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Towards Sustainable Urban Development: Energy Modelling for Milan's Built Environment

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Declaration

I, Maryam Alehasin , declare that this master's degree thesis, titled "Towards Sustainable Urban Development: Energy Modelling for Milan's Built Environment", is my original work and has not been previously submitted for any academic degree or diploma. The research work presented in this thesis was conducted under the supervision of Prof. Mutani and was carried out in accordance with the ethical standards and guidelines of the institution. All the sources of information used in this thesis have been duly acknowledged and cited in the bibliography. I confirm that the data and results presented in this thesis are accurate and have not been manipulated or falsified in any way. I take full responsibility for any errors or omissions that may be found in this thesis.

Maryam Alehasin

2023

I would like to dedicate this thesis to my dear professor, Professor Mutani,
and my loving parents.

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I would like to express my deepest appreciation to Professor Mutani for her invaluable guidance and support throughout the completion of my thesis. Her encouragement, insightful feedback, and dedication to teaching have been essential to my academic growth.

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Abstract

This master's thesis presents a place-based approach that utilizes energy performance certificates as the statistical model for building energy modeling. The objective of this thesis is to develop an energy model that calculates energy consumption for domestic hot water and space heating in residential buildings in Milan, Italy, at both the urban and district levels. The model also evaluates the efficiency of renewable energy sources, particularly solar technology, to contribute to a cleaner and more sustainable future. To conduct a reliable study of the energy performance of buildings at an urban scale, various factors such as population dynamics, climate conditions, building characteristics, and urban context typology were considered. The study employed geographic information system (GIS) tools, particularly QGIS software, for place-based modeling and to assess the spatial distribution of energy-related variables and energy consumption data. Overall, the research findings emphasize the importance of integrating solar technologies to reduce reliance on conventional heating systems, enhance building resilience, and towards achieving smart cities and enhancing the energy efficiency of the existing building stock. The calculation indicates that following the trend line of PV production the desired goal will be achieved in the year 2056.

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Chapter one

Introduction

1.1. Introduction to the work

With the rise of urbanization, energy consumption has increased, leading to urgent action to address the negative effects of climate change caused by urban energy sources. Currently, more than half (55%) of the global population resides in urban areas, and this is predicted to increase to over two-thirds (68%) by 2050. In Europe, the level of urbanization was 74% in 2018 and is expected to surge to 83.7% by 2050.(Revision of world urbanization prospects, 2018) Urban areas consume 80% of the world's Gross Domestic Product (GDP), use two-thirds of the world's energy, and emit over 70% of the world's yearly carbon emissions. (Empowering Cities for a Net Zero Future, 2021) One of the highest contributors to CO_2 emissions worldwide is the urban building sector. (Santamouris, 2001) The buildings within the European Union are accountable for 40% of our total energy consumption and 36% of greenhouse gas emissions. These emissions predominantly arise from activities such as construction, usage, renovation, and demolition of buildings. (In focus: Energy efficiency in buildings, 2020)

There is a significant potential to lower energy consumption and related emissions since the building industry is at the center of urban energy supply and demand. Energy-efficient regulations and awareness campaigns could be put in place to support these cuts. For instance, the European Union has established goals for energy efficiency to reach a decarbonized stock by 2050. By reducing energy consumption and promoting sustainable practices in cities, urban planning is crucial to make it necessary to include these concerns in urban development initiatives. The majority amount of energy consumption is by the building sector, which can be an area of interest for implementing sustainability. The Sustainable Development Goals (SDGs) of the United Nations pursue to encourage cleaner energy generation and reduced use, particularly in cities and communities. The UN Energy Action Plan intends to boost renewable energy capacity globally, set renewable energy objectives in 100 nations, and achieve yearly efficiency gains in at least 50 countries. To attain these goals, it is critical to understand and optimize the energy consumption patterns of diverse users, the variables impacting energy use, available energy supplies, and greenhouse gas emissions.

Residential buildings in Europe exhibit the highest energy consumption, primarily for space heating, with natural gas being the most commonly used fuel, followed by electricity and renewables. Understanding the consumption patterns, self-consumption potentials, and spatial distribution of energy use and production within a city is crucial for modeling the energy-environmental-economic-social performance of a smart energy system and facilitating the transition to a post-carbon future.

1.2 Research objectives

The objective of this thesis is to develop an energy model that calculates energy consumption for domestic hot water and space heating in residential buildings in Milan at the urban and district levels. The model will also evaluate the efficiency of renewable energy sources, such as solar technology, for a cleaner and more sustainable future. Nevertheless, because a lot of input data is needed, it could be challenging to determine the type of energy model. Utilizing open-data sources ensured the accuracy of the modeling process. In order to do a reliable study of the energy performance of buildings at an urban scale, some factors were considered, including population factors like presence and behavior, climate conditions, geometric and typological features of buildings, and urban context typology. Additionally, the surface-to-volume ratio (S/V) is an essential feature that demonstrates the importance of building form in controlling heat flow to/from the outdoor environment. Detached houses have higher energy consumption compared to condominiums since the S/V ratio is higher. Moreover, the aspect ratio H/W (Height/Width) of urban canyons and the solar exposition of buildings play significant roles in energy consumption. Research studies have shown that space heating and cooling consumption differ depending on residential building typologies, cities, aspect ratios, and building orientations.

The geographic information system (QGIS) is a free critical tool for evaluating the spatial distribution of energy-related variables and energy consumption data. In this work, QGIS software was used for location-based modeling. Energy consumption in cities is an important issue that needs serious attention. Understanding building energy performance and applying renewable energy can reduce greenhouse emissions and minimize their impacts on climate change. The two options for producing clean energy used in this work are Photovoltaic (PV) and Solar Thermal (ST) technologies, in order to evaluate the potential energy that can be produced using the "r.sun" tool from QGIS software. The primary goal is to do a pre-feasibility analysis of the energy potential consumption while taking the geomorphological characteristics of the studied area. Carrying out this evaluation will eventually facilitate the transition to a more sustainable energy future which is the main goal of this thesis by helping to contribute to the knowledge of the viability and potential of various renewable energy technologies.

Chapter two

Literature Review

2.1 Overview of the concept of sustainability

New urban developments offer an opportunity to address climate change while creating sustainable, livable, and energy-efficient urban areas (Dogan, 2017). Cities worldwide are increasingly setting targets for greenhouse gas (GHG) emission reductions in an effort to minimize environmental impacts and counteract climate change (Sokol, 2017). The energy usage of buildings has a significant influence on climate change and urban sustainability, particularly in densely populated urban areas. Cities are responsible for 75% of GHG emissions, with the building and transportation industries being the primary contributors (UNEP 2018). According to data gathered in recent years, global energy-related carbon dioxide emissions increased by 1.7% in 2018, following a 1.6% increase in 2017. The building sector is responsible for approximately 28% of these emissions and will have a significant role in transitioning to a clean energy (The critical role of buildings, 2019). "In Italy and in most European countries, energy policies are focused on two prior actions to reduce energy consumption and GHG emissions: an improvement in energy efficiency and exploitation of the available renewable energy sources" (Mutani & Todeschi, 2020a). To achieve energy sustainability in urban contexts, many solutions can be employed, including improving energy efficiency and utilizing available renewable energy sources. Strategies such as implementing a district heating network, using building envelopes and urban spaces to produce renewable energy, and having a mix of user types with varying energy loads in the same area can be effective (Mutani & Todeschi, 2020a). Due to the limited availability of renewable energy sources in urban areas, a combination of these solutions is needed along with energy use reduction, management, and monitoring strategies (Mutani G. T., 2018). It is essential to balance energy demand and supply at the smallest scale possible, such as at the building, block of buildings, or district level, rather than at a larger urban or territorial scale (Mutani G. a., 2017). However, because each city, built environment, and population is unique, there is no one-size-fits-all solution for energy planning at an urban or territorial scale. (Mutani G. &., 2020).

As it tackles the need to balance environmental, social, and economic issues in the built world, sustainability is an important idea in the subject of urban planning. Sustainable urban planning seeks to create resilient, equitable, and livable cities that are environmentally responsible, economically viable, and socially inclusive, and also it can be helpful to reduce impact and promote environmentally friendly design and operation methods.

2.1.1 Environmental Sustainability

Environmental sustainability is a key element of sustainable urban planning. Environmental stress occurs whenever the need for human comfort necessitates the use of energy. There exists a significant interconnection between the environment and energy, whereby changes in one variable can cause an impact on the other. Energy, as the capacity to perform work, is indispensable for various biological and human activities.(Taghizadeh-Hesary et al., 2022) An energy resource refers to a material that has the potential to produce heat, support life, and generate electricity. (Kirikkaleli & Adebayo, 2021) Currently, the predominant source of energy is derived from fossil fuels. Nevertheless, fossil fuels pose challenges as they are non-renewable within the span of human time and can lead to various adverse environmental impacts.(Sharif et al., 2020) In order to achieve worldwide climate goals and prevent disastrous climate change, there is a need for a fundamental shift in the world's energy sources. (K. Ali et al., 2022) In order to maintain ecological balance and meet the needs of both present and future generations, environmental sustainability is essential.

2.1.2 Social sustainability

Social sustainability is another critical aspect of sustainable urban planning. A socially sustainable city is one that is equitable and inclusive, where all citizens have access to basic services, such as healthcare, education, and affordable housing. Social sustainability is achieved through the provision of affordable housing, the creation of public spaces that encourage social interaction, and the promotion of diversity and inclusivity (Wang et al., 2021).

2.1.3 Economic sustainability

A key component of sustainable urban development is economic sustainability. A healthy city needs to have an active local economy that offers employment opportunities and encourages innovation. By combining residential, commercial, and industrial activity in one location, sustainable urban design may support a sustainable economy. Sustainable urban planning aims to build thriving, socially inclusive cities that are also environmentally responsible. Key components of sustainable urban planning are environmental sustainability, social sustainability, and economic sustainability.

2.1.4 Sustainable energy

Renewable energy refers to energy derived from natural resources, including sunlight, wind, rain, waves, tides, and geothermal heat, which have the ability to naturally replenish within a relatively short period, typically a few years. It encompasses various technologies that harness these natural resources to produce useful energy services. Examples include wind, wave, tidal, and hydropower, including smaller-scale hydropower systems. Solar power, both photovoltaic and solar thermal, as well as geothermal energy, are also part of renewable energy sources. Biomass and biofuels, including biogas, are additional components of this category. The renewable fraction of household and industrial waste is also considered as a renewable energy source, taking into account naturally replenished components like potato peel. It is worth noting that while certain parts of household and industrial waste are renewable, such as organic waste, other components like plastic products are not. Generally, the definition of renewable energy includes only the naturally replenished portion of waste. (Lund, 2014)

In comparison to fossil fuels, renewable energy sources including solar, wind, hydro, and geothermal power are more environmentally friendly. In 2018, the International Energy Agency (IEA) reported that renewable energy sources generated 26% of the world's power; by 2024, this is predicted to rise to 30%. (IEA, 2019). The IEA also believes that during the following five years, the fastest-growing source of power generation will be from renewable sources.

“A particularly promising renewable energy source is solar energy. The installed capacity of solar photovoltaic (PV) technology increased by 33% in 2018 alone, demonstrating the industry's rapid expansion in recent years” (IRENA, 2019). Solar PV technology's price has also dropped dramatically, making it more affordable than conventional fossil fuels. According to a Lazard analysis, the price of utility-scale solar PV has dropped by 89% in the last ten years (Lazard, 2020).

Wind power is another renewable energy source that has seen significant growth. In 2019, the global wind energy capacity reached 651 GW, an increase of 10% compared to the previous year (GWEC, 2020). The IEA estimates that wind energy, rising from 4% in 2015, may supply up to 18% of the world's power by 2040. (IEA, 2019).

The majority of the world's renewable energy comes from hydropower, which generates 16% of all electricity (IRENA, 2019). Although hydropower has certain negative environmental effects, such as habitat destruction and ecological changes in rivers, it may be a low-carbon and economical source of electricity when managed appropriately. Another renewable energy source with room for expansion is geothermal energy, which harnesses heat from the earth's core. Beyond lowering greenhouse gas emissions, using sustainable energy sources has many other advantages. It can also enhance energy availability in remote regions, boost employment, and improve energy security. According to research by the International Renewable Energy Agency (IRENA), 11 million people worldwide were engaged in the renewable energy sector in 2018; by 2050, that number is projected to rise to 42 million (IRENA, 2019).

