF)	1.15	1.10	0.94	4.90
1971-1990	Multi Family House (MF)	0.8	0.75	0.98	3.70
1991-2005	Multi Family House (MF)	0.59	0.57	0.77	2.20
Since 2006	Terraced House (TH)	0.34	0.28	0.33	2.20

Table 2. Composition of the envelope, wall. Period of construction before 1919, Terraced house (according to TABULA)

Element	**Conductivity** (W m^{-1} K^{-1})	**Density** (kg m^{-3})	**Specific heat** (J $kg^{-1}K^{-1}$)
Gypsum Plaster	0.21	900	850
Stone and mortar masonry	1.00	800	1,045
Gypsum Plaster	0.41	900	850

The windows ratio of each facade is defined as function of the period of construction, ranging from 0.20 for buildings constructed between 1901-1920 to 0.45 for the newest ones. The internal temperature is set up at 20°C, as required by the current standards for residential buildings. The internal gains are defined

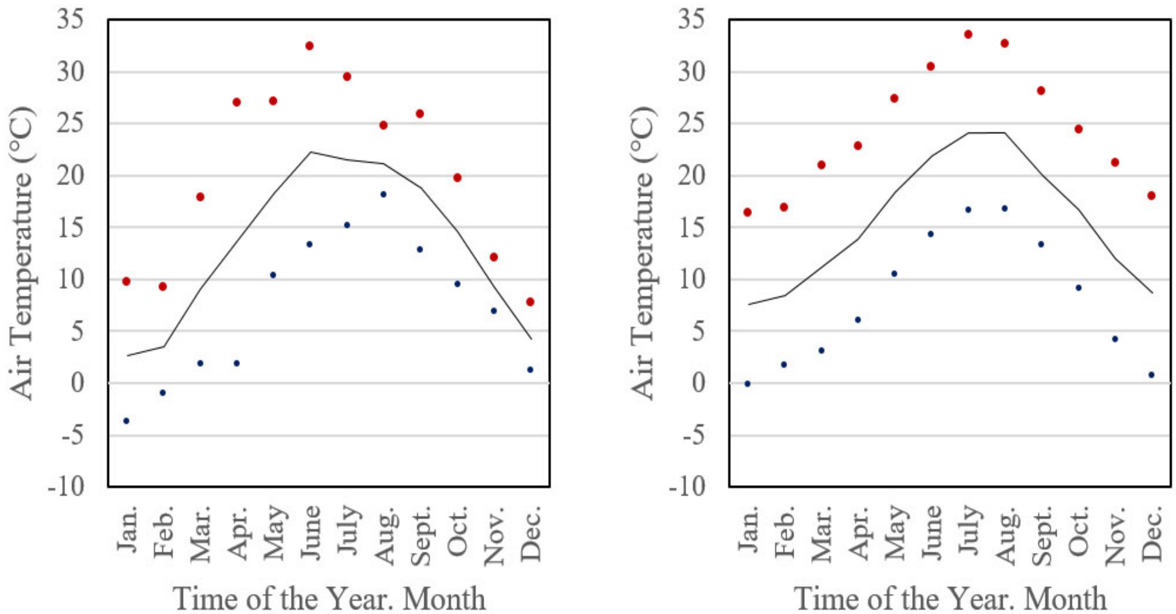


Figure 8. Meteorological data for the city of Settimo Torinese. Monitoring data (left) and Typical Meteorological Year from Meteonorm (right). Red dots represent the maximum monthly temperatures and blue dots represent minimum monthly temperatures.

considering both the occupants and the appliances, according to the Swiss normative SIA 2024[29]. Both occupants and appliances are defined, as function of the livable surface area in the buildings, as well as the hourly daily profile[29]. The infiltration rate of the buildings is defined assuming an average winter Air Change per Hours (ACH) as function of the tightness of the envelope construction[30]. A tight envelope has an average ACH of 0.2-0.6, a loose one of 1.0 to 2.0.

In order to compare the results obtained with CitySim with the monitoring data from the city of Settimo Torinese, we created a new meteorological file including the monitored data of the year 2014-2015 (see Fig. 8) for the closest ARPA weather station of Brandizzo at the same altitude of Settimo Torinese. The new climatic file is based on the Typical Meteorological Year (TMY), as created by Meteonorm[31] by considering the hourly trend of outside air temperature but with the same average, maximum and minimum monitored monthly temperatures.

During the heating season from October 15th to April 15th, it is interesting to notice that the monthly average air temperature varies from -1.3 to +10.7 °C on the yearly average of 13.3 °C, consequently impacting the buildings space heating energy consumption. During the winter season, due to the urban microclimate, the average air monthly temperature is 2.6 °C lower during the month of January, with a minimum hourly temperature of -4.9 °C.

