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Integration of aerial thermography and energy performance certificates for the estimation of energy consumption in cities ☆

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ABSTRACT

Based on the major role of the building sector in the energy transition, multiple policies on the topic have been issued at the European level, resulting in a need for methodologies to support energy retrofitting campaigns. Based on a preliminary segmentation of the building stock in terms of year of construction and surface-to-volume, this study aims to model the energy demand of buildings at urban scale from the integration of data elaborated from the available Energy Performance Certificates with thermographic data returning the actual heat losses of the buildings. The new proposed approach proved to be more reliable than methods currently available in the literature, providing energy performance classification of all buildings with 80 % accuracy. Conclusions remark on the potential of such analysis, with ready-made solutions to be used by Public Administrations for city-scale energy assessments, thus making them able to comply with European legislation and – potentially – design Renewable Energy Communities.

1. Introduction

Cities play a key role in the energy transition, being responsible for around 70 % of energy-related emissions and having the potential to cost-effectively cut them by two-thirds [1]. Nevertheless, this is challenging because of a vicious cycle regarding climate change, which increases the demand for heating and cooling [2], responsible for more carbon emissions.

This condition has been recognised by the European Union, with legislative tools – by the Parliament and the Council – and action plans – by the Commission – fostering the transition towards post-carbon cities, especially by targeting an improvement in the building stock. Indeed, the annual deep renovation rate of the building sector is only 1 % on average in the EU, with reports from the Building Performance Institute of Europe showing the need to increase it to 3 % by 2030 to achieve European targets [3]. The problem is even more rooted in Italy, where ownership fragmentation causes the need for binding tools as the only effective policies [4].

The requirement of a paradigm shift in the building energy sector is the focus of the Fit for 55 package [5], which introduced the necessary measures to ensure the 2050 goals for EU Greenhouse Gases (GHG) reduction – 80–95 % compared to 1990 levels – will be met. This package includes the revision of several directives, among which the Energy Performance of Buildings Directive (EPBD) is the most relevant for building energy performance. The first version of the EPBD [6] introduced the energy classification system, basing it on the Energy Performance Certificate (EPC) as required before selling or renting and after renovation processes. The recast [7] reinforced the role of the EPCs by setting a minimum performance objective – quantified in the certification process – for all buildings and introducing in the certificate itself recommendations for further enhancing the energy performance. Moreover, it defines a path towards the complete phasing out of fossil fuels in the energy systems, fostering electrification. The Energy Efficiency Directive recast [8] gave even more relevance to the topic by introducing the "energy efficiency first" principle. This makes it mandatory to consider energy efficiency in all policies, both sectorial on energy and not. The European level promotes actions for climate neutrality through open calls and missions; an example is the EU Mission "Climate-Neutral and Smart Cities" [9], promoting the realisation of Climate City Contracts – comprehensive plans for climate neutrality – together with stakeholders and citizens, with energy and buildings being two of the key topics.

This focus on energy efficiency, with binding regulations – such as

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Nomenclature

AoI	Area of Interest
EPBD	Energy Performance of Buildings Directive
EPC	Energy Performance Certificate
EU	European Union
EUI	Energy Use Intensity
GFA	Gross Floor Area
GHG	Greenhouse Gas
GIS	Geographic Information System
LB	Literature-Based
NITB	New Informed Thermography-Based
ROC	Receiver Operating Curve
SVR	Surface-to-Volume ratio
TB	Thermography-Based
UBEM	Urban Building Energy Model

the minimum performance objective – imposed at the international level, made it necessary to identify the worst-performing buildings in order to better target renovation policies and direct interventions. EPCs, the official instrument of the EU for classifying the energy performance of buildings or building units, in Italy cover only around 10 % of the total building units, often with questionable accuracy [10]. Therefore, there is a need to map the energy performance of large building stocks by resorting to building energy simulation tools or algorithms [11].

1.1. Background

1.1.1. Urban building energy modelling

Urban Building Energy Models (UBEMs) have gained specific interest in this context. As observed by Salvalai et al. [12] there is increasing attention on the topic, with more than 600 studies published yearly. Still, the definition of UBEM is debated. To ensure completeness, the most comprehensive definition, proposed by Ferrando et al. [13] in a comprehensive review of the current state of UBEM development will be adopted. It includes both top-down and bottom-up models. Top-down modelling defines the variables affecting energy use on an aggregated level, observing consumption patterns as connected to identified drivers, while bottom-up models take advantage of large databases with disaggregated data and aim to define the aggregate energy demand.

The main obstacle to the implementation of bottom-up energy models is the need for extensive data [14], classified into four principal groups according to Wang et al. [15], namely geometric, non-geometric, weather and validation data. As a result, most scholars resort to representative archetypes [16], of which the number is highly correlated to the model accuracy [17].

Archetype definition is organised in three subsequent steps, which are the grouping of similar elements, characterisation and calibration based on historical data [11]. While some studies such as the one by De Jaeger et al. [18] resort to statistical methods for grouping, most publications adopt a segmentation based on specific building parameters. One of the most used parameters is the building age, adopted for example in ref [19–22], as especially buildings built before 1960 show poor building envelope performances. Building type – defined according to pre-defined categories (such as single or multi-family house) or indicators such as the Surface-to-Volume Ratio (SVR) – is another recurring parameter e.g., in ref [19,22,23]. In particular, the SVR is proportional to energy consumption, with lower compactness resulting in higher consumption [24].

1.1.2. Energy performance certificates

Introduced in the European Union in 2002, the Energy Performance Certificates (EPCs) of buildings have been exploited both for policymaking on urban and national scales [25] and as input datasets for the realization of UBEMs – especially in the archetyping phase –, despite their relatively recent introduction [4,23,26,27]. In Italy, the EPCs issued yearly constantly increased from 2005 – when they were introduced – to 2023, when there was a 3 % decrease compared to 2022 [28]. The potential to continuously increase samples, derived from the constant widening of the dataset, makes EPC-derived data more attractive every year [29] despite the problems of data gaps. The use of EPC data has been further widened by the requirement – set in the EPBD itself – to ensure public access to such information [30].

Despite their wide application and a general reliability label, multiple studies have also claimed issues in EPC-derived data [31], with 30 % discrepancies between simulated and measured results [24]. These derive from four principal categories, described by Raushan et al. [25], namely lodgement errors, measurement errors, outliers and anomalies, duplicate entries, human errors and systematic errors.

1.2. Scope, novelty and structure of the work

The goal of this research is to consider values returned by aerial thermography as key indicators of the energy performance of buildings. A comprehensive review by Martin et al. [32] discussed the principal applications of thermography on multiple scales, from the building to the regional scale, highlighting a general lack of studies considering whole cities, and also the possibility to assess the thermal characteristics of the envelope from remotely sensed thermographic pictures. However, considering that the accuracy of the surface temperature is lower compared to the one from contact surface sensors, it is relevant to foresee applications based on the relative differences within the building stock rather than on absolute values. Indeed, as claimed by Dochev et al. [33], several assumptions have to be made to compute precise U-values from aerial thermography, thus deciding to use surface temperature as an indicator of building envelope insulation quality. This application is particularly appealing also in light of the conclusions stated by Sun et al. [34], claiming that the building envelope system is one of the most significant factors affecting building energy consumption. A previous study by the same authors [35] demonstrated the reliability of the method but also introduced the necessity for widening both the study area and the density of the training data – in that case, a single EPC was used for every volumetric unit – but, most importantly, to use pictures acquired during nighttime not to have biases deriving from solar radiation. Similar infrared thermography applications for UBEMs were already present in literature e.g., in a study on the city of Bologna, Italy [36] and in Beijing, China [37]. However, in these studies thermal pictures were used together with RGB ones to get information on the building stock based on the construction material or to define the U-value, without direct reference to building energy performance calculation or classification.

As a potentially groundbreaking advancement from existing literature, the present study aims to explore the potential of directly using the "thermal signatures" of buildings, detectable from aerial thermographic images, as a proxy of energy performance.

Section 2 provides an overview of the inputs gathered and the models adopted, proposing three alternative approaches. The case study is introduced at the end of that section. Section 3 presents the principal findings of the three alternative approaches, both intermediate and final, while in the discussion (Section 4) the final results of the methods are presented as integrated. The strengths and weaknesses of each of the three methods are considered before the presentation of the conclusions and the introduction of the guidelines for future research.

2. Materials and methods

According to the aim of the study, the methodology was defined to explore the use of existing EPC data alone and together with thermographic pictures for segmenting the residential building stock and defining the energy performance of the buildings, thus defining the total energy demand accordingly and assessing the added value provided by using thermographic data in increasing the extension and accuracy of output data.