2.2 Sustainable Development Goals (SDG)

The Sustainable Development Goals (SDGs) are a set of 17 global goals established by the United Nations in 2015 as a blueprint for achieving a more sustainable future for all. The SDGs encompass a wide range of interconnected issues, including poverty eradication, health and well-being, quality education, gender equality, clean energy, sustainable cities and communities, responsible consumption and production, climate action, and biodiversity conservation, among others. These goals recognize the need for a holistic approach that balances social, economic, and environmental dimensions of development. By addressing these challenges collectively, the SDGs aim to create a world that is equitable, inclusive, and environmentally sustainable. Achieving the SDGs requires collaboration and concerted efforts from governments, businesses, civil society, and individuals worldwide, emphasizing the importance of partnerships and collective action to create lasting positive change for people and the planet. (THE 17 GOALS | Sustainable Development, 2022) Figure 1 shows all the SDGs, the highlighted parts are the one related to this work.

Figure 1. "Sustainable Development Goals." (source: THE SUSTAINABLE DEVELOPMENT GOALS REPORT 2022, https://www.un.org/development/desa/disabilities/envision2030.html)

2.2.1. SDG 7: Affordable and clean energy

This SDG emphases ensuring that everyone has access to affordable, reliable, sustainable, and modern energy. It recognizes the crucial role of energy in achieving various aspects of sustainable development, such as poverty eradication, improved healthcare, education, clean water, and industrial growth. It targets to promote the expansion of renewable energy sources, enhance energy efficiency, and improve access to electricity in developing nations. It highlights the importance of increasing investments in clean energy infrastructure, research, and development, as well as adopting sustainable practices in energy production and consumption. Additionally, it acknowledges that affordable and clean energy access is fundamental for economic progress, social advancement, and environmental sustainability. It calls for collaborative efforts among governments, businesses, and communities to accelerate the transition towards sustainable energy systems and ensure that modern energy services are universally accessible. (SDG Indicators, 2022)

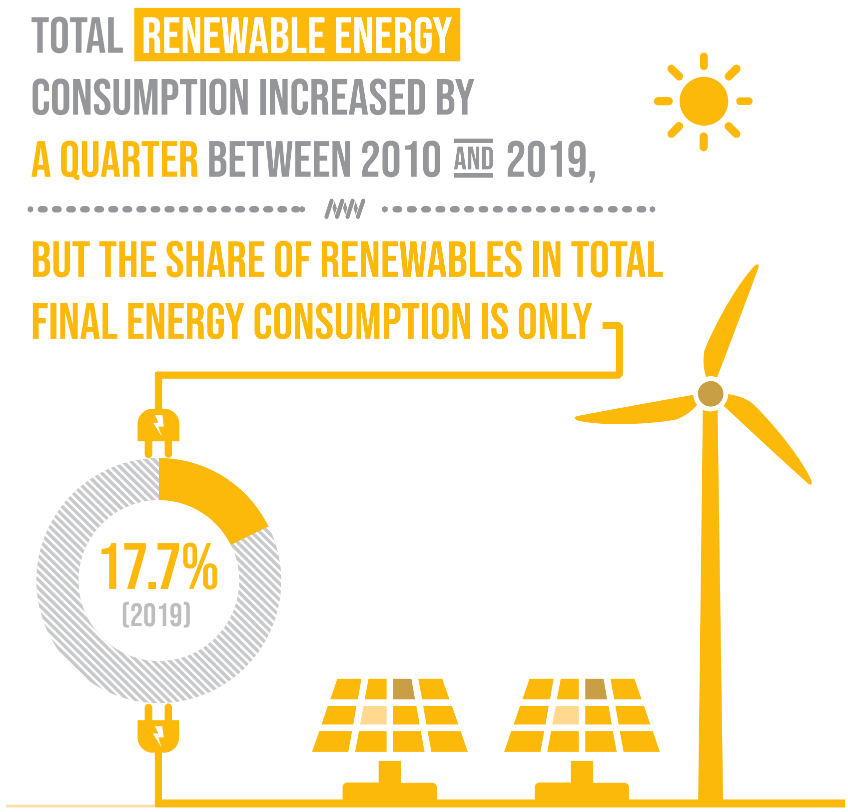

Figure 2. Renewable energy between 2010 and 2019. source: THE SUSTAINABLE DEVELOPMENT GOALS REPORT 2022: UNSTATS.UN.ORG/SDGS/REPORT/2022/

In Figure 3 indicates financial resources from international sources directed towards developing countries. In 2019 International public financial support for clean energy in developing countries declined for the second consecutive year, with $10.9 billion, down by nearly 24% from the previous year. The five-year moving average also decreased from $17.5 billion to $16.6 billion. Loans accounted for over 52% of commitments, grants comprised almost 17%, and investments in collective investment vehicles grew by 91% in 2019. Although least developed countries (LDCs) received a higher percentage of commitments (25.2% compared to 21%), the actual amount decreased from $3.0 billion to $2.7 billion. (SDG Indicators, 2022)

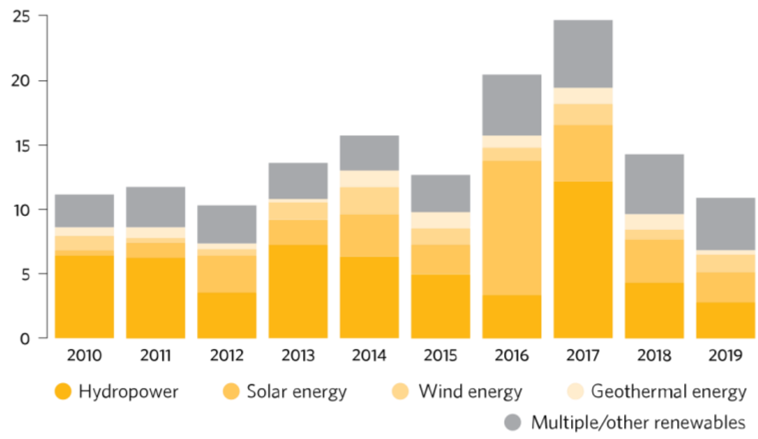

Figure 3. “International financial flows to developing countries in support of clean and renewable energy, by type of technology, 2000–2019 (billions of US dollars at 2019 prices and exchange rates)” (Goal 7 | Department of Economic and Social Affairs, n.d., p. 7) source: THE SUSTAINABLE DEVELOPMENT GOALS REPORT 2022: UNSTATS.UN.ORG/SDGS/REPORT/2022/

2.2.2. SDG 9: Industry, Innovation and Infrastructure

This SDG emphases on resilient infrastructure, inclusive industrialization, and innovation. It emphasizes the importance of accessible and reliable basic services like transportation and energy, especially in developing countries. SDG 9 also promotes sustainable industrial practices, technological advancement, and job creation while minimizing environmental impact. (Goal 9, 2022)

2.2.3. SDG 11: Sustainable cities and communities

SDG 11, also known as Sustainable Development Goal 11, focuses on making cities and human settlements inclusive, safe, resilient, and sustainable. It highlights the importance of creating sustainable urban environments that can accommodate the growing population and ensure access to basic services, adequate housing, and transportation systems. SDG 11 aims to promote inclusive and sustainable urbanization by improving urban planning and management, enhancing the quality of slums and informal settlements, and providing equal access to green and public spaces. Additionally, it emphasizes the need for cities to mitigate their environmental impact, reduce pollution, enhance resilience to disasters, and promote sustainable and efficient use of resources. SDG 11 recognizes the crucial role of cities in achieving sustainable development and calls for integrated policies and strategies to create cities that are livable, environmentally friendly, and socially inclusive. (Goal 11, 2022)

2.2.4. SDG 12: Responsible consumption and production

SDG 12 centers around achieving sustainable consumption and production patterns. It emphasizes the need to reduce waste, minimize environmental impact, and promote efficient resource use. SDG 12 calls for the adoption of sustainable practices, responsible use of natural resources, and the development of sustainable public procurement policies. (Goal 12, 2022)

2.2.5. SDG 13: Climate action

It is a critical goal of the United Nations' Sustainable Development Goals because it emphasizes the urgent need to take significant measures to combat climate change and its impacts. This SDG aims to strengthen resilience and adaptive capacity to climate-related hazards, integrate climate change measures into national policies, promote education and awareness on climate change mitigation, and mobilize financial resources to support climate actions. It recognizes that climate change is a global challenge that requires collective efforts from governments, businesses, and individuals to reduce greenhouse gas emissions, promote sustainable practices, and transition to a low-carbon economy. By addressing climate change, SDG 13 contributes to the overall sustainability of the planet and the well-being of present and future generations. (Goal 13, 2022)

2.2.6. SDG 17: Partnership for this goals

SDG 17 underscores the significance of global partnerships and collaboration in achieving other Sustainable Development Goals. It emphasizes the need for collective action, knowledge-sharing, and resource mobilization to address global challenges and promote sustainable development. (Goal 17, 2022)

2.3 Overview of the concept of clean energy in cities

Cities are major energy users, making up over 70% of greenhouse gas pollution and about 75% of the world's energy usage. (Liu et al., 2022)The transition to clean energy is critical for addressing climate change and achieving sustainable development goals in cities. Clean energy is defined as forms of power or heat that are environmentally friendly and inexhaustible, such as solar, wind, geothermal, hydro, and biomass (Kumar & Sharma, 2017).

As more and more cities throughout the world implement various regulations to encourage the use of clean energy, renewable energy sources are becoming more and more crucial for ensuring the sustainability of urban ecosystems. These strategies include implementing energy-efficient building designs, using district heating and cooling systems, encouraging the use of electric vehicles, and expanding renewable energy infrastructure (Wang et al., 2018). The integration of clean energy systems into urban infrastructure requires innovative policies, incentives, and investment mechanisms to support their development and deployment.

The benefits of clean energy in cities extend beyond environmental sustainability to economic and social benefits. Using sustainable energy can increase employment possibilities, enhance energy security, and lower consumer energy bills. (Kumar & Sharma, 2017). In addition, clean energy technologies can improve urban inhabitants' quality of life by lowering air pollution and noise levels, enhancing public health, and expanding access to energy services for low-income households.(Wang et al., 2018).

2.4. Solar technology

2.4.1 The technology of photovoltaic panels (PV)

"The primary disadvantages of utilizing fossil fuels are the escalating political and environmental issues associated with them. To address these challenges and meet the increasing global demand for electricity, photovoltaic systems offer a solution by converting solar energy from sunlight into electricity. This environmentally friendly technology has sparked the interest of numerous researchers who have explored various system configurations to optimize PV production while minimizing costs." (Charfi et al., 2018)

PV panels are composed of semiconductor materials, typically silicon, which absorb photons from sunlight and generate an electric current. The electric current is then converted into usable electricity through an inverter and can be used to power homes, businesses, and even entire communities (Khalilpour et al., 2021).

Despite their many benefits, the widespread adoption of PV panels still faces several challenges. The upfront cost of installation, which can be unaffordable high for many people and organizations, is one of the main obstacles to adoption. However, as the technology continues to improve and production costs decrease, it is expected that the cost of PV panels will continue to decrease, making them a more accessible option for a larger segment of the population (Wang et al., 2020).

2.4.2. The technology of solar thermal collectors (TC)

A solar thermal collector is a device designed to absorb and convert sunlight into thermal energy, which can then be used for various applications. (Kalogirou, 2009) the collector works by capturing solar radiation and converting it into heat energy. The key component of a solar thermal collector is the absorber, which is typically a dark-colored material with high thermal conductivity. The absorber absorbs the sunlight and transfers the heat to a working fluid, such as water or a heat transfer fluid, circulating through the collector. The heat transfer fluid carries the thermal energy to a storage system or directly to the intended application. (Kalogirou, 2009)

Kalogirou explores that there are different types of solar thermal collectors: The flat-plate collectors, which consist of a flat, insulated surface with an absorber plate and transparent cover. These collectors are commonly used for heating water in residential and commercial settings. The author also discusses evacuated tube collectors, which utilize a series of glass tubes containing absorber plates. Evacuated tube collectors are known for their high efficiency and are suitable for applications requiring higher temperatures, such as space heating or industrial processes. (Kalogirou, 2009)

Proper design and engineering are crucial to maximizing the collector's ability to capture and convert solar energy. Factors such as tilt angle, orientation, and insulation play a crucial role in optimizing the performance of a solar thermal collector. The concept of collector efficiency quantifies the ratio of useful thermal energy output to the amount of solar energy input. There are different methods of enhancing efficiency, such as selective coatings on the absorber surface and tracking systems that follow the sun's path. (Kalogirou, 2009)

The utilization of solar thermal collectors holds the potential in producing hot water and steam for various industrial uses, and there are encouraging market prospects for the advancement of solar heating in industrial applications. (Muhammad et al., 2023)

2.5. Energy Modeling on an urban scale

Energy modeling has become an important tool in urban planning for the design and evaluation of sustainable built environments. Several studies have utilized various energy modeling techniques and factors to evaluate building consumption. One of the primary goals of energy modeling is to assess the energy performance of urban areas and to identify potential energy-saving measures. There are significant issues regarding planning and implementing large-scale sustainable and energy-efficient scenarios for urban planners and policymakers (Lund, 2007). Enhancing a building's energy performance can be implemented throughout building energy models to optimize and analyze different design scenarios. Numerous energy models have been developed for use in energy-driven applications such as energy planning, energy supply-demand calculation, retrofit analysis, forecasting renewable energy impact, emission reduction, and optimization (Hong et al., 2015; Jebaraj & Iniyan, 2006; Reinhart & Cerezo Davila, 2016; Suganthi & Samuel, 2012; Torabi Moghadam et al., 2017).