2.3.4 Urban energy simulations: refurbishment scenarios

In order to understand the impact of the buildings envelope on their energy demand, as function of the period of construction, ten main refurbishments are proposed, based on the current city (so called Case study A), and presented in Fig. 9:

- Case study B: improvement of the floors thermal insulation, according to the usual refurbishment, as defined by Tabula. This refurbishment varies per each period of construction.
- Case study C: improvement of the roofs thermal insulation, according to the usual refurbishment, as defined by Tabula. This refurbishment varies per each period of construction.
- Case study D: improvement of the walls thermal insulation, according to the usual refurbishment, as defined by Tabula. This refurbishment varies per each period of construction.
- Case study E: improvement of the glazing thermal performance, replacing the current glazing as required by Tabula. This refurbishment varies per each period of construction.
- Case study F: complete refurbishment of the site, by including all of the previous points (case studies from B to E). This refurbishment varies per each period of construction.
- Case study G: improvement of the floors thermal insulation, by adding 0.35 cm of EPS insulation.
- Case study H: improvement of the roofs thermal insulation, by adding 0.35 cm of EPS insulation.
- Case study I:improvement of the walls thermal insulation, by adding 0.35 cm of EPS insulation.
- Case study J: improvement of the glazing thermal performance, replacing the current glazing with triple glazing (U-value equals to 0.7 W $m^{-2}K^{-1}$).
- Case study K: complete refurbishment of the site, by including all of the previous points (case studies from G to J).

All the physical properties of the refurbished envelope, according to Tabula, are expressed in Tables 3 and 4.

Table 3. Standard refurbishment according to Tabula, per each period of construction for roofs and walls. Properties of the insulation (thickness) and final U-value of the element.

Period of construction	Type	Roof thickness (m)	Roof U-value ($W\ m^{-2}K^{-1}$)	Wall thickness (m)	Wall U-value ($W\ m^{-2}K^{-1}$)
Before 1919	Terraced House (TH)	0.10	0.30	0.11	0.32
1919-1945	Single Family House (SF)	0.11	0.30	0.09	0.34
1946-1960	Single Family House (SF)	0.12	0.29	0.09	0.34
1961-1970	Multi Family House (MF)	0.11	0.27	0.09	0.32
1971-1990	Multi Family House (MF)	0.10	0.26	0.07	0.33
1991-2005	Multi Family House (MF)	0.08	0.27	0.06	0.31
Since 2006	Terraced House (TH)	-	0.22	-	0.27

Table 4. Same as Table 3 except for floors and windows

Period of construction	Type	Floor thickness (m)	Floor U-value ($W\ m^{-2}K^{-1}$)	Windows U-value ($W\ m^{-2}K^{-1}$)
Before 1919	Terraced House (TH)	0.11	0.31	2.00
1919-1945	Single Family House (SF)	0.11	0.31	2.00
1946-1960	Single Family House (SF)	0.11	0.31	2.00
1961-1970	Multi Family House (MF)	0.11	0.26	2.00
1971-1990	Multi Family House (MF)	0.10	0.28	2.00
1991-2005	Multi Family House (MF)	0.08	0.30	2.00
Since 2006	Terraced House (TH)	-	0.30	1.80

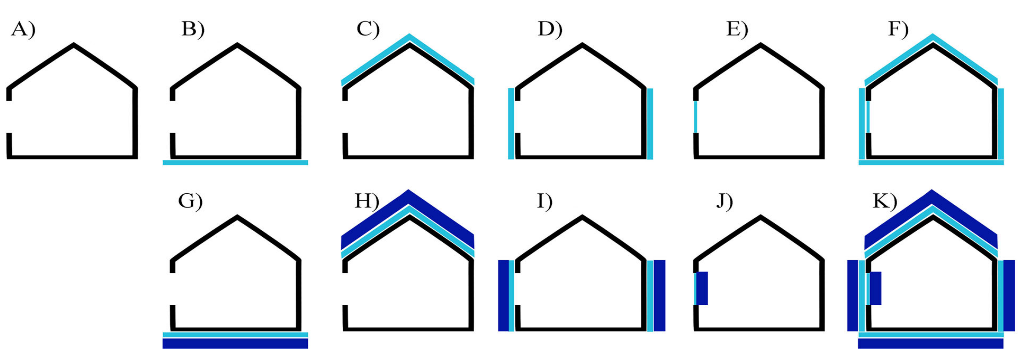


Figure 9. The case studies performed.

The thickness of the insulation required in case studies G to K is 35 cm. It is defined from the Swiss Minergie-P Label, and corresponds to a zero-energy building. This value is derived from the characteristic curve of heat loss with respect to the insulation's thickness and which considers that an insulation with a thickness above 35cm does not bring any additional significant protection to the element.