Emerging from the literature review, in this study we use the method established by Conticelli et al. [4] as a benchmark and referred to as the "literature-based (LB) method". Such a method does not imply the use of aerial thermography but only takes into account EPC data, as described in detail in Section 2.2.1. As represented in Fig. 1, it proposes the definition of the Energy Use Intensity (EUI) based on the construction period, then calculating the total energy demand accordingly. While in the original research the method is not validated, in this study results are tested against a set of EPCs kept aside in the training phase.

Building upon a previous study that preliminarily integrates aerial thermography in building energy performance assessment at the city level [35] – indicated in this paper as "thermography-based (TB) method" –, this research proposes a "new informed thermography-based (NITB) method", aiming to observe the potential improvements given by widening the sample and adding segmentation. A schematic representation of the workflow is provided in Fig. 2, in which the refinements in data analysis are highlighted. The methodology can be schematised in two parts. The first (data analysis) is about pre-processing data – both geometrical and non-geometrical, gathered respectively from GIS repositories and EPCs – for training, while the second (energy classification) is the actual attribution of the energy class to each volumetric unit. An additional – optional – part concerns the calculation of the total energy demand, as a function of the energy performance – correlated, even if not directly, to the energy class – and the Gross Floor Area. Validation is carried out by comparing data against a set of EPCs not used in the training phase.

2.1. Data gathering and preparation

The proposed methodology relies on information coming from Energy Performance Certificates and Infrared Thermography, semantically enriching existing information on volumetric units. Therefore, these elements have to be gathered and pre-processed.

The EPCs are collected from "datipiemonte" [38], the portal of the open data of the Piedmont Region. It provides data in an extremely disaggregated form, section by section, thus making it necessary to join different tables in order to have the necessary information available simultaneously. After having selected the parameters relevant to the study, they have been aggregated selecting the proper formula or defining the criteria based on which – in case of discrepancies – data from one section are to be preferred to the ones from another one. Then, EPC data were aggregated based on the volumetric unit. The indicators to be extracted from the EPCs are:

1. the building address, proxy for georeferencing and referring EPC data to volumetric units;
2. the period of construction, grouping the year of construction in eight classes; in case of discrepancies between the EPCs about the same address, the classification is based on the average of the reported years of construction;
3. the Surface-to-Volume Ratio (SVR), reported in the EPC; in case of data gaps, it is calculated based on the heat loss surface and the heated volume;
4. the energy performance class; in case of duplicate values, the worst one is considered, assuming:
   a. if the EPC is issued for a single building unit after renovation, the renovation has tackled only that unit, which is likely to be better performing than the others
   b. if the EPC is issued for renting or selling the house, the worst performing is likely to represent the baseline before renovations
5. the EUI expressed in kWh/m^2.

As for the Infrared Thermography, the SDG11 Lab – the research laboratory where the research was carried out – commissioned a dedicated flight to DigiSky S.r.l., who carried out the acquisition on 23rd March 2023 from 6 to 8 PM with a FLIR A8581 MWIR HD thermal camera. This camera, equipped with a 1.3 MP sensor, acquires in the spectral range of 3–5 μm, with a $\pm1^{\circ}$C accuracy. The resulting thermal orthophoto, produced with a Ground Sampling Distance of 25 cm, covers an area of approximately 2 km^2. Considering the relatively small area, its homogeneity – in terms of both building materials and heights – and the lack of relevant green spaces potentially affecting the urban microclimate, it is assumed that potential differences due to microclimate conditions are negligible. Despite the nighttime acquisition, realised in the absence of solar radiation, it was verified the potential correlation between surface stroke by the Sun in the late hours of the day and roof temperature returned by the thermographic picture. The correlation coefficient equal to 0.23 ensured that there is no correlation between roof orientation and temperature.

The elaborations are performed on the volumetric unit, that is the maximum level of disaggregation possible without knowing the administrative divisions. Indeed, volumetric units are parts of the buildings which have the same footprint and height. Geospatial data on volumetric units are provided by the Turin Municipality as part of the Municipal Technical Map, updated yearly. The attribute table provides information on the footprint – which was re-computed through GIS –, the height of the structure and the number of floors. Nevertheless, the information contained in such a thematic layer is not sufficient for the sake of this research, thus needs to be enriched with additional data coming from the building layer – from the same Technical Map – and the national statistical body, ISTAT. At first, a spatial join was performed between the buildings and the census sections, in order to complete the information on the year of construction – which in some cases is marked as unknown. Census data report the number of residential buildings as divided by period of construction, so – after a selection phase in which non-residential buildings were removed – a difference was performed for each year class between the census data and the buildings from the

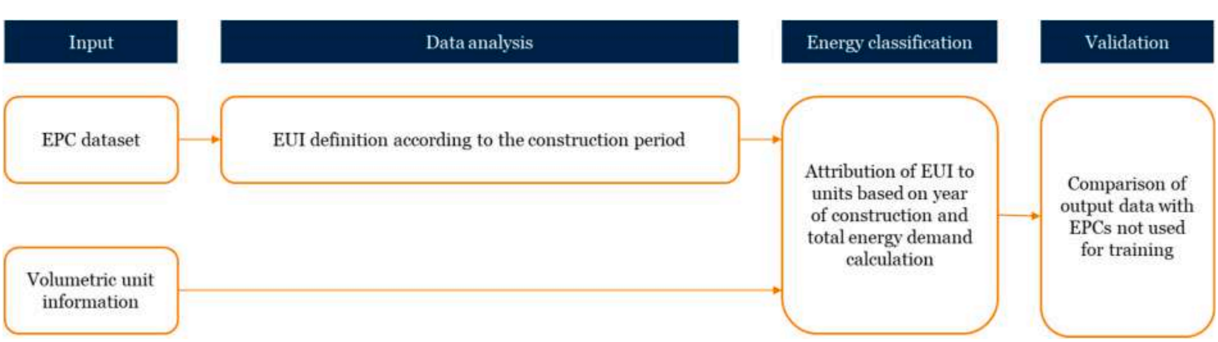

Fig. 1. Scheme of the literature-based method (LB) proposed by Conticelli et al. [4], replicated and validated in this study.

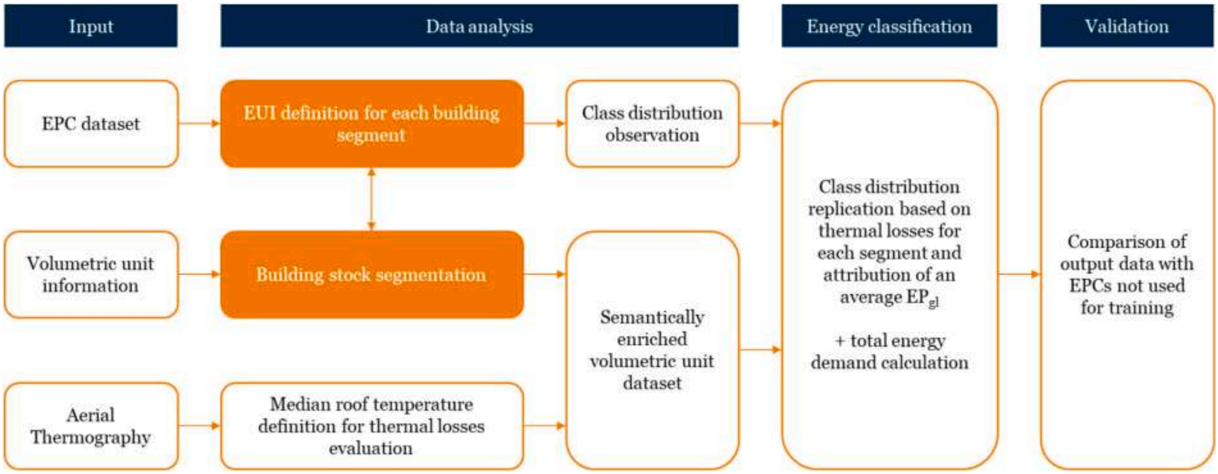

Fig. 2. Scheme of the new Informed Thermography-Based method (NITB) proposed in this research, highlighting in orange the new original steps compared to the previous thermography-based (TB) study [35]. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Technical Map, thus understanding the periods for which there were less records than expected. The buildings which could not be assigned in this way were esteemed to be in the most recurring class of the census section. At this point, another spatial join populated the volumetric units layer with building-related information. Therefore, it was possible to remove all units pertaining to non-residential buildings. Additionally, minor buildings – garages and service buildings, defined by Legislative Decree [39] – are also removed because generally they are not heated. Another piece of information which was corrected is the number of floors, excluding non-heated attics and filling in data gaps by dividing the height by 3 m – the average height of a storey in a residential building.