"Energy consumption models are useful for describing energy use and greenhouse gas emissions in a real-world context, and they can consider cultural differences that may affect the selection of energy retrofitting measures or the use of renewable energy sources" (Mutani & Todeschi, 2020b). These models can also be utilized to evaluate future scenarios and the impact of potential retrofitting measures, as well as to identify critical areas where interventions are required. Several factors, such as building shape and typology, heating and cooling system efficiencies, user behavior, urban context, and local microclimate, affect the energy performance of buildings (Lauzet et al., 2019). To simulate energy consumption at an urban scale, Urban-Scale Energy Modeling (USEM) is necessary to account not only for building-level characteristics but also for the built-up urban context (Mutani & Todeschi, 2019). According to Li et al. (2017) and Carozza et al. (2017), USEMs generally use three approaches: top-down, bottom-up, and hybrid. To be reliable, an energy model requires an accurate and complete input database, and its results should be compared with measured energy consumption data to validate the model (Dogan & Reinhart, 2017). However, the main challenge for these models at an urban scale is managing a large amount of data that may have varying levels of accuracy and scales to designate the features of all the buildings and people throughout a territory, as well as processing the data quickly (Ryan & Sanquist, 2012).

“In 2016, Puglisi and colleagues proposed a technique to estimate energy consumption for heating, cooling, and domestic hot water in residential buildings”(Mutani & Todeschi, 2020a; Puglisi et al., 2016). They used dynamic building energy performance models that consider climate conditions and internal heat loads to create monthly load profiles. The method involved grouping dwelling types into 20 clusters based on building and environmental characteristics. Meanwhile, Roulet (2002) studied energy balance by analyzing temperature variations inside and outside the building, using the ISO 13970 standards to calculate heat losses at a constant internal temperature, internal and solar heat gains, and annual heat required to maintain comfort. He also factored in the dynamic effect of internal and solar gains.

When it comes to implementing energy modeling, there are two levels that can be considered: individual buildings, known as Building Energy Modeling (BEM), or the entire urban environment, known as Urban Building Energy Modeling (UBEM). BEM involves three primary approaches, which include white-box models (based on physics and forward modeling), black-box models (based on statistics and empirical data), and grey-box models (a combination of both physics and statistics) (Foucquier et al., 2013; X. Li & Wen, 2014). Urban energy models fall into two categories: top-down and bottom-up models (Hong et al., 2020).

To take into account the interaction between buildings and their environment, the use of urban building energy modeling (UBEM) and urban-scale energy models (USEM) has gained traction. These models enable the analysis of various building types and urban layouts through large-scale simulations that encompass both static and dynamic factors. This allows for a comprehensive understanding of the geometrical relationship between buildings and their surroundings in terms of energy consumption and performance. (Ang et al., 2020; Basu et al., 2019)

2.4.1.Bottom-up model

The bottom-up method is well-suited for conducting detailed analyses of buildings on an urban scale. In order to perform urban building energy modeling, data sources that include both geometric and non-geometric information about every building are typically required (U. Ali et al., 2019).

Beginning with consumption simulations of individual buildings, where each character is evaluated, the results are then combined to assess the energy consumption of a neighborhood or city, or to determine potential energy savings from redevelopment interventions. Collecting a large amount of data is essential for achieving accurate results on an urban scale (Hong et al., 2020) .

2.4.2.Top-down model

To determine average building consumption, they begin with urban consumption data and compare it with climatic data and results from censuses and statistical surveys. These models have the ability to compare various economic factors, but cannot differentiate between consumption variations within an urban space. Consequently, they are unable to distinguish between emissions distribution, for instance (Mutani & Vicentini, 2013).

The top-down models use big-picture economic factors and statistical data to make predictions about energy usage. On the other hand, the bottom-up models take into account specific clusters of buildings that have similar characteristics (like size and shape) and analyze them at different levels. Top-down models are useful when analyzing large-scale data, while bottom-up models help identify ways to make urban buildings more efficient (Foucquier et al., 2013; Hong et al., 2020; Jebaraj & Iniyan, 2006; X. Li & Wen, 2014; Suganthi & Samuel, 2012; Torabi Moghadam et al., 2017). Top-down techniques have been frequently utilized to estimate urban energy use because they are reasonably simple to employ. To estimate the total thermal energy used by residential structures, Meha et al. devised a generalized top-down approach (Meha et al., 2020).

The top-down model of urban energy modeling starts at the city or neighborhood level and works its way down to individual buildings. In this approach, the total energy consumption of the urban area is estimated based on macro-level data such as population, land use, and economic activity. This data is combined with energy consumption data from large-scale energy systems, such as power plants and district heating and cooling systems.

2.4.3. Comparison between Top-down and Bottom-up model

To estimate energy consumption at scale, the top-down models treat the whole building sector as a single energy unit. (Swan & Ugursal, 2009) Conversely, bottom-up modeling methods estimate the energy consumption of specific buildings or groups of buildings by focusing on individual structures and end-uses. (Wenliang Li a, 2017) Bottom-up models that function at a disaggregated level are further subdivided into physics-based, data-driven, and reduced-order techniques. (Tianzhen Hong a, 2020) Top-down modeling mostly concentrates on historical data, socio-economic variables including population, weather, and fuel prices, as well as statistics energy use. (M. Kavgic a, 2010)In order to match historical time-series datasets of energy consumption or CO2 emissions, these methodologies typically look into the relationships between the energy sector and economic outcomes (M. Kavgic a, 2010). Econometric and technical top-down models are examples of top-down modeling methodologies. (Swan & Ugursal, 2009)In order to depict economic outputs, econometric models determine the relationship between the energy sector and factors like fuel price and income. (M. Kavgic a, 2010)Technological models take into account variables that affect energy use, such as technological progress, saturation, and structural reforms. (M. Kavgic a, 2010)

The population distribution information and annual energy balances were used in the model to predict the overall demand for space heating. The study obtained global end-use energy consumption statistics from the International Energy Agency as well as population distribution data from the national census database. To identify the total yearly household energy consumption trajectory of households in the United Kingdom, Summerfield et al. created a model. (AJ Summerfield, 2010) Regression models were used by the Annual Delivered Energy Price and Temperature (ADEPT) model to examine the association between household energy consumption, heating season temperature, and energy price. (AJ Summerfield, 2010)

In order to examine the link between energy consumption and GDP development in six western Balkan nations, Shkurti et al. suggested a top-down macro-econometric model (Albania, Bosnia and Herzegovina, Croatia, Serbia, Montenegro, and Macedonia). (Shkurti, 2018) The information was gathered from Global Development Indicators, taking into account variables like per-capita electricity consumption and oil price. To determine the energy savings for the residential sector, Adam et al.developed top-down methods. To calculate the energy savings in the domestic sector, the models are taken into account together with thermal energy and electrical (lighting, appliances, etc.) consumption. (Adam & Badea, 2017)

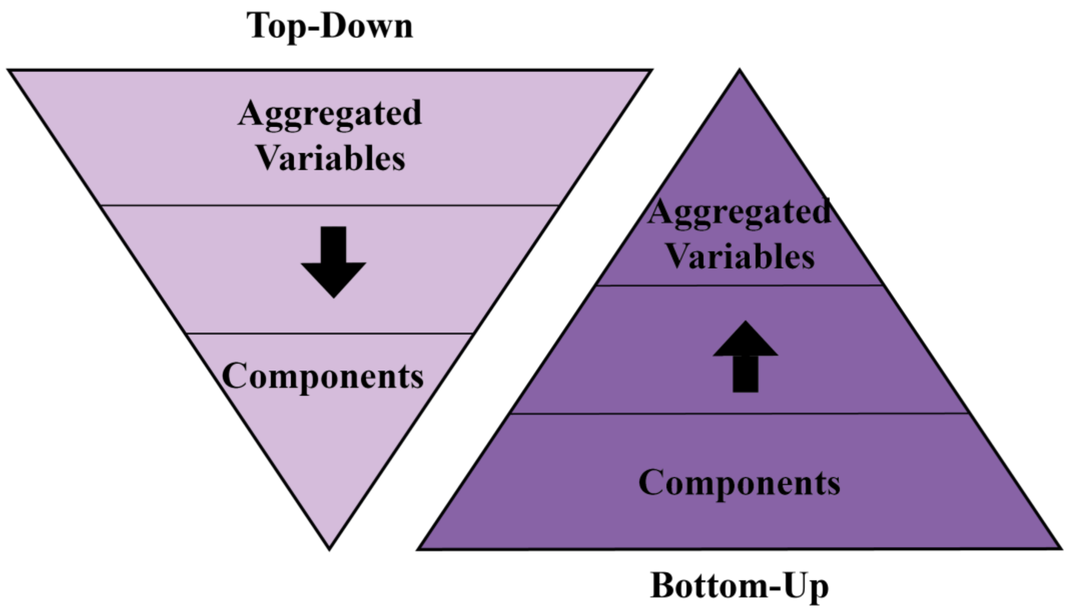

Figure 4. Top-Down VS. Bottom-Up Model.

“The terms "top-down" and "bottom-up" are used to describe two types of models: aggregate and disaggregated models. The former focuses on economy-wide aspects, while the latter emphasizes sectoral and technological details. This categorization of energy-economy models into top-down and bottom-up approaches is often attributed to competing paradigms. However, it is important to note that the differences between these approaches are not primarily conceptual or rooted in conflicting theoretical foundations, but rather pertain to the level of sectoral and technological aggregation and the extent of ceteris paribus assumptions.” (Weyant, 1985)

2.4.4. Hybrid models

Hybrid models incorporate the energy requirements of several standard buildings and modify them to evaluate the energy consumption of an entire city. By utilizing a detailed spatial representation of the building stock, which includes socio-economic data, it becomes possible to associate energy consumption with individual buildings, thereby providing a comprehensive understanding of energy requirements on a building, neighborhood, or city level. (Mutani & Vicentini, 2013) The division between top-down and bottom-up approaches are becoming less distinct and allowing for more integrated approaches (van Beeck, 1999). Hybrid models utilize the energy demands of certain benchmark buildings and modify them to assess the energy consumption of an entire city. These models merge macroeconomic top-down models with at least one bottom-up simulation. (Prina et al., 2020).

2.5. Data driven modeling

“These methods utilize statistical regression, machine learning, and algorithms to analyze and process data. Statistical approaches involve using historical data on energy consumption and conducting regression analyses to attribute energy demand to specific end-uses. By establishing these relationships, the model can then estimate the energy consumption of residential buildings within the housing stock.” (Swan & Ugursal, 2009) “Although data-driven methods can effectively capture the statistical correlations between building energy consumption and its attributes , they heavily rely on mathematical patterns within the available data and disregard the fundamental principles of building thermodynamics and energy systems. Consequently, these purely data-driven approaches fall short in providing precise assessments of energy outcomes for initial design stages or novel building modifications (such as introducing new window materials) that were not included in the training dataset” (Nutkiewicz et al., 2018; Yu et al., 2010).