2.4 A new SDSS to support urban energy saving scenarios

Results obtained by the proposed methodology are then implemented into the GIS environment in order to visualize the impact of the refurbishment of the buildings, as well as the energy saving scenarios. The purpose was to produce a strong visualization tool through which maps become a '*visual index*' to provide solutions to the urban actors with the aim of optimizing the renovations[32,33]. As reported by Ascione et al.,[34] the quality of planning processes can be significantly improved when necessary information are efficiently handled. In this sense, a SDSS which is a tool devoted to support the decision processes in spatial urban energy problems is created[?,35]. Generally, a SDSS can be considered as an interactive computer system for assisting the user/s to perform efficiently decision processes[36]. A SDSS acquires, manages and stores geo-referenced data performing the analysis of spatial problems in a real-time. In this sense, maps can visualize and process very large web databases. Moreover, it provides an interactive environment for performing effective visual activities[37] thanks to the visual interface, which enables exchanging of information between the user and the system to support the stakeholders through all decision phases[36]. The proposed SDSS is able to visually support the stakeholders and decision makers during different focus groups and workshops[37,38]. Using GIS-based procedures helps to the stakeholders to express their preferences by visualizing their alternative scenarios, increasing trust in the results.

3 Results and discussion

3.1 Urban energy simulations

The energy model was set up, and the results obtained with CitySim were compared to both with the monitoring data (realized during the years 2014-2015) and the Tabula database. We compared results for the periods 1946-1960, 1961-1970, 1971-1990 and 2005-2016 since they had a sufficiently large representation of monitored buildings. Indeed, we were able to compare our results with more than 210 monitored buildings. Fig. 10 summarizes the comparison of the data. The relative difference was calculated as the difference between the results obtained with CitySim, and the averaged data from the monitoring and TABULA webtool. Indeed,as defined in the methodology, the input data required for the energy model are both defined based on the TABULA database (building characteristics) and on the monitored data (meteorological data). It can be highlighted that all the simulations stay below a 10% of difference, showing the strength and consistency of the proposed archetype model. It can be noted that for the 1946-1960 period the modeling approach overestimates the energy consumption (by 6%) while with for the other periods there is a slight underestimation (-3% for 1961-1970, -8% for 1971-1990 and -4% for 2005-2016). It can also be seen in Fig. 10 that the deterministic model generally gave better results as compared to the statistical model.

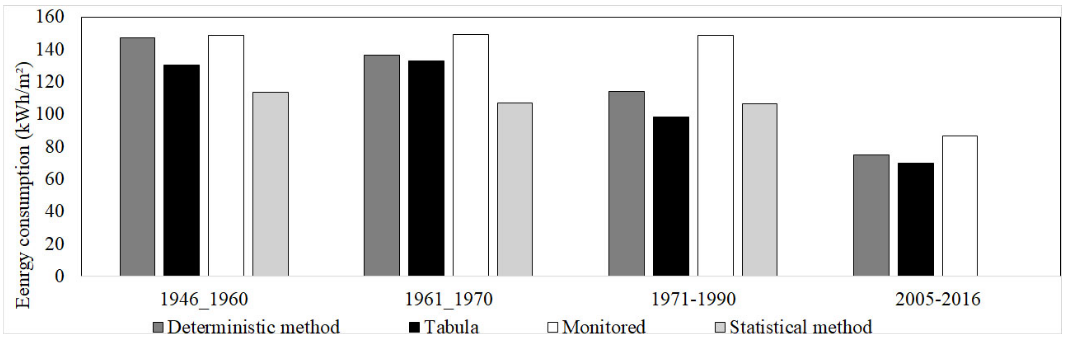
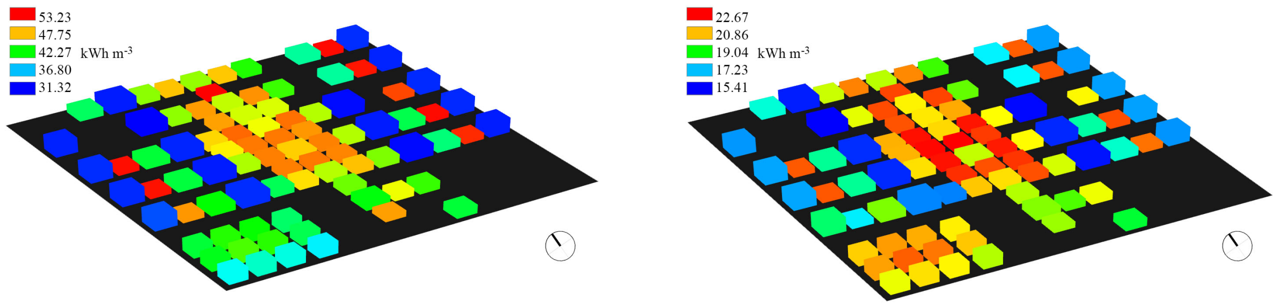


Figure 10. Comparison of the total consumption from measurements, Tabula and engineering models.