Further processing enabled the calculation of the Gross Floor Area (GFA) and the surface-to-volume ratio (SVR). The latter required the identification of the shared walls, to identify the parts which have to be excluded from the heat loss surface.

2.2. Energy class definition

The definition of the energy performance and of the total energy demand is carried out in three ways: first, the LB method [4] is reworked as a benchmark; second, the TB method [35] is replicated and third, the TB method is expanded and improved within the new NITB method.

2.2.1. Literature-based method

Conticelli et al. [4] proposed a methodology to scale up the energy performance studies to a whole town – Castelfranco Emilia (Modena, Italy) – by dividing the building stock into classes according to the year of construction. This classification is considered as the principal parameter for defining the energy performance, due to the direct implications the construction period has on the morphology and construction techniques. This derives from the changes in the Italian legislative framework, characterised by some milestones reported by [10]. In particular, two milestones to be considered are Law 373/1976 [40], introducing the first requirements for thermal insulation, and Law 10/1991 [41], promoting rational energy use. Additionally, the first EPBD [6] defined the energy performance calculation. These milestones can be seen as a proxy of the different normative gaps, to be considered when considering the eight-classes classification adopted according to ISTAT, namely: before 1918, 1919–1945, 1946–1960, 1961–1970, 1971–1980, 1981–1990, 1991–2005, after 2006.

The calculation of the EUI is based on EPC data. In particular, a weighted average based on the heated surface was performed to define a reference EP_{gl} for each period of construction. The weighted average, chosen in the original research [4], would require extensive data filtering (not performed in the reference study), as it can lead to incorrect values in case of biased inputs. For this reason, it is believed that a median or a simple average should have been preferred. 80 % of the EPCs – randomly selected – are used in this step, keeping the remaining 20 % for validation.

Finally, the authors aggregate energy consumption by zones [4]. They make explicit use of the areas identified within the municipal regulatory plan – in which areas are homogeneous in terms of land use and building regulations –, summing total consumptions accordingly.

2.2.2. Thermography-based method

The thermography-based method, first introduced in 2023 [35], is principally based on temperature values quantified by a thermal orthophoto. The surface temperature is returned on square tiles with 25 cm sides, thus requiring aggregation of the information by each volumetric unit roof. Differently from the previous research done by the authors, in this case a dedicated nighttime acquisition was made available, thus showing values not biased by solar radiation. As a result, no qualitative selection of shadowed areas was required, allowing the aggregation to be performed directly through the zonal statistics GIS tool, which makes it possible to compute the principal statistics of the cells falling within a pre-determined area. Considering that slight offsets may cause cells not pertaining to the roof – especially of the road asphalt surfaces, characterised by higher temperatures – to fall in the area for which the statistics are computed, it is preferable to use the median values instead of the average, to remove or reduce biases caused by unwanted extreme temperatures values.

The second input is provided by the Energy Performance Certificates. A single EPC, the one most recently issued, is kept for each building. 80 % of the EPCs were randomly to observe the distribution of energy classes in the district, leaving the other 20 % for the validation phase. The resulting shares are believed to be representative of the general condition of the district. Moreover, the EUI is computed as the median EP_{gl} value – the sum of primary energy demand for all the different energy uses including heating, cooling, ventilation, Domestic Hot Water, lighting and appliances, quantified in kWh/m^2 – reported for each class in the EPCs. It is to be highlighted that the class is not only connected to the $EP_{gl,}$ so it is preferable to use the median value instead of the average in order to limit the impacts of extreme values.

Assuming a constant internal temperature of residential buildings – set by law [42] to be 20°C with a ±2°C tolerance – the surface temperature returns the heat losses of the envelope, one of the principal drivers for the building energy classification. Therefore, the temperature values resulting from thermography were ordered progressively. Finally, a direct correlation between the distribution of the energy class observed through the EPCs and the whole building stock is established. Despite the relevance of the HVAC systems for energy classification, the quality of the envelope was used as the only proxy for attributing the energy class based on a general homogeneity in the heating systems, 86 % of which are natural gas boilers.

Once each volumetric unit has been assigned to an energy class, the corresponding EP_{gl} is attributed, thus enabling the calculation of the total primary energy demand. This is calculated by multiplying the EP_{gl} by the GFA – quantified as the footprint area multiplied by the number of floors.

2.2.3. New informed thermography-based method

In the new informed thermography-based method, before observing the distribution of energy classes and calculating the average EUI, training data are segmented.

As observed in literature (see Section 1.1.1), the first criterion considered to cluster the building stock is the period of construction, using the eight classes adopted in the literature-based method too; second, the building typology is used by resorting to the SVR. It is the principal parameter to express the building morphology and – despite not taking into account the window-to-wall ratio – it is a good indicator of the thermal losses of the building. For this criterion, buildings are divided into four classes according to Torabi et al. [43]: towers (SVR $<$ 0.45), multi-family houses (0.45 $<$ SVR $<$ 0.56), terrace houses (0.56 $<$ SVR $<$ 0.71) and detached houses (SVR $>$ 0.71). As a result, eight segments are defined according to the year of construction and four based on the SVR.

For each segment the distribution of the energy performance class is studied, then attributing in a global Primary Energy performance index (EP_{gl}) to each class of each segment as the median value of the global EP_{gl} of the buildings with an EPC. As with the other two methods, 80 % of the total number of EPCs – randomly selected – is used as a training set, in order to keep the remaining 20 % as a test set for validation.

2.3. Validation

20 % of the available EPCs are used as a test set to validate the output of each method. The records to be used for validation are selected randomly from the original database. Considering it is not possible to validate the total energy demand due to data availability – as this data is not made publicly available due to privacy issues –, only the energy class is considered. In particular, the variance between the estimated energy class and the actual one, returned by the EPC, is analysed.

2.4. Case study

The case study is located in Turin, Italy. It is part of the *Barriera di Milano* district, an area characterised by physical, social and economic marginality. It is bounded by green areas on the North and East – the parks flanking Stura di Lanzo and Po rivers –, a big avenue (*Corso Giulio Cesare*) on the West and minor roads on the South. It is highly heterogeneous, with the former railway trench – which will host the second metro line of the City [44] – separating the two areas. In the South, the historical area, pivoted around *Piazza Respighi*, with an organic urban morphology and small building units; in the North, several social housing districts realised after World War II [45]. Social housing districts were realised in this area as they were close to the principal industrial areas of the city. However, this proximity caused the area to be heavily affected by bombings during the War, thus requiring partial or complete reconstructions. For this reason – as it emerges from Fig. 3 – most buildings date back to the period between 1946 and 1960, with the remaining gaps being filled by 1970. The industrial boom of the post-war period led to an urgent housing need, resulting in quick constructions often characterised by poor building quality, resulting in the current need to renovate – from a structural and energetic point of view – the housing stock. Recent transformations, located especially between *Via Botticelli* and *Corso Taranto*, have affected mainly the commercial building stock, not considered in this research.

A total of 673 volumetric units was considered in this research, in a 2 km^2 study area. On average, they are four floors tall and have a Gross Floor Area equal to 1208 m^2.

3. Results

In this section, results are presented disaggregated, analysing the outcomes of the three applications introduced in the methodology.

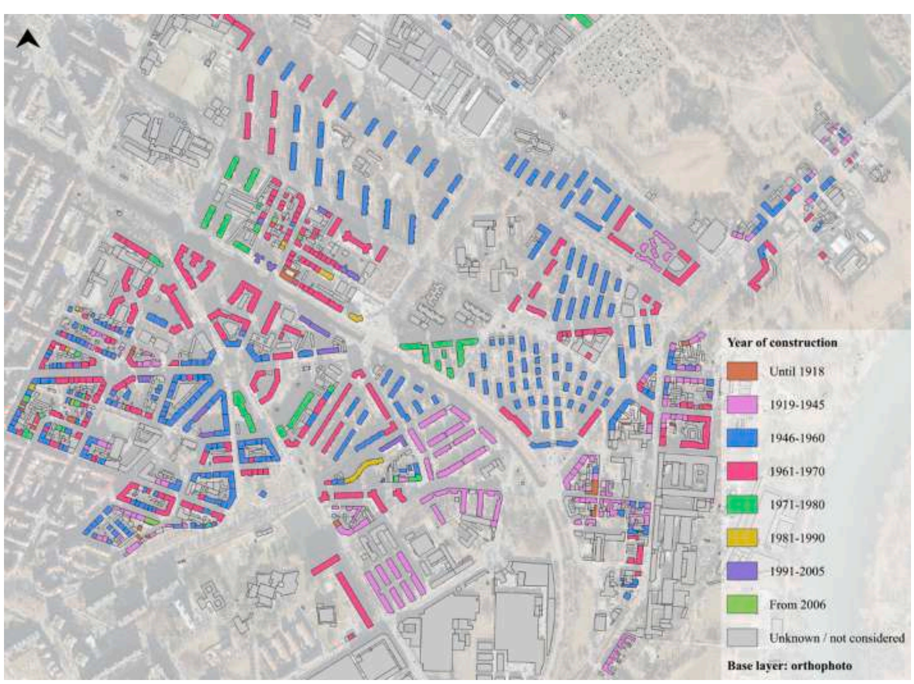

Fig. 3. Construction period of the building stock.