The use of place-based models is crucial in energy planning at various levels, such as urban, municipal, or territorial scales. These models consider the unique features of the specific territories, populations, and resources by incorporating spatial variables into the methodology and analysis tools. (Mutani, 2023)

2.6 Methods for assessing residential buildings' energy requirements

Several factors impact the energy consumption of a building stock in an urban context, including the design of the built environment, the materials used for external surfaces, socio-economic characteristics, obstructions, and climate and microclimate conditions(Swan & Ugursal, 2009). Improving the morphology of the built environment could lead to lower energy demand by affecting the relationship between urban form and buildings(Gobakis & Kolokotsa, 2017). The solar exposure of buildings may be influenced by their shape and height, which affects the energy production (Shi et al., 2017). Three energy-related parameters can be used to describe the spatial configuration of the built environment: the buildings' surface-to-volume (S/V) ratio, the canyon's height-to-width (H/W) ratio, and the main orientation of the streets (MOS). A building that has a low surface-to-volume (S/V) ratio, has less surface area in relation to its overall size. This can be helpful because it reduces the amount of heat that can enter or escape from the building, making it more energy-efficient. However, a low S/V ratio also means that the building has less surface area to capture and absorb sunlight, which can be used as a source of heat. "Therefore, a low S/V results in less heat acquisition from the sun" (Mutani & Todeschi, 2020a).

2.6.1 Building Variables and Parameters

In urban development, buildings are the most significant factor, because of their major impact on the environment, economy and society. The characteristics of a building, including its geometry, thermos-physical features, and system efficiencies, influence its structure behavior and energy consumption throughout the year. In order to analyze and evaluate a building's performance, input data must be collected at varying levels of detail. In this work, the main characteristic of the buildings in Milan such as height, number of floors, area, etc, are influenced by the period of construction.

2.6.2. Geometric and Non-Geometric Building Data for Energy Efficiency

Geometric data involves information about the physical characteristics of a building such as its shape, number of floors, walls, windows, and type of dwelling heated volume, and heat loss surfaces of the building. On the other hand, non-geometric data pertains to factors like the U-values of the building envelope, construction assemblies, and Heating, Ventilation, and Air Conditioning (HVAC) systems. However, gathering information about a large number of buildings at an urban scale can be challenging due to limited data availability and concerns regarding the privacy of building occupants (Nerini et al., n.d.) . This information is used to calculate the density factor, which is the surface area to volume (S/V) relation. The S/V ratio is an important parameter in building performance research because it decides how much energy is needed to heat or cool the structure. A building is more efficient has a low S/V ratio and requires less energy to heat or cool compared to a building with a higher S/V ratio. Thermos-physical features, which are fundamental to building engineering models. Such as the thermal transmittance; also known as the U-value, is a tool to measure a building's element's ability to transfer heat. It is needed for calculating the quantity of energy required to heat or cool the structure. The next feature is the coefficient for absorption, which is a measurement of how much solar energy a structure absorbs, which influences the quantity of heat that reaches the building. Another feature is the emissivity of the envelope, which is a measure of how well the building's exterior surfaces radiate heat, which affects the amount of heat that leaves the building. The last feature is the thermal capacities of heated zones, which are used to calculate the amount of energy required to heat or cool the building.

Another input data is system efficiencies and operation conditions, which include space heating, and domestic hot water (DHW). These systems consume energy to maintain indoor comfort conditions, and their efficiency and operation conditions affect the building's energy consumption. For example, a building with a highly efficient HVAC system will consume less energy than a building with an inefficient HVAC system.

Characterizing Building Stock:

Characterizing building stock involves two steps: a typology for building archetypes and a geometry definition. The first step is creating a typology, which means categorizing buildings into different types or archetypes based on specific details. This step requires more specific information about each individual building class, resulting in a more detailed dataset. The second step is the geometry definition, which involves working with existing datasets to extract information about the shape and size of buildings. This can be done using various software such as GIS or other remote sensing data processors. The period of construction influences the data collection process, and the level of detail required for the analysis.

In a case study conducted by Mutani G., (2016) in Turin, Italy, the author linked the space heating demand in residential buildings to several key factors. These included climate, compactness (surface-to-volume ratio), construction period, percentage of heated volume, and thermophysical characteristics, which are influenced by construction traditions.

Building Data Sources and Integration:

Building data can be collected from different sources, including building permits, surveys, energy audits, and smart meters. The collected data can be integrated into GIS to relate it to the surrounding context and visualize it in accessible formats. GIS is a powerful tool for building performance analysis because it allows for the integration

2.7 Energy Performance Index

The Energy Performance Index (EPI) is a metric used to assess and quantify the energy efficiency and performance of a building or a group of buildings. It provides a numerical value that indicates the energy consumption and efficiency of a building in relation to a standard or benchmark. The EPI takes into account various factors such as energy consumption, energy sources, building size, occupancy patterns, and climate conditions. (*Colliers | Energy Performance Index (EPI)*, 2023; *Regain Paradise | Energy Performance Index |EPI |Energy Performance Index BEE*, n.d.)

The calculation of the EPI typically involves measuring the energy consumption of the building or using energy simulation models to estimate the energy use. This energy consumption is then normalized based on factors such as the building's floor area, climate data, and occupancy levels to provide a standardized comparison. The resulting index value represents the building's energy performance relative to a reference value or a set of benchmarks. (*Colliers | Energy Performance Index (EPI)*, 2023)

The EPI is an important tool for evaluating the energy efficiency of buildings and for identifying areas where energy-saving measures can be implemented. It allows building owners, policymakers, and energy professionals to assess the energy performance of buildings, track improvements over time, and compare different buildings or building portfolios.

The specific calculation methodology for the Energy Performance Index may vary depending on regional or national energy performance standards and certification programs. These standards often define the specific parameters, data requirements, and benchmarking criteria used in the calculation process.

2.7.1. EP_gl_nren (Energy performance for non-renovated buildings)

Energy performance in the context of non-retrofit buildings pertains to the energy consumed by a structure to maintain a comfortable indoor environment for its occupants. This encompasses energy utilization for heating, cooling, ventilation, lighting, and other building-related services. The energy performance of such buildings is influenced by various factors, including the building envelope, heating and cooling systems, lighting installations, and occupant behavior. In comparison to modern, energy-efficient buildings, non-retrofit structures that have not undergone energy-efficient improvements typically exhibit lower energy performance, leading to increased energy consumption and associated expenses. Assessing the energy performance of non-retrofit buildings becomes crucial in identifying opportunities for energy-saving upgrades and mitigating the environmental impact associated with their operational activities.

2.7.2. EP_gl_ren (Energy performance for renovated buildings)

Energy performance for retrofit buildings refers to the measurement and evaluation of the energy efficiency improvements achieved through retrofitting existing buildings. Retrofitting involves making modifications to the building's design, systems, or components to enhance energy efficiency, reduce energy consumption, and lower carbon emissions. The energy performance of a retrofit building is assessed by comparing its energy usage before and after the retrofitting measures. This evaluation considers factors such as insulation upgrades, window replacements, HVAC system improvements, lighting enhancements, and the integration of renewable energy sources. The goal is to achieve significant energy savings, improve thermal comfort, and reduce environmental impact. Energy performance assessments for retrofit buildings often involve conducting energy audits, analyzing energy consumption data, and using simulation tools to estimate potential energy savings. The results of these evaluations help inform decision-making, prioritize retrofit strategies, and quantify the benefits of energy efficiency measures in terms of cost savings, reduced carbon footprint, and enhanced building performance.

2.8. Present research works

The medium-level category of methods combines aggregated statistical data with spatially-resolved data obtained through geographical information systems (GIS) and light-detection-and-ranging (LiDAR) approaches. For instance, (Singh, 2015) combine high-resolution land use statistical data with GIS maps to determine building footprint area, and use PV system performance simulations to estimate rooftop PV potential in Mumbai, India. (Palmer, 2018)use a rooftop assessment methodology in Plymouth, UK, by extracting 3D urban features from medium resolution LiDAR data and combining them with statistical scale-up methods from individual roofs within a segment of the city, which is later applied to the entire UK. Similarly, (Takebayashi, 2015) assess the rooftop PV potential in Osaka, Japan by combining GIS data used in solar shading calculation routines with surveyed data on building use and the number of buildings in different categories.

The high-level category of studies refers to those that employ advanced methods for rooftop digitization, insolation calculations, and consider various aspects and shading of buildings. For instance, (Bergamasco, 2011) use GIS, along with computational algorithms for roof shading, topology, and surface occupied in roofs across Turin, Italy, by combining geographical and cadastral data. Similarly, (Hong, 2017) use GIS maps for insolation calculations and building suitability assessments, and calculate building shadows for the technical, physical, and geographical rooftop PV potential assessment in the Gangnam district in Seoul, Korea. (Hofierka, 2009) develop a 3D model of Bardejov, Slovakia, using GIS-based digital orthomaps and elevation models to study the city's PV potential. Jakubiec and Reinhart (2013) utilize a suite of GIS data, LiDAR measurements, and daylight simulations (Daysim engine) to accurately predict and validate a rooftop PV output in selected buildings within Cambridge, Massachusetts, and then the city itself. (Jakubiec, 2013) This led to the development of www.mapdwell.com (Mapdwell 2017). Google has also developed Project Sunroof that uses GIS data, 3D modeling from aerial imagery, and shading calculations to predict PV energy generation potential at a rooftop level across hundreds of cities in the United States (Google 2017). These methods tend to be more computationally intensive . (Arnette, 2013)

2.9. Nomenclature

Table 1, Nomenclature.

ADEPT	Annual Delivered Energy Price and Temperature
BD	Building Density
BEM	Building Energy Modeling
C	(Space) cooling
CO2	Carbon Dioxide
D/G	Diffuse-to-global

DHW	Domestic Hot Water
DSM	Digital Surface Model
DTM	Digital Terrain Model
E	Electrical appliances
EP	Energy Performance index
EP_GL_NREN	Non-retrofit energy performance index
EPC	Energy Performance Certificates
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GIS	Geographic Information System
H	(Space) Heating
H/W	Height/Width
HVAC	Heating, Ventilation, and Air Conditioning.
IEA	International Energy Agency
3D	Three dimensions
IEQ	Indoor Environmental Quality
IRENA	International Renewable Energy Agency
ISTAT	Italian National Institute of Statistics

LDS	Least Developed Countries
LiDAR	Light Detection and Ranging
ML	Machine Learning
MOS	Main Orientation of the Streets
PR	Performance Ratio
PV	Photovoltaic
PVGIS	Photovoltaic Geographical Information System
RES	Renewable Energy Systems
QGIS	Quantum Geographic Information System
S/V	Surface-to-volume Ratio
SDG	Sustainable Development Goals
STC	Solar Thermal Collectors
TC	Thermal Collector
TL	Linke Turbidty
UBEM	Urban Building Energy Models
UN	United Nations
USEM	Urban-Scale Energy Modeling

Chapter three

Methodology

3.1 General Methodology

The objective of this study is to evaluate the energy consumption of residential buildings using a data-driven energy modeling with a GIS place-based approach for the City of Milan. The main purpose of this energy model is to provide a comprehensive understanding of the current energy performance and efficiency potential of the existing building stock in Milan. By analyzing the data obtained from this model, it is possible to assess the contribution of buildings towards reducing energy consumption and increasing the adoption of renewable energy sources such as solar thermal and photovoltaic technologies on an urban scale. Figure 5 shows the methodology flowchart, the process contains two phases: Pre-modeling and energy modeling. The Pre-modeling phase comprises three stages: data collection, data pre-processing, and creation of the geo-database. These steps are carried out before proceeding to the energy modeling phase. During this phase, the input data are processed and linked to the territorial unit of the model (such as neighborhood, district, municipal or building scale) to create a comprehensive database.

The present study implements a place-based approach to provide a detailed description of the urban context. This approach uses various parameters that effectively capture the characteristics of buildings and their immediate surroundings. The geo-database is then utilized for the energy modeling, which involves the application of the model to the city of Milan as a case study. An iterative process of comparing the results with measured data is carried out in the calibration phase until an acceptable degree of accuracy is achieved, making the model reliable. During this phase, modifications can be made to the input data that affect the energy consumption of buildings to improve the results.