The annual energy demand required for heating, as defined by CitySim for each case study can be analyzed for each period of construction. The maximal energy demand is required for buildings built before 1919, with an average demand of 158 kWh m^{-2}. The lower demand is for the ones built between 2005 and 2016, showing a reduction by 53% compared to building of the first period of construction, with an average demand of 74 kWh m^{-2}. It is quite interesting to notice that the energy demand of the first two periods of construction is quite similar (difference by 1%), and it increases between the next periods of construction, with an average reduction by 7% between the periods 1919-1945, 1946-1960 and 1961-1970. The difference doubles during the next periods of construction (1971-1990, 1991-2005 and 2006-2016) by 14%, 15% and 23%, respectively. Finally, it is quite interesting to see the connection between the urban environment, the physical properties of the buildings, and their energy demand. Fig. 11 shows the annual heating demand of the site, by assuming that all buildings are built during the first phase of construction (before 1919) and during the last one (2005-2016). Buildings realized during the last phase of construction present a lower energy demand compared to the previous phase, but their thermal behavior is also directly related to the solar exposure: the higher is the sun exposition, the lower is their energy demand. By contrast, buildings built during the first phase are more impacted by their surface to volume ratio, consequently, the buildings with the higher demand are the ones that are less compact.



(a) Before 1919

(b) 2005-2016

Figure 11. Annual heating demand of the first period of construction (please note the difference in scale due to limitations of the visualization tool).

Additionally, we compared the results from the statistical methods and with the deterministic model for the whole of the city. The results are shown in Fig. 12. As demonstrated previously with the comparison with the monitored and Tabula data, the deterministic model showed a better correspondence. The fact that the older buildings (and the less well insulated) are located in the city center typically means that they have higher energy consumption. This can then be visualized with the map and distribution of buildings in the city.

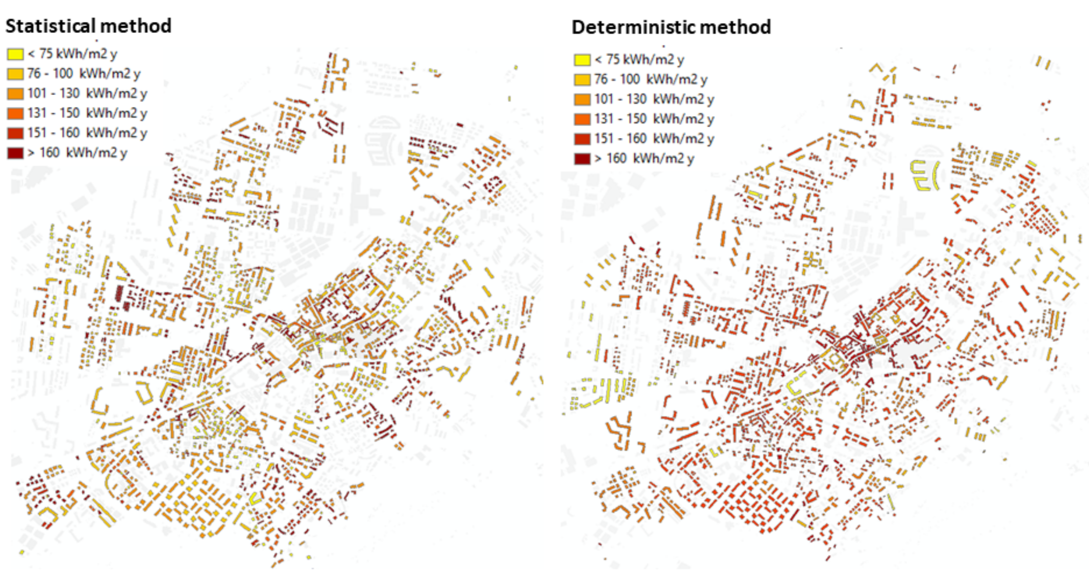


Figure 12. Statistical and deterministic method energy consumption maps.

3.2 Urban refurbishment scenarios

The simulations performed with CitySim underline the impact of the period of construction on the energy demand of buildings. Based on the previous results, two main refurbishments are proposed using the archetype presented in the methodology part. Firstly, a refurbishment according to the usual refurbishment presented by the Tabula and secondly according to the Minergie-P certification.

Fig. 13 shows that the energy demand of buildings is reduced following the renovation based on the Tabula recommendations. The refurbishment of vertical surfaces (walls and windows) are the elements that have the most impact on the demand. Naturally, the energy demand is lightly reduced thanks to the normal refurbishment, showing an average reduction of 60% for the entire site, and a lower one for the new buildings (by 30% on average for the site). When looking at the impact of the single elements on the demand, it is quite interesting to notice that a similar refurbishment has a different impact according to the period of construction. As an example, replacing the existing windows with the new ones (with an U-value of 2.0 W $m^{-2}K^{-1}$) reduces significantly the demand (-19%) in buildings built before 1919 while it will only decrease the demand by 5% in buildings built between 1991 and 2005. This again highlights the importance of targeting the appropriate buildings and of tailoring the best possible renovation scenarios according to their specificities.