3.1. Literature-based method: EPC-based consumption analysis

The first results, to be used as a benchmark for assessing the results of the proposed NITB methodology, are produced following the replication of the study published by Conticelli et al. [4].

This study focuses on the year of construction to define an estimated primary energy consumption. As shown in Fig. 3 – classifying the building stock according to the year of construction – a clear prevalence of buildings of the same age can be observed, the one including buildings from 1946 to 1960. From this, it derives a prevalence of a single EUI value.

Total consumptions – plotted in Fig. 4 – range from 511 kWh/year to 4.17 GWh/year per volumetric unit, with peaks which can be seen around *Piazza Respighi*, in the Southern part of the AoI. Moreover, it is possible to observe homogeneous results in areas with homogeneous building typologies, as they were built in the same period and have comparable GFAs. This is especially valid for the social housing districts, with serial constructions in a single area. Considering the methodology used at this moment depends on the construction year and the GFA, this result is not surprising.

By crossing the EUI attributed to construction year classes and energy performance classes from the training dataset, it is possible to define the energy class attributed to each volumetric unit. According to this classification, most buildings are classified as F, with EP_{gl} values comprised between 200 kWh/m^2 and 246 kWh/m^2. The most notable exception is given by buildings realised between 1981 and 1990, whose average EP_{gl} is 147.85 kWh/m^2, thus making them classifiable as A. This represents a general problem of the LB method, with building segments characterised by a limited number of EPCs being more affected by exceptions – in this case, most buildings have high energy performance – and biases. Nevertheless, in this case the impact on the total district consumption is limited, based on the low incidence of this segment (1.2 % of the total GFA). Finally, buildings realised from 1971 to 1980 and from 1991 to 2005 fall into class D.

Validating these results according to the validation dataset, it results that discrepancies reach a six-class difference in four cases. Nevertheless, the general results are satisfactory, with 23 cases (33 %) with no difference and 35 (50 %) with a single class difference out of seventy volumetric units considered.

From the analysis of the results aggregated on the zone level it emerges that the parts of the AoI characterised by the most energy-intensive buildings are located in the Southern area despite their small dimensions, whereas planned districts display average values.

3.2. Thermography-based method

The first analysis of the thermography-based methodology concerned the Infrared orthophoto. The time of the thermographic acquisition – from 6P.M., after sunset – makes it possible to query directly the resulting orthophoto – shown in Fig. 5 – without additional preprocessing. Indeed, there is no direct radiation which modifies the output by creating differences between shadowed and sunlit portions. Values range from −5°C to +20°C, with a peak of values – slightly more than 700 pixels – around 9°C.

When referring the thermal values to the residential volumetric units by calculating the median through the zonal statistics tool – with resulting values plotted in Fig. 6 –, the range is reduced from −1.09°C to +15.94°C, based on the heat stored by the envelope or dispersed in the environment. A single unit, located in *Strada dell'Arrivore*, has a negative temperature value, while most buildings are comprised in the range between 5°C and 10°C. Inside this class, the highest number of units – 193 – falls into the 7–8°C cluster. While it is relevant to consider absolute temperatures – returning the heat storage capacity of the external envelopes, with minimum values corresponding to lack of heat leakages –, the focus has to be kept on the distribution of relative differences, which allows to order buildings by their heat storage performance. As the focus is on the observation of relative differences rather than on the definition of the absolute temperature, the accuracy of the thermal camera does not affect the final results. In this step, it is sufficient to have proper camera calibration to ensure precise and consistent outcomes.

As for the spatial patterns, it is possible to observe a general prevalence of buildings with low-quality envelopes – with roof temperatures from 9°C to 15°C – in the Southern part of the analysed area. On the contrary, lower temperatures could be observed especially close to *Via Bologna*, in the Eastern part.

The second key input is provided by the EPCs. As previously mentioned, only one – the most recently issued – was taken for each volumetric unit. The class distribution observed in the dataset has a

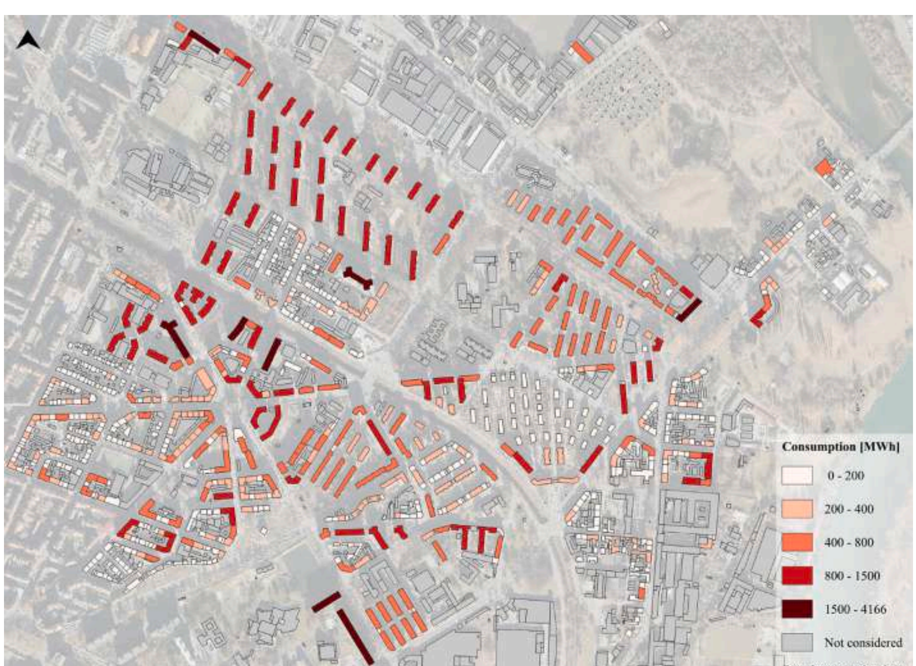

Fig. 4. Estimated consumptions according to the literature-based method (LB) by Conticelli et al. [4].

Fig. 5. Portion of the thermal orthophoto.

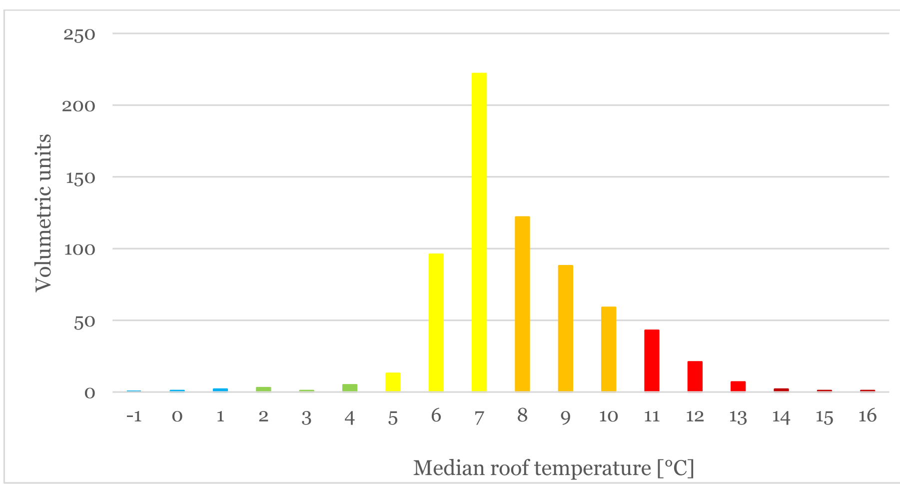

Fig. 6. Distribution of median temperature values in the AoI.

general tendency towards low-performing classes, with only 3.93 % of buildings included in the three more performing classes. On the contrary, the three least performing classes account for 85.14 % of the total, with class F being the most relevant one including 38.36 % of the total.