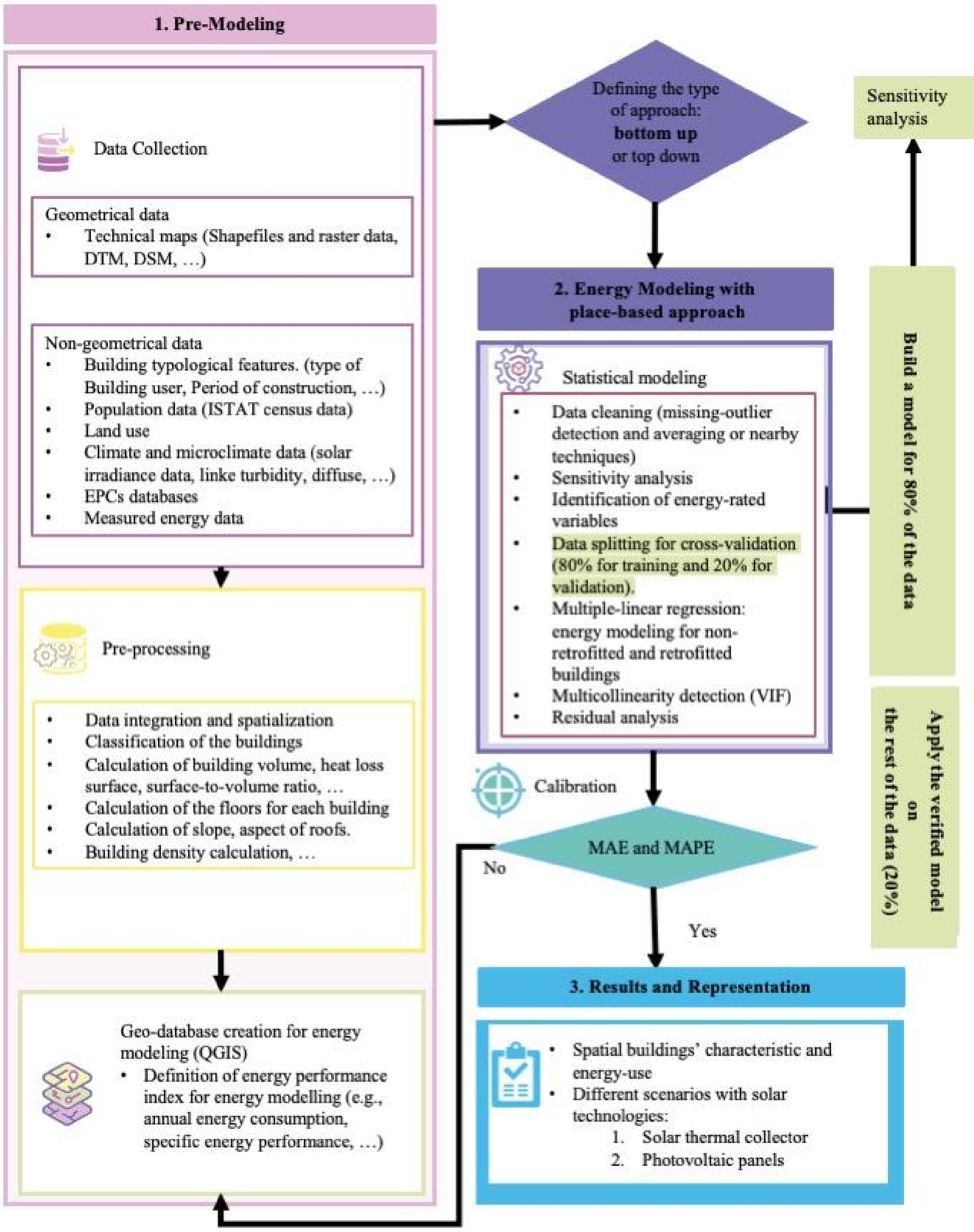

Figure 5. Methodology flowchart of urban scale energy modeling with a place-based approach.

By utilizing this model, indicators and variables associated with energy consumption are identified and analyzed. This allows for the evaluation of various scenarios incorporating solar technologies, as well as the spatial distribution of energy consumption across the urban area. The primary application of this model is to determine the most effective energy policy for sustainable urban development. Given that the civil sector and particularly residential buildings contribute significantly to energy consumption in Milan, the evaluated building stock pertains to the residential sector, including energy-use for space heating (H) and domestic hot water (DHW). (Figure 5)

3.2. QGIS Methodology

Geographic Information Systems (GIS) have the ability to reference all energy-related data at a local level and can be instrumental in recognizing and employing energy models at the urban level. GIS tools can also provide decision-makers and urban planners with the opportunity to see realistic and layered illustrations of urban energy consumption and spatial and temporal variables and to conduct both qualitative and quantitative analyses with various scenarios for future smart and sustainable cities (Nageler et al., 2017). QGIS software offer decision-makers and urban planners the ability to visualize realistic and detailed representations of urban energy usage. They provide valuable assistance in analyzing and comparing different scenarios for creating smarter and more sustainable cities in the future. This means that using GIS allows decision-makers to see how energy is used in cities and to explore different ways of making cities more sustainable and efficient. It helps them make informed choices and plan for a better future. (Alhamwi et al., 2017; Caputo & Pasetti, 2017). GIS presents both possibilities and obstacles in evaluating urban demand, as it involves examining not only building factors but also the neighboring urban context and the prevailing climate conditions (Mutani & Todeschi, 2021).

QGIS software is an open-source Geographic Information System (GIS) that provides a platform for creating, analyzing, and visualizing spatial data. One of the many applications of QGIS is in calculating domestic hot water and electricity production at an urban scale, as well as estimating the amount of solar energy received on the rooftops of buildings.

To calculate the domestic hot water and electricity production at an urban scale, QGIS software can be used to create a comprehensive database of building characteristics such as building age, size, construction materials, and orientation.

This database can then be used to calculate the energy demands of each building, including the amount of electricity and hot water required to meet the building's needs. This can be done using energy modeling software such as EnergyPlus or OpenStudio, which can be integrated with QGIS.

Moreover, QGIS can be used to estimate the potential for solar energy generation on the rooftops of buildings. This can be done using solar radiation models that estimate the amount of solar radiation received at different locations and times of day. These models can take into account factors such as building orientation, shading from nearby buildings and trees, and the angle of the sun. Once the potential for solar energy generation has been estimated, the energy output of different types of solar panels can be calculated using software such as PVsyst.

To use QGIS for solar energy calculations, first, it is necessary to obtain data on the location of the buildings, their orientation, and the surrounding landscape. This process was done by importing satellite or aerial imagery into QGIS and overlaying it with building footprints. After the building footprints have been digitized, additional information on the building characteristics such as roof pitch, orientation, and shading was added to the database. Solar radiation models is a tool to estimate the amount of solar energy received on the rooftop of each building. After the potential for solar energy generation has been estimated, it is possible to calculate the energy output of different types of solar panels using software such as PVsyst. This software takes into account factors such as the type of solar panel, its efficiency, and the location and orientation of the building to estimate the amount of energy that can be generated.

According to the article by Rau, C. (2017), that describes a place-based approach, where data is collected, pre-processed, analyzed, and used to build a model that is tested, calibrated, and applied in the field. QGIS is a free and open-source tool that not only maps and visualizes data but also manages and creates information. Spatializing data allows for a better understanding of the work.

The methodology used to calculate DHW and space heating is shown at Figure 6; Firstly, the vector layer "Residential_Buildings" was added, and the perimeter of the buildings was calculated using the "Calculate Geometry" function. The layer was then joined by location with the period pf construction or ISTAT database. The buildings were classified and two new fields, heated air gross volume (V) and heat loss surface (S), were added. The surface-to-volume ratio (S/V) was calculated. For high-density cities like Milan, calculating the real surface-to-volume ratio (S/V) is a complicated step. Virtual layers and queries are used to measure the border length and identify the lowest buildings. Coefficients are used to correct the final S/V to S/Vreal for each type of building, and related geometric variables are calculated for possible retrofit scenarios. Energy consumption data can also be computed using the same procedure, such as Energy Performance index, energy consumption for space heating/cooling, and DHW. By adding a virtual layer and importing the Residential_Buildings layer. A query was written for border length calculation, and the buffer was calculated for the virtual layer with a distance of 0.01m. The intersection for the virtual layer was then calculated, and the height differences of each building were determined using HDIFF from the intersection layer. A new ID (ID_2) was created, and the virtual and intersection layers were joined by location, with only the HDIFF and ID_2 columns being joined in the virtual layer from the intersection layer. In the joined layer, the area of intersection and S_cond were calculated. The resulting layer was exported as CSV, and a pivot table was created with ID as row labels and the sum of S_cond as values. The CSV was uploaded into QGIS and joined with the building's ID on the building's layer at point 1. Three new fields were then added: number of floors, number of floors before and after 1970, and calculation of the real number of floors per building. The gross heated volume of residential buildings in both census section and building scale was calculated using the "join by attributes" function. The exact number of inhabitants in each building was also calculated, as well as DHW consumption of inhabitants in one day and for one year. The energy performance index was then calculated, and energy saving and economic saving were determined. Finally, a priority of retrofit interventions was defined.

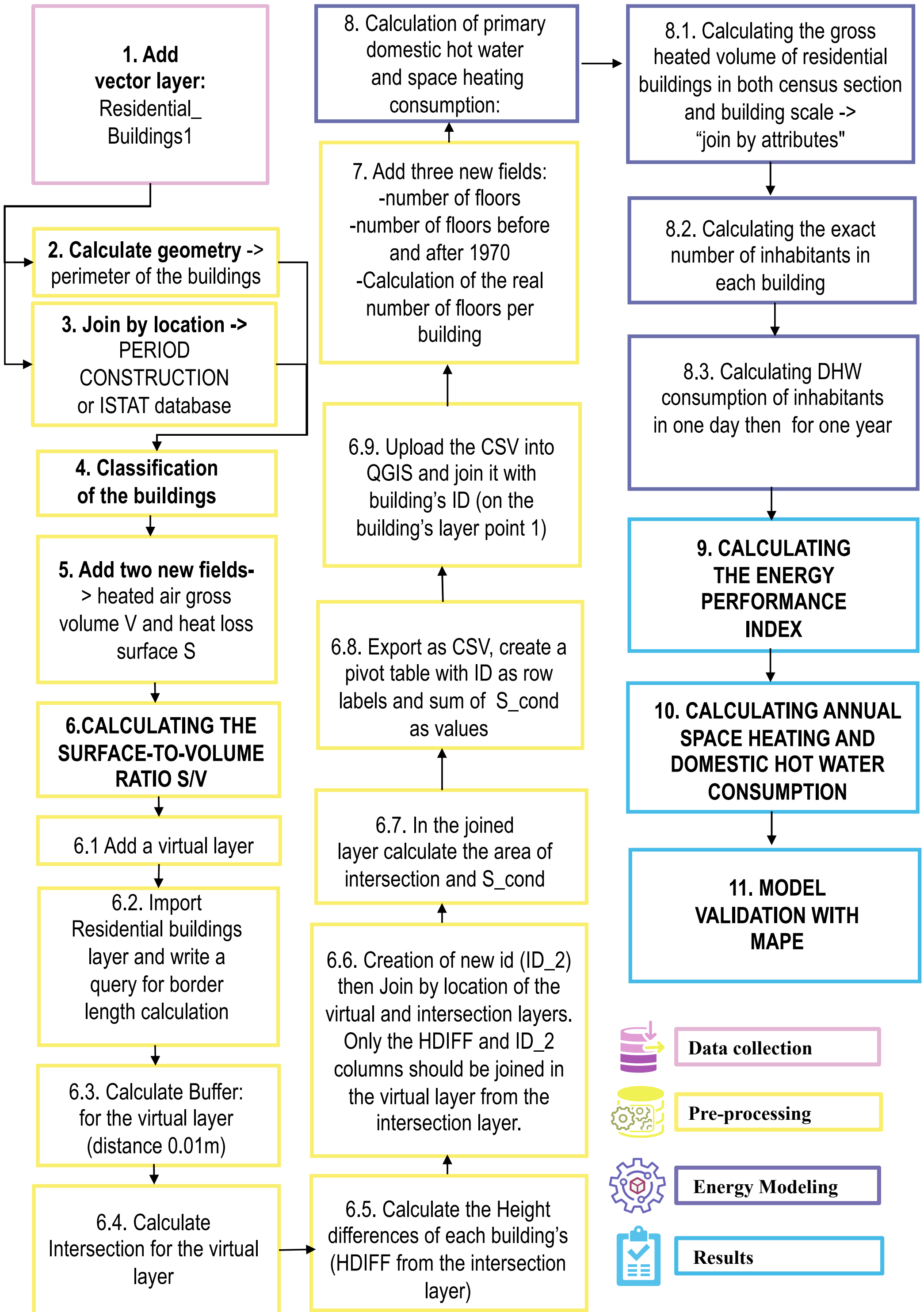

Figure 6. Flowchart methodology for the calculation of DHW and space heating consumption.