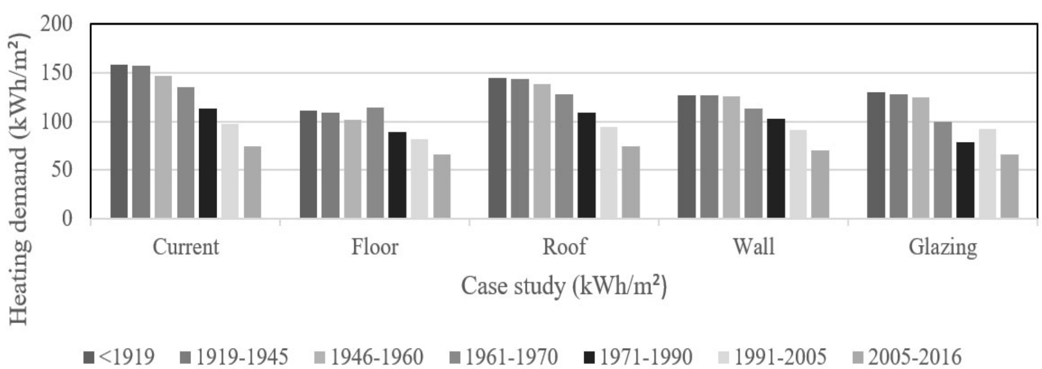


Figure 13. Heating demand following the TABULA usual renovation.

The second refurbishment follows the Minergie-P label. It is quite noteworthy to highlight that the refurbishment proposed are not linearly expressed (see Fig. 14. As an example, the refurbishment of the floors according to Minergie-P label (adding 35 cm of EPS insulation), implies a reduction of the heating demand by circa 35% during the first three periods of construction, but just by 20% in the period of construction 1961-1970. This is related to the physical properties of the envelope, which was more energy efficient compared to the other ones (with a U-value of 0.94 W $m^{-2}K^{-1}$), as well as its impact on the thermal behavior of the buildings. Additionally, it is important to notice that the maximal energy savings are obtained when refurbishing the walls (including opaque and transparent parts), reaching a reduction of around 60% in the periods 1961-1970 and 1971-1990. Indeed, it is during this period, due to the economic growth, that the constructions were built faster, with cheaper materials and without using the thermal mass as passive energy component in the thermal behavior of buildings. Consequently, buildings of this period, are less energy efficient compared to the older ones. Although, this is the best refurbishment available on the market, but due to the physical characteristics of buildings, their historical value, as well as the economic impact, it is not always possible to apply this kind of renovation.

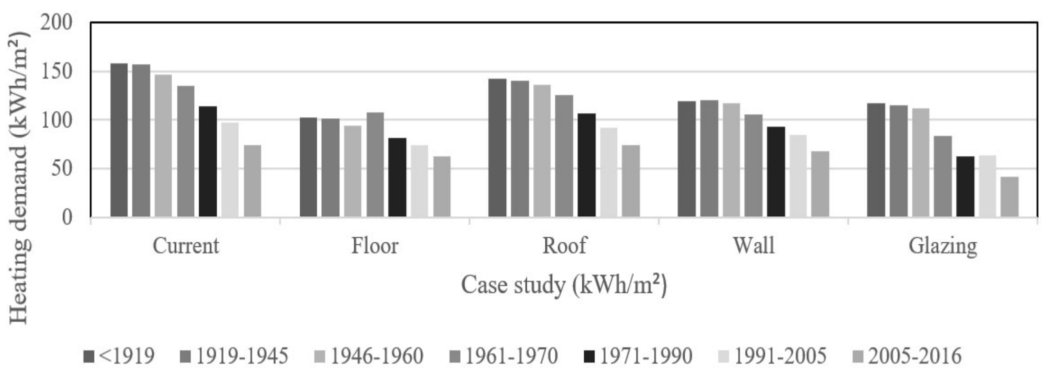


Figure 14. Heating demand following the Minergie-P renovation.

3.2.1 Spatial distribution of building energy consumption through GIS visualization tool

Applying the energy consumption of archetypes to all of the building areas in Settimo Torinese produced the spatial distribution of building energy consumption this City. In this view, the output from the sets of archetypes simulation was used as inputs for the visualization of the data, updating GIS tool with the new building energy consumption values. The energy reduction, from the renovation of each building from a particular period of construction, was mapped back in the GIS environment, providing a complete dataset with the renovation scenarios. The results are visible by maps in which the energy consumption values are displayed with a colorful ramp to illustrate the main differences in the magnitude of consumption and its spatial variation (Fig. 15 and Fig. 16). The effects of the selected refurbishment solutions, improvement of the opaque and the transparent surfaces, were evaluated both separately and combined with the archetype carrying out 70 simulations (considering buildings age).