Fig. 7 returns the spatialisation of classes attributed according to the thermography-based method. While no clear spatial pattern emerges for the most performing classes, specific results can be presented from class D. Indeed, most of the buildings located around *Via Cravero*, part of the mentioned planned districts, are included in this class. *Corso Taranto* splint buildings are classified as E. Finally, a clear concentration of low-performing buildings can be observed around *Piazza Respighi*, where worst quality envelopes are located – according to the thermal picture.

Validation returns 37.8 % of cases with perfect correspondence between the energy class attributed through this method and the validation dataset. This value increases to 68.9 % when considering as correct the differences within a ± 1 class. However, differences also reach a four-class discrepancy, in particular in the case of a building classified as B, where the actual EPC ranking was F. In general, a tendency towards overestimation can be observed, with 47.3 % of units against 14.9 % for which the classification returned a worse value than the real one.

The total energy need is quantified to be 194 GWh/year, with each volumetric unit consuming approximately 209 MWh/year on average, on an average GFA equal to 1200 m^2. In this case, it is interesting to note that the planned district around *Via Cravero* shows the lowest values, with most buildings consuming less than 100 MWh/year. This is due not only to a good energy performance class – generally D – but also to the reduced GFA. In this case, this differs from what can be observed for the splint buildings along *Corso Taranto*, as they are more energy intensive – one building overcomes 1.3 GWh/year – because of their morphology, being high-rise buildings with footprints ranging from 636 m^2 to 691 m^2.

3.3. New informed thermography-based method

3.3.1. Building stock segmentation

The first results of the new informed thermography-based method derive from the segmentation of the building stock. These results

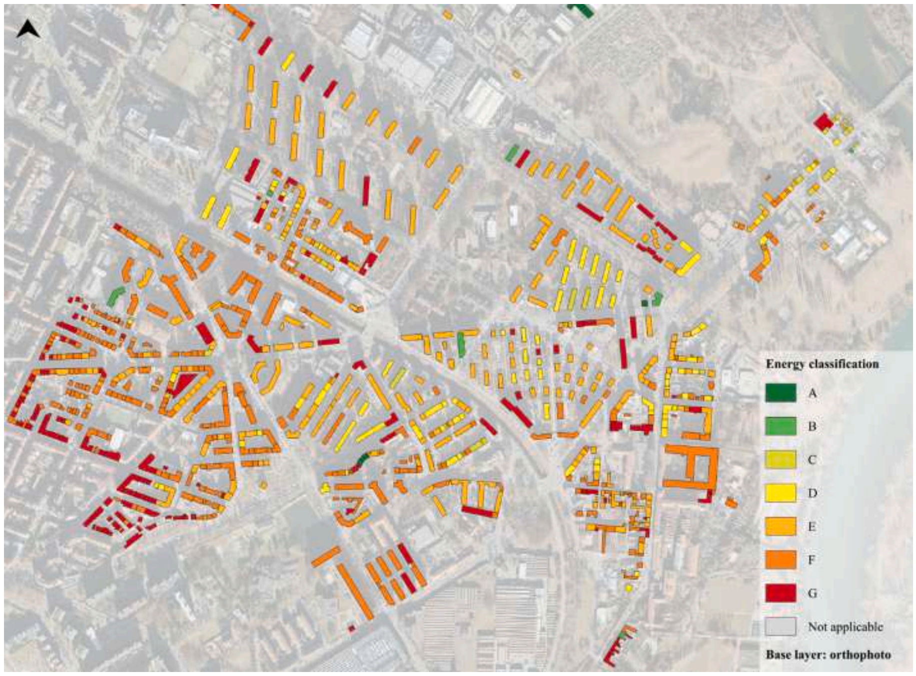

Fig. 7. Energy classification according to the thermography-based method (TB).

represent a refinement of the data introduced when presenting the case study (paragraph 2.4), first analysing the urban morphology, and then integrating building age and typology.

Considering the nature of the district, intended to meet as much as possible the housing demand, it is not surprising that the most common building type is the high-rise building, homogeneously diffused in the whole analysed district. In particular, along *Corso Taranto*, the architect Nello Renacco designed sixteen splint buildings, seven or ten floors tall. However, at the crossing between *Via Bologna* and the former railway trench, the 18th social housing district is characterised by a dominant multi-family house typology, with three-storey buildings in an urban structure similar to the one of the garden city.

The categories deriving from the construction year and SVR classification are returned in Fig. 8. By crossing previous results, it emerges that the most numerous segments are the towers from the period from 1946 to 1970 – that are 31 % of the total – followed by the same typology from the period 1919 to 1945. The only exception to the considerations done hereinabove is the class of detached houses, in which buildings realised before World War II outnumber the ones of the post-war period. In three cases, just one volumetric unit falls in a class: it can be observed for terrace houses from 1981 to 1990, towers and detached houses realised after 2006.

3.3.2. Energy classification

Once the building stock has been segmented according to the year of construction and SVR, volumetric units are ordered progressively according to the thermographic values and the class distribution observed from a dataset of EPCs aggregated in 257 building units is replicated. 106 volumetric units are classified as F and 95 as G; as opposed, only one unit falls in class B and none of them in C, thus displaying the general low performance of the building stock of the area of analysis. The breakdown of the class distribution across the eight building age classes and four SVR classes is shown in Fig. 9. It emerges the high incidence of class G from 1919 to 1970, while the only class B building is a tower

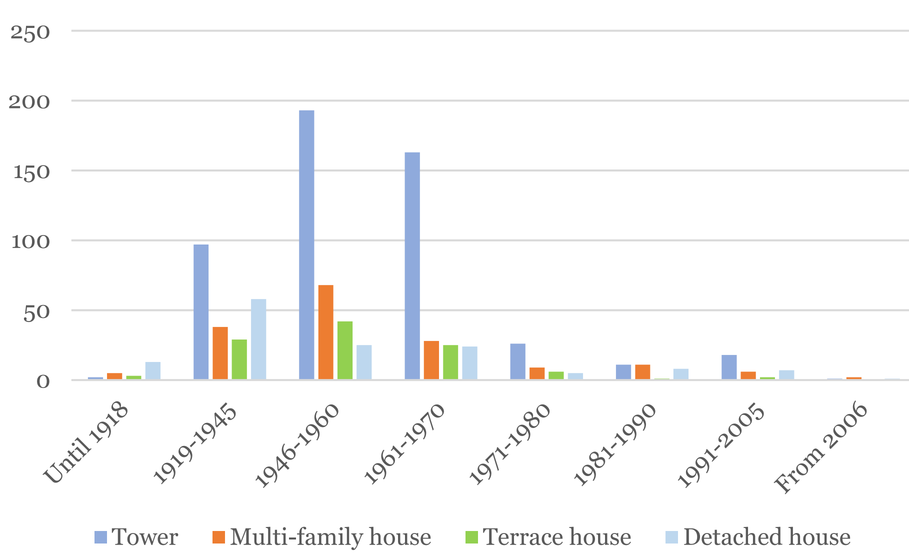

Fig. 8. Building stock segmentation.

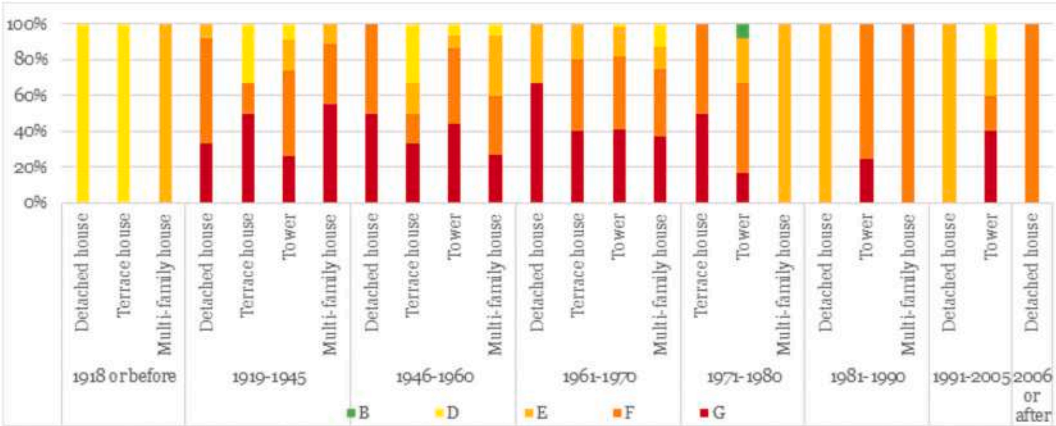

Fig. 9. Class distribution across the segments according to the EPC dataset.

realised in the time range from 1971 to 1980. Due to the low number of EPCs issued for specific segments, it is possible to observe absolute homogeneity inside some of them. For example, all detached and terrace houses realised before 1918 fall into class D, while detached houses realised from 1981 to 1990 are classified as F.