This study examines the use of two types of solar panels for energy production: photovoltaic panels (PV) and solar thermal collectors (STC). The STCs used in this study were of the flat and vacuum type, with optical efficiencies ranging from 77.5% to 79.4% and heat loss coefficients k1 of 4.35-1.02 and k2 of 0.01-0.0032. The PV module used was made of monocrystalline silicon and had an efficiency of 22%.The study focuses on thermal energy consumption for space heating, which is related to the solar energy produced by solar collectors. By optimizing the orientation and area of exposed roofs and tailoring demand profiles to end-users needs, self-consumption can be maximized, resulting in reduced energy consumption and greater sustainability. For solar irradiation calculation, in Figure 7 the flowchart methodology is illustrated. In the first step, the national DTM of 10m of Lombardy from the geoportale Lombardy open data source was downloaded. The map was then converted to a raster with a unit of pixels of 1 meter. Next, the obtained raster was clipped for the city of Milan by a mask layer. The DSM Generator tool from the plugin was then used, with a building level height of 3.1 meters and a pixel resolution of 2 meters. After running the process, the obtained DSM map was saved as a .tiff image. The solar irradiation calculation was then performed by adding solar/sky characteristics such as transmissivity-turbidity factor-diffuse to global radiation and using "r.sun.insoltime" for the solar irradiation calculation for a month or typical day. A raster map was obtained and converted to a point for obtaining numbers from the image in kWh/m2/day. The points were evaluated for rooftops with "Join by location" for each day/month/year. Database calculations were performed for the solar irradiation by day/month/year, and a map for solar irradiation by day/month/year was created. Finally, the energy produced by solar thermal collector and photovoltaic technology was calculated for 30 % of building roof tops. (Figure 7)

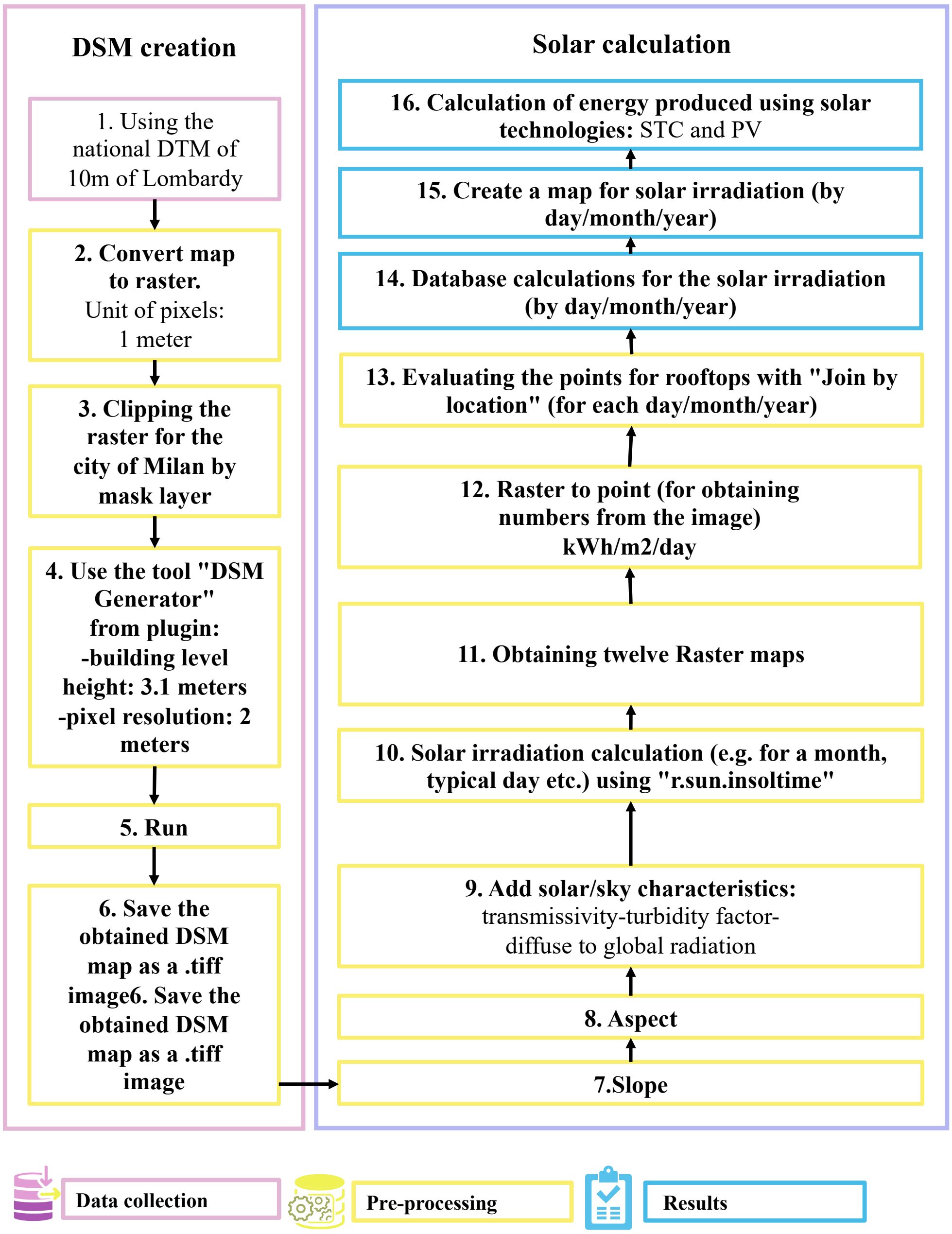

Figure 7. Solar irradiation calculation methodology flowchart.

Chapter four

Result and Discussions

4.1 Case study of Milan

4.1.1. Climate, Demographics, and Sustainability Policies in Milan: A Case Study for Energy-efficient Building Design and Retrofitting

Milan is a city in northern Italy that is situated in the Po Valley and is encircled by the Alps and the Apennines to the north and south, respectively. Warm summers and mild winters are characteristics of the city's humid subtropical climate. The hottest month, July, averages around 25°C, while the coldest month, January, averages approximately 4°C. The city has considerable seasonal weather fluctuations, including sporadic winter cold snaps and summer heat waves.

According to the study by Tootkaboni et al., Milan's climate is characterized by a high degree of seasonality and significant intra-annual variability, with precipitation concentrated in the spring and autumn months. The city experiences high levels of air pollution, particularly during the winter months when temperature inversions can trap pollutants in the valley. The local government has put in place a number of initiatives to enhance air quality, including traffic restrictions, a push for the use of public transit, and investments in renewable energy sources. (P. Tootkaboni et al., 2021)

The National Institute of Statistics ISTAT has reported that the population of the region has remained quite stable over the last few years, with an estimated range of 1,350-1,400 k-inhabitants, of which 20% are foreigners. Residential buildings constitute about 43,000 or approximately 66% of the total building stock, with a total of 700,000 dwellings. These dwellings were constructed primarily during four periods: 23% in the period from 1919-1945, 28% in 1946-1960, 20% in 1961-1970, and only 5% after 1991 when the first two Italian laws on energy-saving in buildings were enacted.

It is interesting to note that a majority of residential buildings, i.e., 70%, have more than five apartments, and 37% of them have more than 16 apartments. Additionally, on average, there are approximately two components per family, which could have implications for the energy demand of the households. These statistics can be useful in formulating effective strategies for energy-efficient building design and retrofitting, given the large number of existing buildings and the potential for reducing energy consumption and emissions in the built environment.

Milan's participation in the C404 global network has enabled the city to exchange ideas and solutions regarding the challenges posed by global warming with 80 other cities worldwide. By engaging in initiatives like Reinventing Cities and joining European funding programs like Clever Cities 5, Milan has been able to explore innovative approaches and policies that have played a vital role in shaping strategies and actions for the sustainability of the PGT. (C. Padovani, & C. Salvaggio, 2023)

Milan has set a goal of becoming carbon-neutral by 2030 and has implemented various policies to promote sustainable practices, such as encouraging the use of solar panels and green roofs and investing in district heating systems. In 2008, the city of Milan made a significant commitment to address the pressing global issue of climate change by joining the Covenant of Mayors, an initiative aimed at reducing greenhouse gas (GHG) emissions and promoting the use of renewable energy sources (E3P, 2015). The goal was to reduce GHG emissions and energy consumption by a significant margin, while increasing the proportion of energy generated from renewable sources. As per the 2005 figures, Milan's GHG emissions were a staggering 5.67 tons of CO2 per capita, with final energy consumption amounting to 18.97 MWh per capita. However, through various measures taken to address climate change, by the year 2020, Milan was able to bring down the GHG emissions to 3.4 tons of CO2 per capita, which represents a remarkable reduction of 40%. This significant reduction was achieved through a combination of energy-efficient measures, greater use of renewable energy sources, and other climate-friendly initiatives. The city of Milan's participation in the Covenant of Mayor's initiative has played a crucial role in achieving these results, and it serves as an inspiring example for other cities around the world looking to address climate change. The city has also put in place a thorough waste management system, which includes segregated recycling collection and the creation of biogas from organic garbage. It is important for urban planners and policymakers to take into account how climate change is influencing Milan's urban environment and to establish adaptation plans for dealing with how extreme weather events, like flooding and heat waves, would affect the city's infrastructure and population. In order to understand the impact of these policies on energy consumption in buildings, a place-based approach is used to describe the urban context, with parameters that consider building density, urban canyon dimensions, sky view factor, main street orientation, properties of urban surfaces, and the presence of green areas and water.

4.2.Data Collection

All the data used in this work was gathered from open-source databases. “Geoportale Lombardia [1]” open-source database was used to download the Digital Surface Model (DSM), Digital Terrain Model (DTM), and the buildings shape file (.shp), which were later imported into QGIS. Both the DSM and DTM can serve as the initial shapefile in QGIS; however, using the DTM for solar irradiation requires converting it to DSM. The conversion is necessary because the DSM contains data on the height of buildings and their roofs, which is crucial for the installation of solar cells, the objective of this work. The DSM (or DTM) is available in different resolution files, including 10 meters, 20 meters, and 1 meter (highest resolution). In this study, a 10-meter resolution was employed due to the higher processing demands and longer processing time associated with using higher resolutions. A DSM represents the Earth's surface and encompasses all features on the terrain, such as buildings, vegetation, and other above-ground objects, providing a detailed representation of both natural and man-made features. On the other hand, a DTM represents the bare Earth's surface, excluding above-ground features like buildings and vegetation. It provides a model of the terrain, displaying elevation values for the ground surface alone.

Another open data source used was Eurostat, which provided data on environment & energy and SDGs statistics. Calculating solar irradiation in the QGIS software necessitates having average daily irradiance data from the Joint Research Centre (JRC). For electricity consumption data for each building, variables such as period of construction and number of inhabitants were required, and these data were obtained from the ISTAT open data. ISTAT provides both shapefile and CSV file that contains detailed data for each census section. A process is required to join the necessary CSV’s data to the shapefile in QGIS software which will be discussed in the next section.

After calculating the data obtained from open-source databases, it is possible to obtain precise energy costs from various sources for comparison and accuracy validation. These sources include WTRG Economics, the Regulatory Authority for Energy Networks and the Environment (ARERA), TERNA, and the Consumer Protection Center. Additionally, the Energy Services Manager (GSE) provides open data for checking revenue related to electricity production in the national grid, categorized by zone and month.

To obtain the Linke Turbidity Factor, which is a worldwide open-source dataset, the SODA website can be utilized. While the SODA website's map is practical for larger locations, it was not suitable for Milan due to insufficient resolution. Hence, a new linke turibidiy map was created specifically for Milan, which will be discussed further in the pre-processing section.

For the diffuse map, which is applicable to global locations, the Global Solar Atlas website offers access to this dataset. Moreover, the International Renewable Energy Agency (IRENA) provides the SolarCity Simulator, a powerful tool for assessing the potential of rooftop-mounted solar photovoltaic (PV) systems and acquiring additional information about renewable energies. This tool proves valuable in validating the accuracy of further calculations in QGIS related to PV technology. For more details, refer to the SolarCity Simulator on IRENA's website Table 2 shows all the data and their sources mentioned above.