A spatial distribution of urban building energy consumption in 2D visualization provides a useful SDSS tool to facilitate the decision-making process and managing aspects. Additionally, Fig. 17 illustrates that the 3D visualization cab be also available, where the stakeholders ad decision makers need to visualize the urban form in a better way. Indeed, through the urban energy maps, it is instantly possible to visualize the impacts of both refurbishment solutions, Tabula and Minergie-P, on the energy consumption of each individual building. This fact eases the identification of the high energy consumption districts.

The largest concentration of space heating energy consumption is situated in the old city center district. This difference is explained by the high presence of the buildings built before 1919 to 1960 in this area **??** From the visualization maps (Fig. 15 and 16) emerges that both case studies C and H in which the roofs are isolated are not effective enough; they just reduce energy consumption between 7% and 9%. Contrary, case studies B and F (from Tabula), G, I, J and K (from Minergie-P) are very effective solutions to improve the energy performances. Comparing two performed solutions, Minegie-P solutions are more impressive while the Tabula renovations (e.g. Case studies D and E) cannot have an effective impact on the current energy consumption for these old buildings. These two case studies are still shown by red and orange colored buildings that means the energy consumption is more than 120 kWh^{-2}.

Moreover, maps show that the new buildings (after 2005) with lowest energy consumption at the current state of the city are mostly located in the Campidoglio Square neighborhood (transformation area) and suburban area. In the consequence, almost all the retrofitting solutions have no significant impacts on energy consumption reduction. Same as the old buildings, roof isolation is the worth scenarios for reducing the energy consumption of these buildings in the city of Settimo Torinese. This solution might be combined with other ones.

Fiat village is another main area in the city of the case study, which is characterized mostly by the buildings age from 1960 to 1970. Various solutions impact very differently on these buildings.Case studies B, D, G and I behave almost in the same way in terms of energy performances. Regarding the glazing replacement (case studies E and J), the energy consumption reduced from the range of 120-140 kWh^{-2}