Fig. 10 shows the spatial distribution of the classes attributed to the volumetric units following the classification. As observed in the training dataset, there are no buildings classified as A and C and there is a clear prevalence of low-performing classes. However, while F-class buildings are homogeneously spread in the district, there is a concentration of G-class buildings around *Piazza Respighi* – in the Southern area, where the roofs with the highest temperatures were observed. Considering that out of the 673 volumetric units analysed in this research, 514 (76 %) are classified in the two less-performing classes, it is difficult to observe specific patterns of the distribution of the remaining three classes (B, D and E), especially considering that only one unit is classified as B. Nevertheless, 28 units out of the remaining are located in the blocks between the streets *Ancina*, *Gottardo* and *Bologna* and *Corso Taranto*, in the social housing district mentioned before.

It is to be noted that it was not possible to assign all buildings an energy class due to data gaps. In particular, it was impossible to classify 14 units, with most of them from the 1991–2005 year of construction category, based on data availability for each segment from the EPCs. For other 9, data gaps concerned either the year of construction or the SVR (when no number of floors nor height is returned) in the volumetric units database.

For each building segment, the average primary energy consumption is calculated. Fig. 11 reports the average specific primary energy consumption for each building segment, while Fig. 12 returns the average specific consumption for energy class. From the former, no clear correlation emerges, apart from a slight tendency to an improvement in energy performance after WWII, counterbalanced by an increase from 1991. On the contrary, across the five classes with at least one input value, it can be observed an increasing trend, from 80 kWh/m^2 of class B to 258 kWh/m^2 of class G. By crossing the segmentation with the attributed energy class, it is possible to observe values ranging from 62 kWh/m^2 – class D towers realised between 1961 and 1970 – to 399 kWh/m^2 – for G-class terrace houses of the period 1946–1960.

In total, 175 GWh are required yearly to meet the energy demand of the area of analysis, with the most energy-intensive buildings located

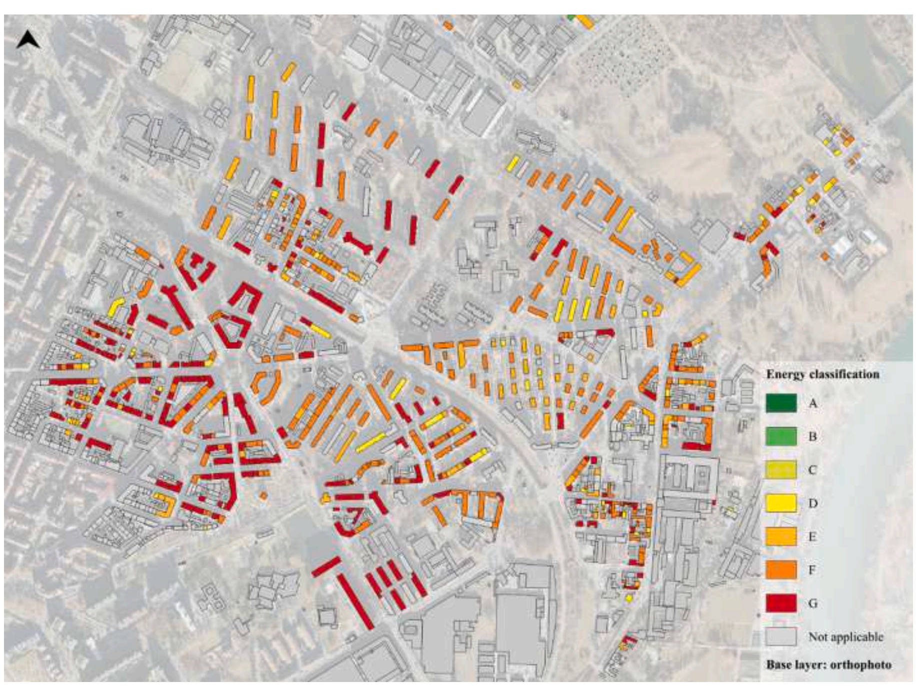

Fig. 10. Energy classification according to the new informed thermography-based method.

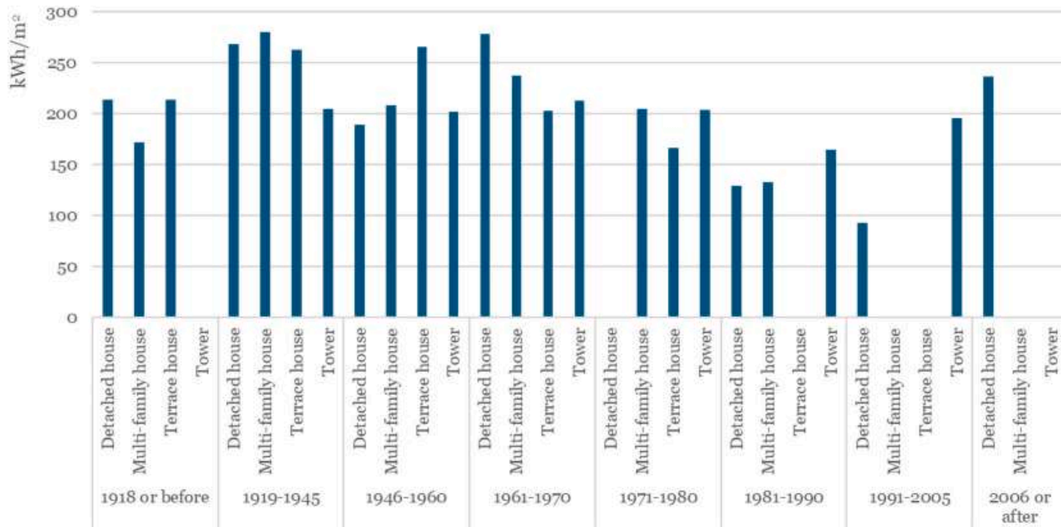

Fig. 11. Average specific primary energy consumption according to the building segment.

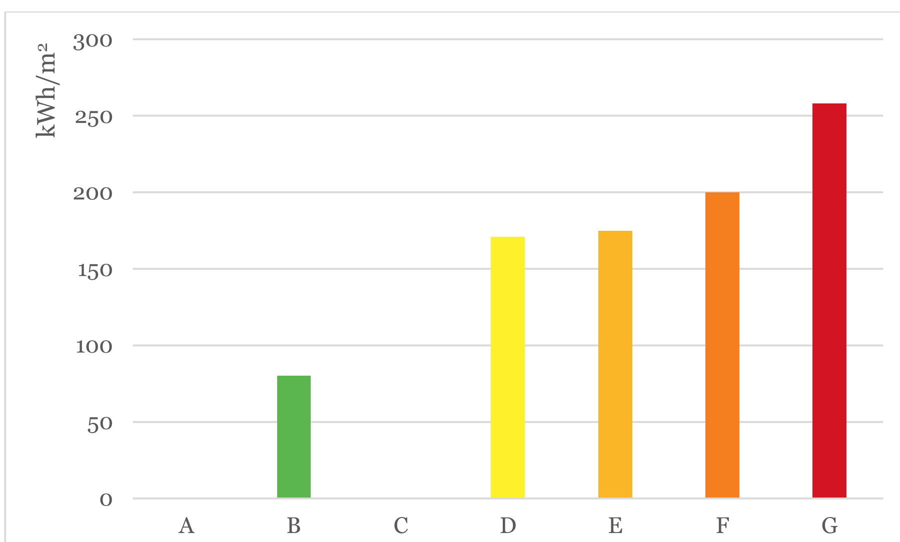

Fig. 12. Average specific consumption according to the energy class.

around *Piazza Respighi*, as shown in Fig. 13. Indeed, those volumetric units are not only among the least performing but also the biggest. On the contrary, the mentioned social housing district close to *Via Cravero* has some of the lowest values as a result of the reduced Gross Floor Area of class D buildings. Intermediate results are observed in the other planned district, the one characterised by splint buildings, in which also the energy class distribution is heterogeneous.

3.3.3. Validation

The last part of this research concerned the validation of the proposed NITB methodology. As mentioned, 20 % of the EPCs were used for this scope, with the classification being assessed for 54 buildings, randomly selected and homogeneously spread throughout the district.