Table 2. data collection and their sources. (open sources databases)

Data	Source	Website link
DSM/DTM	Geoportale Lombardia	https://www.geoportale.regione.lombardia.it/
Building Shape file	Geoportale Lombardia	https://www.geoportale.regione.lombardia.it/
Census section	ISTAT	https://www.istat.it/it/archivio/104317
Statistics of environment & energy and SDGs	EuroSTAT	https://ec.europa.eu/eurostat/data/database
Average daily irradiance data	JRC	https://re.jrc.ec.europa.eu/pvg_tools/en/#MR
Crude Oil	WTRG	http://www.wtrg.com/daily/crudeoilprice.html

Surveys/monitoring of electrical energy	TERNA	https://www.terna.it/it/sistema-elettrico/transparency-report/total-load
Natural gas and electricity	ARERA	https://www.arera.it/it/dati/gp27new.htm https://www.arera.it/it/dati/eep35.htm
Fuels for space heating	Consumer Protection Center	https://www.consumer.bz.it/it/confronto-prezzi-combustibili-riscaldamento-alto-adige
Revenue related to electricity production	GSE	https://www.gse.it/servizi-per-te/fotovoltaico/ritiro-dedicato/regolazione-economica-del-servizio https://www.gse.it/servizi-per-te/fotovoltaico/ritiro-dedicato/documenti
Linke Turbidity	SODA	https://www.soda-pro.com/help/general-knowledge/linke-turbidity-factor
Diffuse	Global Solar Atlas	https://globalsolaratlas.info/support/faq
Solar simulation and Global Atlas for Renewable Energy	IRENA	https://www.irena.org/Energy-Transition/Project-Facilitation/Renewable-potential-assessment/SolarCity-Simulator).
EPC	CENED	https://dati.comune.milano.it/dataset/ds623_database_cened2__certificazione_energetica_degli_edifici_nel

4.2.1 Buildings classification and Energy Performance Certificates (EPCs)

The Energy Performance Certificate (EPC) is a database that provides detailed information about the energy efficiency levels of buildings, as well as their energy classes and current state. The data for this study was obtained from the EPC database, which included 210,423 energy performance certificates (EPCs) for residential buildings in Milan, released from October 2015 to December 2022. The technical map of Milan by QGIS software, all the EPC information was georeferenced, and the geometric and typological data of the buildings were rectified (for 209846 of EPCs). Importantly the period of construction, number of floors, and description of the buildings were employed to resume the process of classification of the buildings in the next step (3.2.2). These buildings were categorized into 7 classes based on their periods of construction, according to ISTAT census data, and several energy-related parameters were calculated. The majority of the residential buildings in Milan were built before 1992, with only 13% being constructed after the implementation of the first two Italian laws on energy saving in buildings. Specifically, 27% of buildings were built before 1945, 25% between 1946 and 1960, and 30% between 1961 and 1976. The period of construction of the buildings must consider the building's construction features and the level of insulation used, in accordance with energy policies. Some significant historical periods with distinct construction technologies include pre-1910, which used load-bearing structures; 1910-1972, which used a combination of load-bearing walls, reinforced concrete structures, and infill walls; 1973-1990, which used reinforced concrete structures with insulated infill walls following Law 373/76; 1991-2004, which used more insulated infill walls to reduce energy consumption, following Law 10/91; and finally, after 2005, when the European Directive 2002/91/EC was implemented, envelope structures with even higher thermal resistance values and more efficient systems were introduced (implemented in Italy by Legislative Decree 192/2005 and subsequent amendments) (Mutani & Vicentini, 2013). Figure 8 illustrates the distribution of building construction periods in the central historical district of the City of Milan, where almost all buildings were built before 1960. This information can be used to evaluate the energy performance of buildings and to develop strategies to improve energy efficiency in the building sector.

4.3 Data pre-processing

The pre-processing phase is an important part before starting the analysis, because the existing shape files are missing some parts to start the calculation. The presented energy modelling also highlights the value of controlling sizable databases, identifying additional variables or substitute variables, and presenting the outcomes. The pre-modeling phase is of the utmost importance because it affects the model's selection and accurateness, and the data's representation enables the results to be shared (Mutani et al., 2023). Starting with the building shape file, some parts needs to be excluded such as the buildings with height less than 3 meters, or areas less than 50 meters. Afterwards, only residential buildings needs to be selected and all other buildings should be deleted. The initial step involves processing the main information from the shp. format of building outlines, which is obtained from the City of Milan, and the geoportale regione lombardia website's open data. The shp. file includes data on the area, height, geometrical features and etc. Nevertheless, before the analyses were conducted, only the residential structures were chosen for further investigation, and a few buildings were excluded (the cleared shapefile contains 38400 geometries). As indicated in Table 3 the first shapefile contains of 75271 buildings, of which the buildings with areas less than 50 m^2 and less than 3 meters in height were deleted.

Table 3, Different type of geometries from Milan's shapefile.

Type of geometry	Number of geometries	Area (m^2)
Residential Buildings	40469	16960023
Different uses of the buildings	34802	14145683
Area less than 50 m^2	14792	360655
Height less than 3 m	11410	1042974
Total number of buildings	75271	31105706

Fromm ISTAT, the CSV, and the shapefile for census sections were downloaded. To assign the period of construction, and number of inhabitants to each building, first the CSV file needs to be joined to the census section shapefile in the QGIS. After the join, to assign each building the data from ISTAT, the join by location tool were utilized. Then the classification can be proceed. The residential buildings were categorized by their periods of construction into 9 categories, as the buildings were constructed with various types of envelopes, levels of thermal insulation, and systems efficiencies

shows the period of construction for residential buildings, majority of the buildings in district 1 and in the city center are built before 1919 and as we go further to the outskirts of the city we have more new buildings, mostly built between 1961-1980.

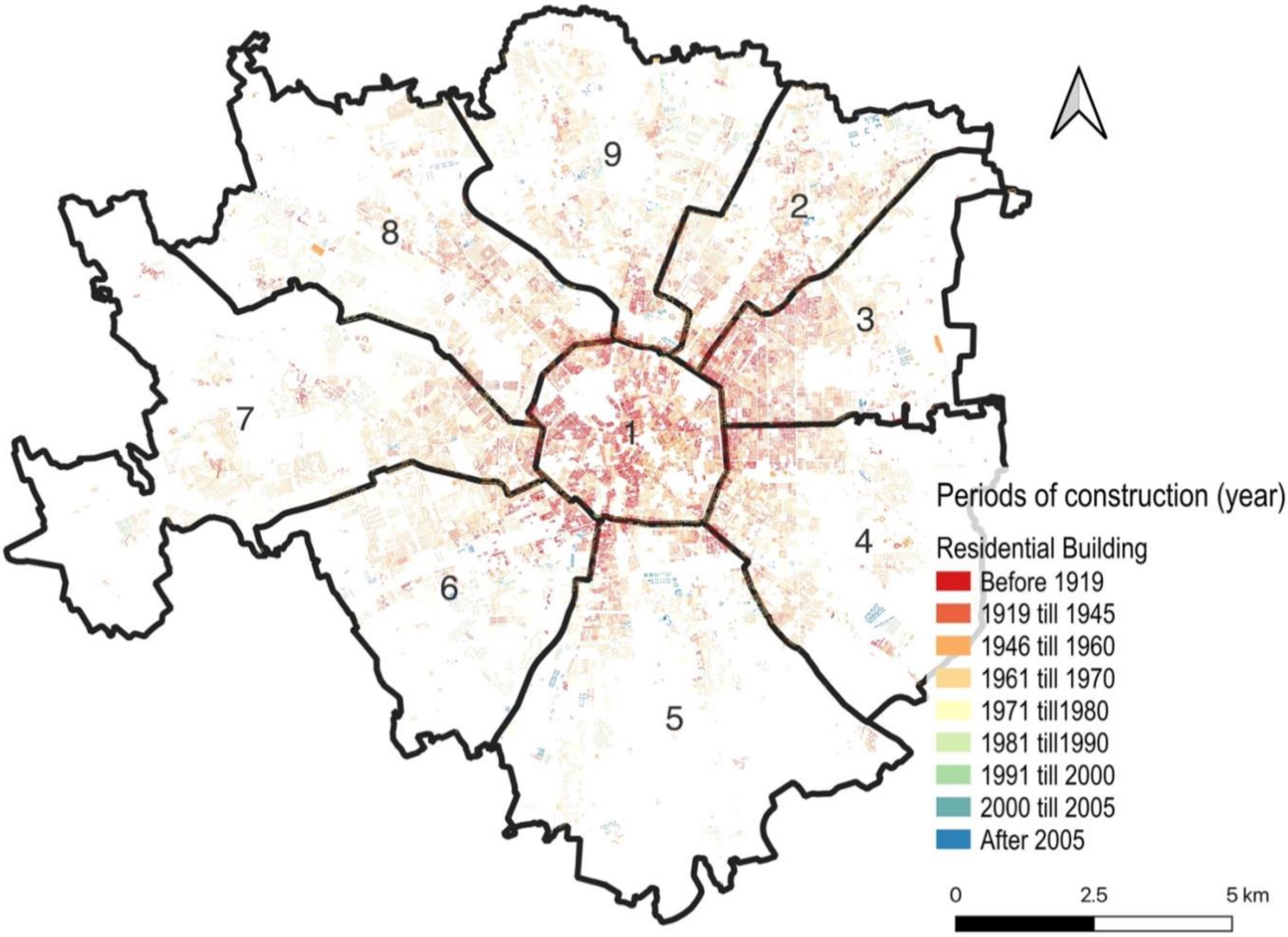

Figure 8. Periods of construction for the residential buildings in the city of Milan.

Based on period of construction, the number of the floors for each building has been calculated using the formula from Table 4.

Table 4. Formula for calculation of the number of floors for different period of construction.

Year	Formula
Buildings built before 1970 (Ministerial Decree of 5 July 1975)	Number of floors= Height (m) / 3.3 (m)
Buildings built after 1971	Number of floors= Height (m) / 3 (m)

The number of inhabitants was assigned to each building from each census section, to correct the data, the number of inhabitants was divided to the gross heat volume for the census data, then the calculated result was multiplied by the gross heat volume for each residential building. In Figure 9 shows the number of inhabitants for each residential building.

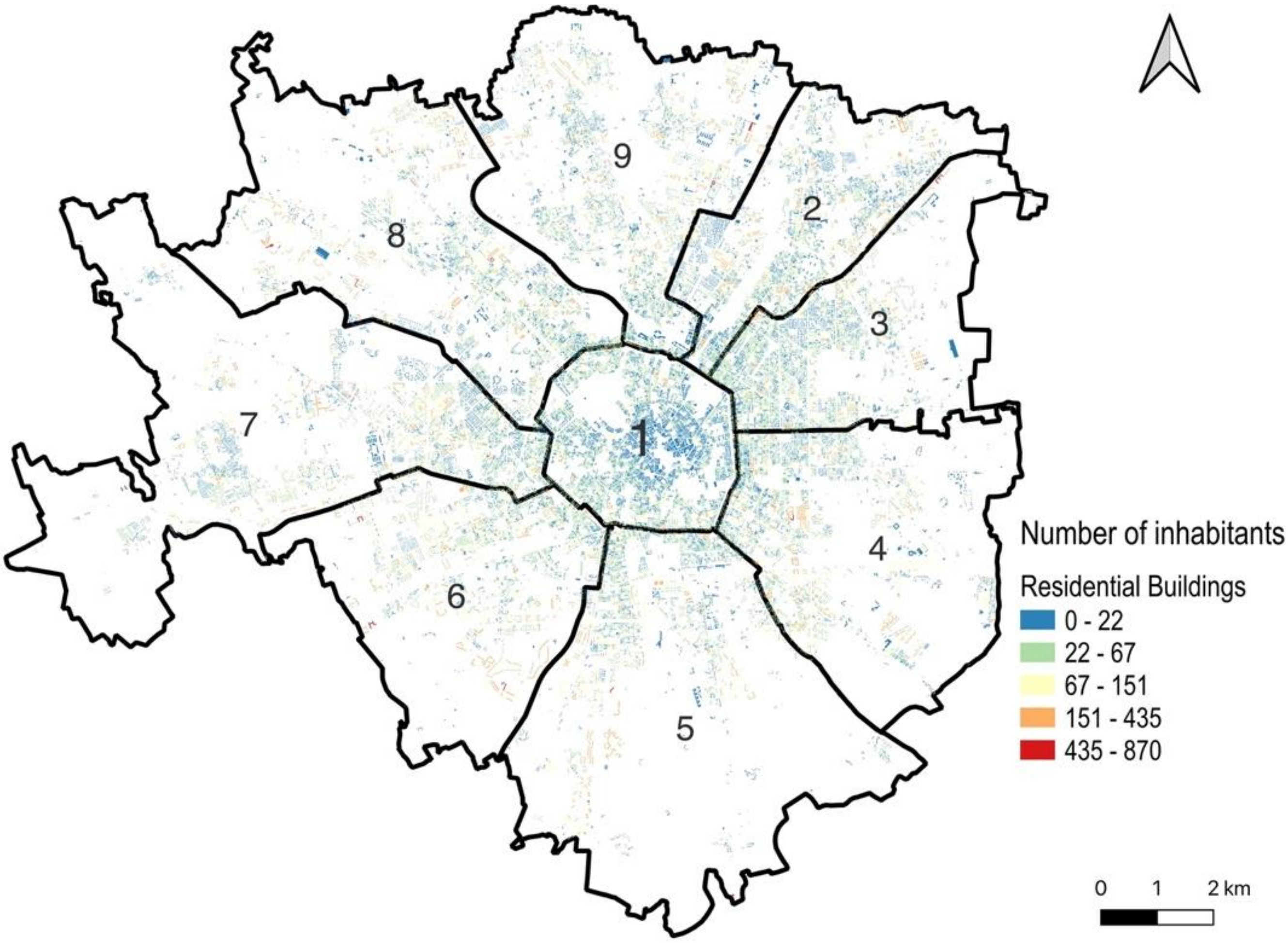

Figure 9. Number of inhabitants for each building in Milan.