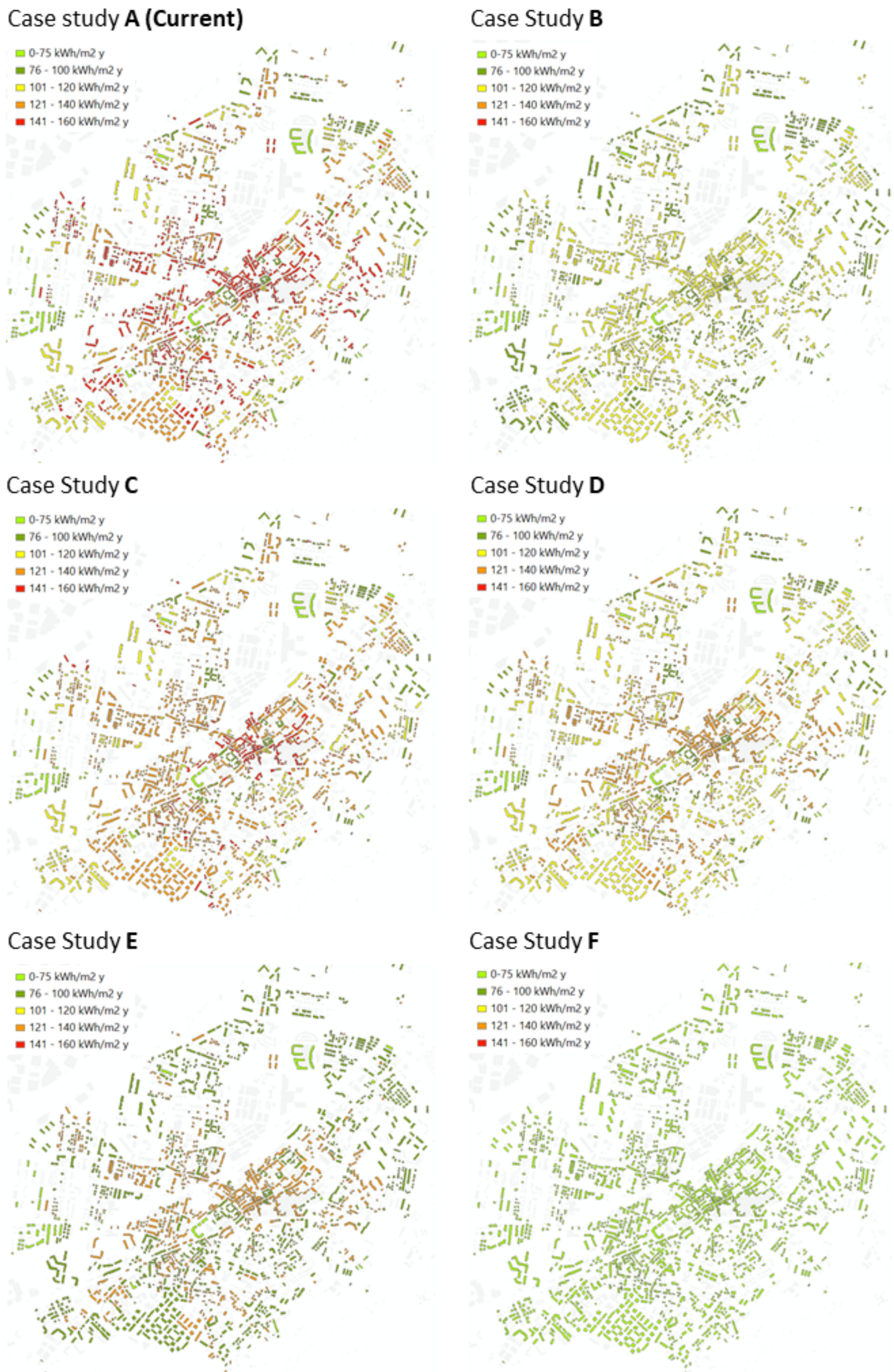


Figure 15. Heating demand Map following the Tabula renovation.

(orange color) to the range of 75-100 kWh^{-2} (green color). Again, floor isolation (case studies C and H) shows the minimum reduction for Fiat village buildings colored orange. Intuitively, Case studies F and K, the global retrofitting energy solutions, have the maximum energy reduction in all the maps. In the entire

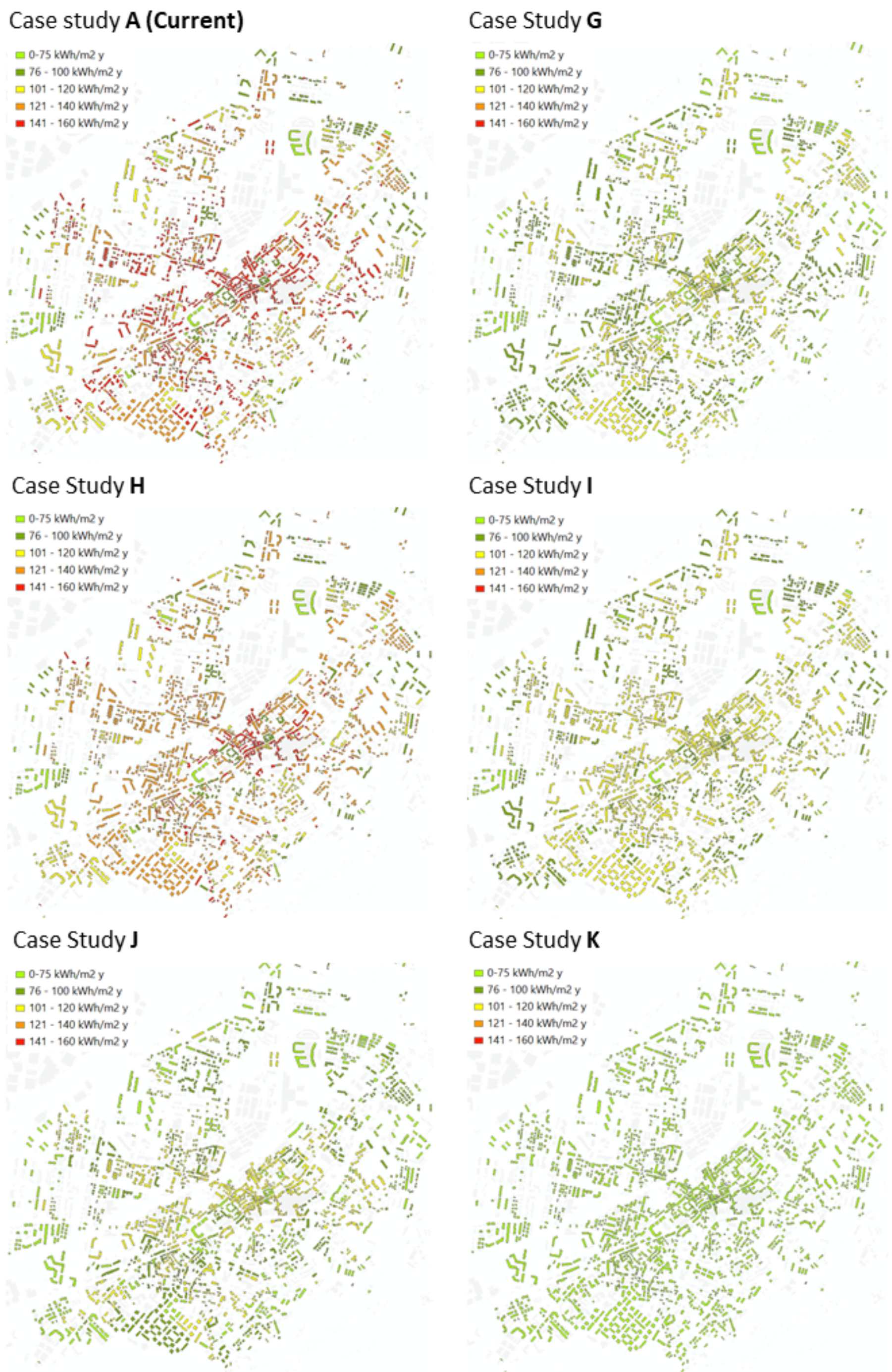


Figure 16. Heating demand Map following the Minergie-P renovation.

city, the total energy consumption diminishes rapidly.