In 80 % of cases, the classification proved to be highly reliable, with variations combined in the order of a single class. In 19 cases (35 %) there was no variation at all, with perfect correspondence between the attributed class and the one provided by the validation EPCs. Extending this group to the two-class discrepancies – the original target stated when drafting the methodology – only 2 units (3.7 %) are wrongly classified.

The maximum discrepancy – four classes – is related to only one building that is classified as G despite having a class C EPC. It must be remarked that in some cases errors in the existing EPC may not reflect the actual performance class of the buildings, thus causing discrepancies between EPC data and the thermal performance derived from thermal images. Also, this may be caused by a lack in the training dataset of class C buildings, highlighting that for this methodology the accuracy is incremental, with better results when extending the area of analysis.

4. Discussion

Once having validated the results of the thermography-based methodology, it can be discussed whether the integration of Infrared Thermography provides a real added value to the calculation or if it represents an increased – but not justifiable – cost in terms of both money for the acquisition and processing time. Therefore, the three methods are compared first according to the class distribution, then with the validation results and in terms of total consumption.

Fig. 14 compares the class distribution according to the three predictive methods and the one observed in the EPC dataset. While it clearly emerges a widespread prevalence of low-performing classes – with 76 % and 57 % of units classified in classes F and G according to the NITB and

Fig. 13. Total estimated consumptions according to the new informed thermography-based method.

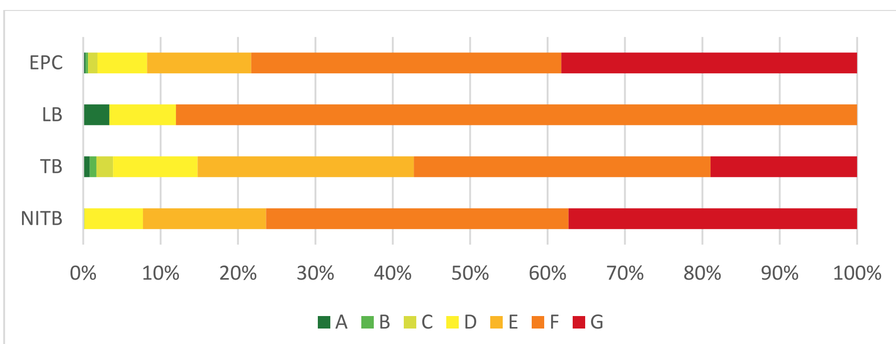

Fig. 14. Class distribution according to the three predictive methods and the EPC dataset.

TB method, respectively –, the LB method shows no class G buildings, while according to the EPCs these account for 38.23 %. Nevertheless, this percentage is reduced also in NITB and TB methods, where class G accounts respectively for 37.3 % and 18.95 %. According to the LB method, class A accounts for 3.38 %, ten times more compared to the share observed in the EPCs (0.31 %). As a result of the random choice of a training subset within the EPC dataset, which excluded the single class A building, the NITB method shows no units classified as A, differently from the TB method. Therefore, it can be observed the potentially high incidence of the random choice on the least numerous classes. Finally, all methods agree in returning class F as the most widespread, with shares ranging from 38.33 % (TB method) to 88.02 % (LB method).

Validation results – pertaining to the energy classification – are presented through the Receiver Operating Curve (ROC) (Fig. 15). ROC identifies true positives – in this case the values returned as correct in the validation phase –, plotted on the Y axis, and false positives, plotted on the X axis. It provides a visual representation of the results, with the shift on the curve showing the accuracy. The more it is shifted leftwards, the more the classification is accurate. The literature-based method proved not to be highly reliable, with its line corresponding to the chance level, standing for equivalence between the results provided by the analysed methodology and a random allocation. Thermography-based method returned better results, with nearly 69 % of true positives, but the New Informed Thermography Based method refined the calculation by a further 11 %, reaching 80 % of true positives.

Recalling the problems introduced in paragraph 3.3.3, with the incremental nature of the NITB method and the possibility to further refine the process, the potential of the analysis clearly emerges. As the accuracy of the NITB method increases when widening the case study and including diverse building characteristics, its potential increases when applied to heterogeneous urban areas. Indeed, compared to simpler methods such as the LR or the TB, the principal advantage of the NITB lays in the possibility of returning the variability in consumption patterns deriving from differences in building characteristics. From this, it derives the potential to remotely perform detailed energy assessments, potentially substituting the EPC. Nevertheless, it is relevant to consider the necessity for site-specificity, deriving class distribution from datasets about the inquired building stock rather than standard values or national-scale aggregations.

Once having demonstrated the refinement of the NITB method compared to the standard one, the comparison with the study proposed by Conticelli et al. [4] aims at understanding the magnitude of the emerged differences. The highest discrepancy – 83 MWh/year – can be observed for the buildings realised in the Seventies, while there is no

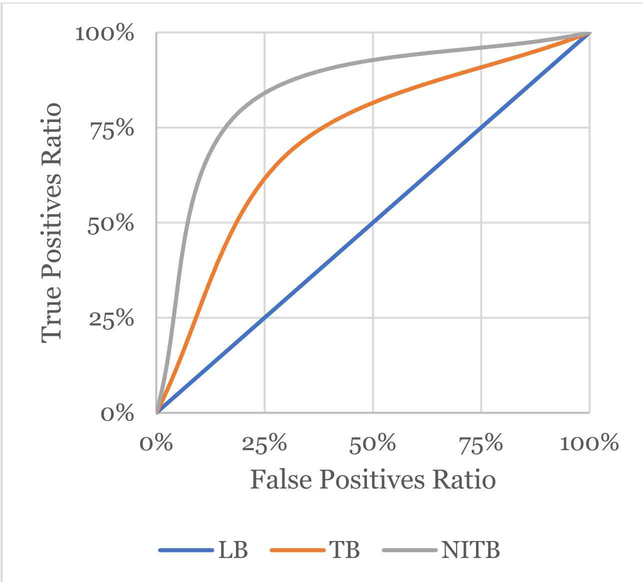

Fig. 15. Receiver Operating Curve (LB: literature-based method; TB: thermography-based method; NITB: new informed thermography-based method).

difference for the most recent class, from 2006. On average, differences are 40 MWh/year for each volumetric unit.

By analysing the spatial distribution of the differences, plotted in Fig. 16, the LB method proposed in Emilia-Romagna underestimates by more than 300 MWh per volumetric unit the primary energy consumption for the most energy-intensive buildings – located in the proximity of Respighi square and at the crossing between Bologna and Cimarosa streets. These underestimations concern big buildings – the smaller one has a GFA equal to 18000 m^2 – realised between 1961 and 1980. On the contrary, it overestimates by more than 150 MWh the yearly consumptions of smaller units – with GFAs comprised between 1000 m^2 and 6600 m^2 – generally realised before, from 1919. Moreover, all buildings with discrepancies between the LB and the NITB methods higher than 100 MWh are towers, with SVR comprised between 0.22 and 0.33. Finally, the characterisation of the buildings with the highest differences concerns the age class, with 63 % of buildings with a differences exceeding 100 MWh/year built between 1961 and 1970. Finally, buildings for which the LB method proposed by Conticelli and colleagues is most reliable – with underestimations lower than 20 MWh/year – are homogeneously spread throughout the AoI.

Based on the previous findings, where specific categories of period of construction emerge as a proxy of the differences, Fig. 17 shows the average specific primary energy consumption values of the buildings grouped by age class, across the three methods. Assuming the EPC values – reported in the LB method – as a reference, it is possible to observe that the TB method generally shows consumptions lower by 16 %, with a peak in buildings realised after 2006 (−31 %), while the NITB method has comparable values (−0.01 % difference). In general, the TB method tends to flatten the differences, with all the values comprised in a ±24.9 kWh/m^2 range from the average (171.6 kWh/m^2), compared to the ±54.8 kWh/m^2 and ±56.9 kWh/m^2 discrepancies from the averages of the LB and NITB methods, respectively.

Fare clic o toccare qui per immettere il testo. It is interesting to note the nearly absolute equivalence between units for which the LB method underestimates – 321 – and overestimates – 333 – the total consumptions. The correspondence can be observed also when calculating the total underestimations – 13.03 GWh – and overestimations – 13.37 GWh in terms of primary energy. Therefore, the NITB method has a similar reliability compared to published methodologies such as the LB one [4], with the added value of being more accurate in estimating energy performance and energy classification building-by-building.