Generally, regarding the Tabula renovation solutions, results demonstrate that case study B (floor isolation) lead to the most heating reduction of approximately 30% slightly behind the case study F (global

(a) Glazing replacement solution from Tabula   **(b)** Glazing replacement solution from Minergie-P

Figure 17. Annual heating demand of the first period of construction (please note the difference in scale due to limitations of the visualization tool).

refurbishment). Similar to the Tabula renovation, the results from the Minergie-P scenarios, also showed that the floor insulation (case study G) was the best energy saving scenario, reducing around 35%. The wall isolation and the windows substitution (Case studies D, E, I and J) are also one of the effective energy saving solutions as well as economic aspects. Especially Minergie-P solution shift the most of buildings to green color.On the other hand, the worth scenarios are C and H.

4 Conclusion and perspectives

Providing useful information to decision makers (urban planners, municipalities or architects) can be a tedious task when designing more sustainable urban areas. On the one hand statistical methods are often used to understand the driving parameters of energy consumption but rarely used to evaluate future urban renovation scenarios. On the other hand the simulation of a complete city or urban area can be extensive in terms of computational resources, data acquisition and modeling.

In order to address these shortcomings, we have proposed in the current study, a new methodology to define an archetype urban area that would be representative of a medium sized city. The objective was to decrease the number of buildings that need to be simulated while at the same time keeping the same average geometrical and physical characteristics of these buildings. Simulations were performed for a full year using the CitySim software. It was demonstrated that the energy demand obtained using such a methodology was very close to the monitored energy consumption and using data from the TABULA database. Furthermore, in a different study, a statistical method was used to evaluate the energy demand of the Settimo Torinese city. We also compared the results obtained using the current method to the statistical one.

In a second step, we developed multiple renovation scenarios according TABULA and to the Minergie-P standard. Both the set of simulation for the refurbishment were done with the CitySim software. The values obtained were also compared with previous studies and databases. Finally, we integrated the simulated scenarios back into a geographical information system to provide a powerful visualization tool for the renovation of a medium-sized city. Such tools can provide critical information on the energy dependency of different parts of the city.

In the near future a full and detailed comparison of both the statistical and deterministic models will be done in order to evaluate the pros and cons of each methodology. As shown in this paper there were some differences between these methods and the results that they produced. It should nevertheless be highlighted that the method that we have proposed here can be generalized very easily as limited geometrical information were needed to perform the simulation.

These types of tools could be used at an early design stage or during the evaluation of urban planning scenarios. Further research will also be necessary for improving this framework by taking into account additional criteria (e.g., socio-economic and environmental) to create a potent Multiple Criteria Spatial Decision Support System (MC-SDSS). The MC-SDSS in progress will allow the development of scenarios taking into account all sustainable aspects towards low-carbon cities. Thanks to the fact that the SDSS is flexible can be updated, more solutions can be implemented in the future.

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Acknowledgements

This work was conducted as part of the exchange of Sara Torabi Moghadam at EPFL. This research has been partially funded by the CTI (Commission for Technology and Innovation) within the SCCER Future Energy Efficient Buildings and Districts, FEEB&D, (CTI.2014.0119).

Author contributions statement

S.T.M. Formal analysis, Investigation, Methodology, Modeling, Visualization, Writing – original draft; S.C. Formal analysis, Investigation, Methodology, Modeling, Visualization, Writing – original draft ; D.M. Analysis, conceptualization, Funding acquisition, Methodology, Supervision, Writing – original draft ; G.M. Supervision the modeling analysis; J-L.S. and P.L. Funding acquisition, Supervision and revision the whole work.

Authors declare no conflict of interest.

Appendix

Table 5. Comparison between the heating demand computed by the proposed energy model, the monitoring data for the city of Settimo Torinese and the results from TABULA

Period of Construction	Deterministic method (kWh m^{-2})	Tabula (kWh m^{-2})	Monitored (kWh m^{-2})	Statistical method (kWh m^{-2})	Difference (%)
1946-1960	146.40	130.19	148.71	113.64	6
1961-1970	135.50	132.82	149.22	107.01	-3
1971-1990	113.67	98.57	148.58	106.26	-8
2005-2016	74.51	69.89	86.68	-	-4