5. Conclusion

This research aimed to define a methodology which combines aerial thermography and data gathering from Energy Performance Certificates in order to perform large-scale energy assessments, further refining the prototype presented in ref [35]. EPCs were used for both training and validating the model, thus making it possible to identify the least energy-performing buildings and – once having defined the necessary geometric parameters – the most energy-intensive ones. The study was performed on residential buildings only, thanks to the possibility of using a

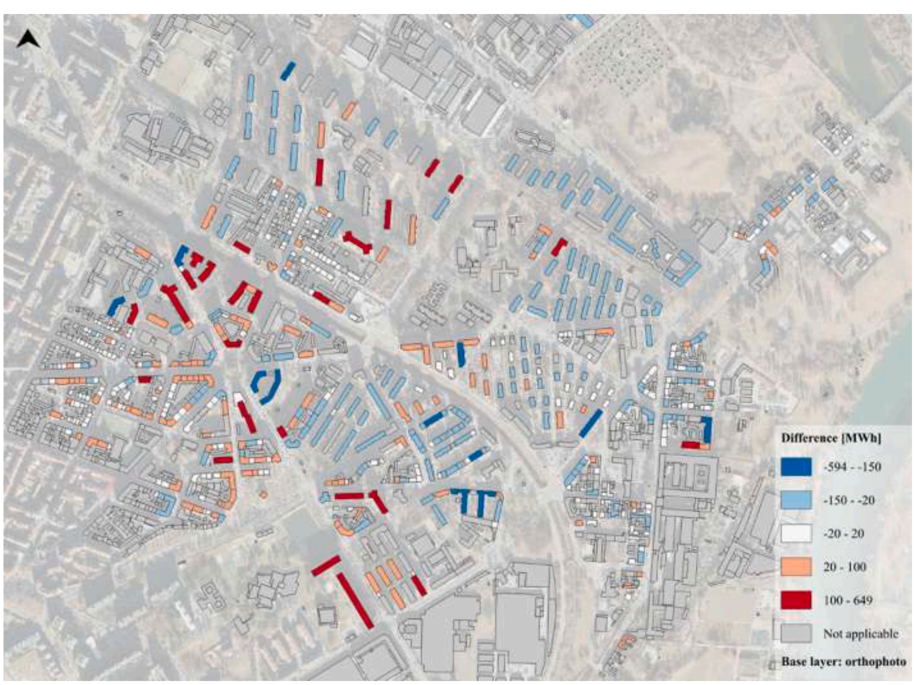

Fig. 16. Difference between the total consumptions estimated through the thermography-based methodology and the LB method by Conticelli et al. [4].

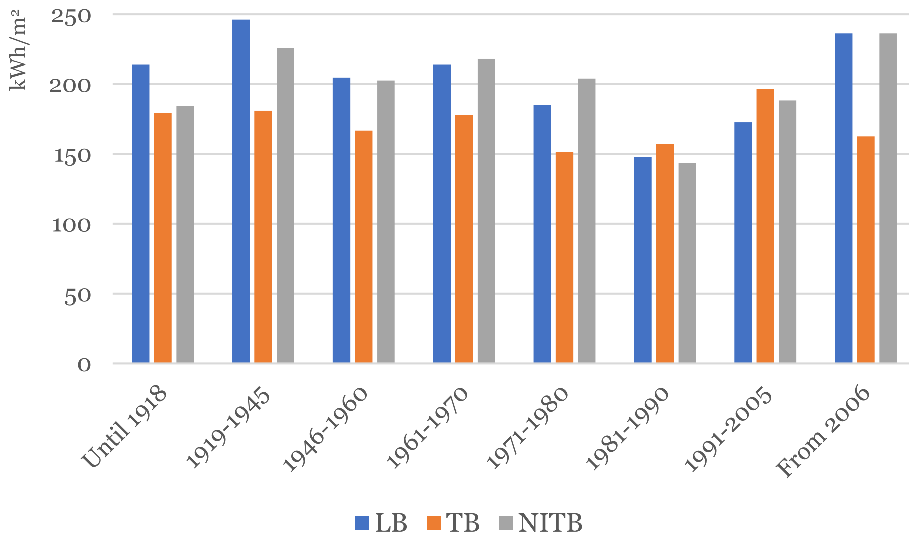

Fig. 17. Average energy consumption as estimated through the three methods (LB: literature-based method; TB: thermography-based method; NITB: new informed thermography-based method).

reference parameter – set by law [42] – for the internal temperature.

The results proved the efficiency of the proposed NITB method and the incremental nature of the resulting energy performance evaluation accuracy. Differently from the LB method [4], the NITB approach proved to be reliable not only at the district scale but also on single buildings, making it possible to use it for the identification of less-performing buildings rather than only for large-scale policymaking. After having gathered and georeferenced the necessary data – mainly EPCs and information pertaining to geometry and use of the buildings – most steps of this procedure can be automated, making it a potential reason of interest for policymakers. Indeed, in order to align with European Directives – among which the most relevant is the EPBD recast [7], setting the goal of retrofitting all class G buildings to improve their performance – it is necessary to adopt efficient and easy-to-use tools which give the possibility to streamline the least-performing building identification process. The final step to obtain a workable and fully automated tool could be to implement an algorithm based on Artificial Intelligence, able to process a wide set of data simultaneously and integrate them to produce such information. Machine learning and big data processing algorithms are particularly helpful not only in the refinement of the calculation but also in the possible extension of the AoI. Finally, cross-validation could be performed, thus understanding the perfect balance between training and validation data. Despite the most time-consuming part being the acquisition, requiring up to several months from the aerial survey to the delivery of the acquired pictures, processing times could be reduced from a few days to minutes with automation.

Despite the satisfactory results, it is possible to identify limitations and further developments for this research. First, in the validation it was mentioned the confinement to a single district as problematic. In particular, this lead to the impossibility of adequately representing all the identified building segments, in light of the homogeneity of the district too. On the one hand, this simplifies archetyping – clustering comparable buildings – while on the other it makes it difficult to have all segments adequately represented. It is to be reminded that primary energy indicators are not the only elements affecting the classification, so it is possible to have buildings in better classes with higher primary energy consumption per square meter. However, in the Italian context, the building stock is generally old, realised before the 1990 s: among the 5.5 million Italian buildings and building units with an EPC, 75 % were realised before 1992 [28]. The method has the potential to be extended to the whole European territory, as it is based on a certification scheme applied in the European Union. However, in order to ensure generalisability, the methodology needs to be further tested and refined in areas characterised by different climates – resulting in discrepancies in the heating demand –, urban morphology and building characteristics. Another barrier to the extension of the method is represented by the costs of the aerial survey. In the absence of satellite data with adequate spatial resolution – even if several high-resolution thermal satellites are set to be launched in the following years – the willingness to pay needs to be assessed, comparing the increase in energy modelling accuracy to the total costs. In addition, it is possible to assess the trade-off between monetary and time cost e.g., using fixed-wing drones, which operate at lower speed (resulting in higher acquisition time) with lower costs.

As for the principal input of both the TB and NITB methods – the thermographic pictures – two elements can be pointed out. First, the Mid-Wave Infrared is adequate for the current scope as it ensures higher spatial resolution compared to the Thermal Infrared and allows comparisons of homogeneous materials, while it does not grant high accuracy in absolute temperature values, due to the complexity of computing emissivity values. Second, in case of demonstrated alterations deriving from varying microclimatic conditions, it is necessary to correct temperature values in order to account for that. First, daily solar radiation can influence results even if the acquisition is carried out after sunset in the case of particularly sunny days. Second, for large-scale analyses, the Urban Heat Island phenomenon or wind flows can have an impact on the results.

Further refinements of the proposed NITB method concern mainly an increase – and potentially a different selection and combination – in the parameters used for archetyping. In particular, it would be crucial to define the thermal variations not only on roofs but also on facades, thus implying scaling up to the third dimension. From this, it would be possible to compute also the window-to-wall ratio in order to determine how façades have different heat losses according to the composition of the façade itself. Fortunately, this information is easily retrieved in the EPCs by observing the share between sunlit and useful surfaces. As for the buildings which do not have an EPC, it is necessary to have a complete three-dimensional model, from the segmentation of which windows can be extracted. Finally, it would be possible to compute the total energy demand not only by considering the primary energy indicators but also by observing the distribution of the energy systems used for heating and cooling. Indeed, EPCs report consumptions divided according to the energy system and the relative combustible used. The inclusion of such information would be particularly important for policymakers, especially for energy network planning e.g., for extending the district heating supply system.

CRediT authorship contribution statement

Sebastiano Anselmo: Writing – original draft, Validation, Methodology, Investigation, Data curation. **Piero Boccardo:** Validation, Supervision, Resources, Project administration, Funding acquisition. **Stefano Paolo Corgnati:** Supervision, Conceptualization. **Maria Ferrara:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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