Another important part is the creation of DSM, as it is described in the methodology flowchart using QGIS software from downloaded DTM. The DTM for 1 meter has a higher resolution, but in this work, the 10 meter was used. To proceed the calculation of solar irradiation, the map for linke turbidity and diffuse for each month was created in QGIS, the data was obtained from JRC and meteonorm software.

Table 5 presents information on the energy performance of residential buildings in Italy, as indicated by Energy Performance Certificates (EPCs), which were released for different reasons such as new construction, retrofits, or sale and lease of buildings. The energy performance of the buildings is classified into different energy classes (A4, A2, A1, B, C, D, E, F, and G) based on their average energy performance (EPgl,nren) in kWh/m2/y. The table also shows the number of EPCs collected for new buildings, retrofitted buildings, and buildings that were put up for sale or lease. The energy performance of a building is indicated by its EPgl,nren, which represents the building's annual energy consumption per square meter of floor area. The lower the EPgl,nren, the higher the energy efficiency of the building. The highest energy class in this table is A4, with an average energy performance of 28 kWh/m2/y, while the lowest energy class is G, with an average energy performance of 277 kWh/m2/y.

Table 5 also shows that the majority of EPCs collected for new buildings are in energy classes A4, A2, and A1, which indicates that new buildings are generally more energy efficient than older buildings. On the other hand, the majority of EPCs collected for retrofitted buildings are in energy classes D, E, F, and G, which suggests that retrofits have not been as effective in improving energy efficiency. Finally, the majority of EPCs collected for buildings put up for sale or lease are in energy classes F and G, which suggests that these buildings may have lower value due to their lower energy efficiency.

Table 5. Energy performance of residential buildings by motivation of EPC release.

Energy Class and Average Energy Performance EPgl,nren	Number of EPC for new buildings	Number of EPC of retrofitted buildings	Number of EPC for sale and lease of buildings
A4 28 kWh/m2/y	2414	395	311
A2 68 kWh/m2/y	2275	1010	584
A1 79 kWh/m2/y	1292	1439	1097
B 99 kWh/m2/y	132	1063	2060
C 118 kWh/m2/y	40	1528	5939
D 139 kWh/m2/y	44	2644	18730
E 158 kWh/m2/y	55	2777	33342
F 189 kWh/m2/y	84	3296	49677
G 277 kWh/m2/y	99	2056	52156

Table 6 illustrates the number of buildings categorized by both energy class and period of construction. The energy classes range from A4 (most energy-efficient) to E (least energy-efficient). It also demonstrates that newer buildings have better energy performance compared to older buildings, with a significant improvement in energy classes for buildings constructed after 1991. However, despite the improvement, the majority of buildings still fall into the most energy-intensive classes F and G, making up 57% of the total. When considering the percentage of buildings by period of construction, it is observed that 45% of the buildings were built before 1960 and 70% were built before 1970.

Table 6. Number of buildings by period of construction and energy class.

Energy Classes	Period of Construction							Total
	< 1945	1946-60	1961-70	1971-80	1981-90	1991-05	>2006	
A4	67	43	31	37	43	6	2598	2826
A3	129	78	33	26	20	16	3060	3362
A2	250	247	165	123	82	54	2933	3853
A1	301	424	381	264	147	58	2309	3884
B	434	480	603	394	186	236	1406	3740
C	1387	1383	1801	1138	474	889	1264	8337
D	5297	4741	5972	3604	1237	1987	1324	24162
E	10087	8638	10911	6429	1947	1862	930	40804

The aim is to develop a model that can accurately represent the energy usage patterns of urban buildings. To achieve this, data from Energy Performance Certificates (EPCs) is being analyzed. Specifically, the focus is on the energy classes assigned to buildings, as well as their efficiency levels and consumption rates for both space heating and domestic hot water. By examining this data, it is hoped that a detailed and reliable urban building energy model can be created. This model could be used to better understand and manage energy usage in urban areas, leading to more efficient and sustainable energy consumption practices. Figure 10 described the EPC process to obtain the energy modeling very clearly.

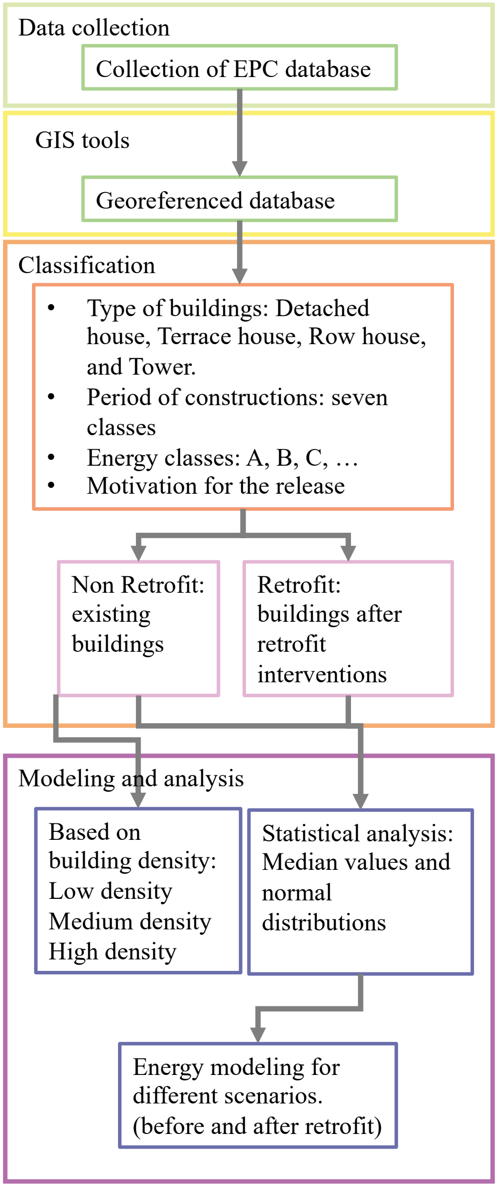

Figure 10. Flowchart of the methodology: EPC database processing.

The next step in pre-processing is to calculate the S/V. First volume and heat loss surface should be calculated. Volume is an important factor in building energy analysis as it directly influences the heat transfer and energy consumption of the building. It can be obtained from multiplying height to the area. The greater the volume, the greater the amount of heat required to maintain comfortable indoor temperatures, and therefore the higher the energy consumption. In this context, the gross volume of residential buildings is a crucial energy-related variable for space heating. The heated surface has been calculated using this formula:

S= (Area*2) + (perimeter*Height)

Equation 1

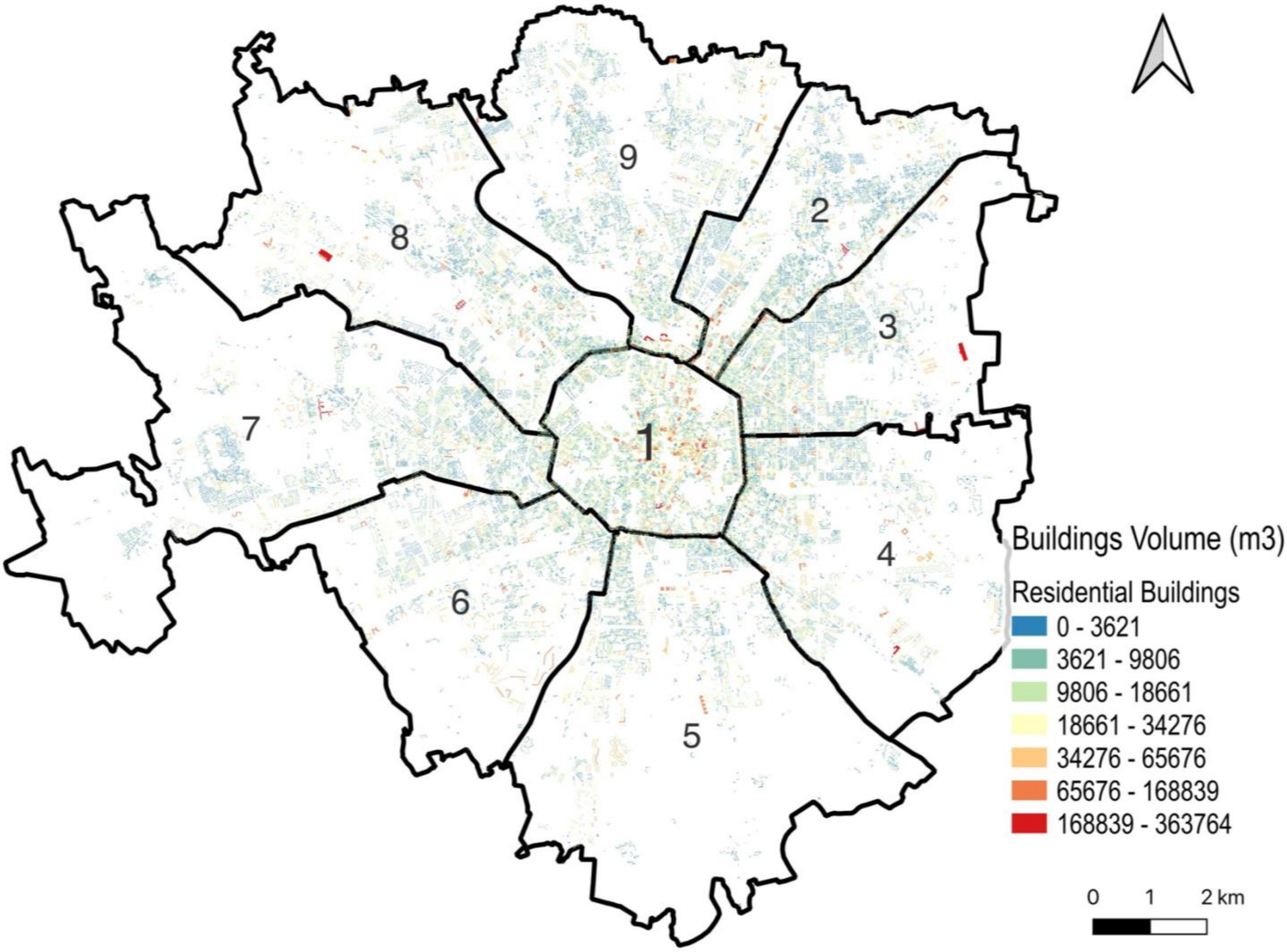

Figure 11. Residential buildings' gross volume.

Figure 11 indicates the gross volume of the residential buildings, which is the total enclosed space within a residential structure. It represents the combined volume of all the rooms, hallways, and other interior spaces of a building, including both living areas and non-living areas like storage or utility spaces. The formula used here in QGIS is multiplying the area by the height of the buildings. Figure 12 depicts the typology of residential buildings in four categories: detached, terrace, row houses, and tower buildings. The buildings were classified based on their structure. Districts 2 and 3 located in the North-Eastern side of the city, are the most populated with a high number of tower buildings and row houses. District 7 also has a large number of row houses and tower buildings. District 9 has the highest number of detached houses. Overall, terrace houses are the most common type of residential building in Milan, followed by row houses and tower buildings. Detached houses are the least common type of residential buildings.

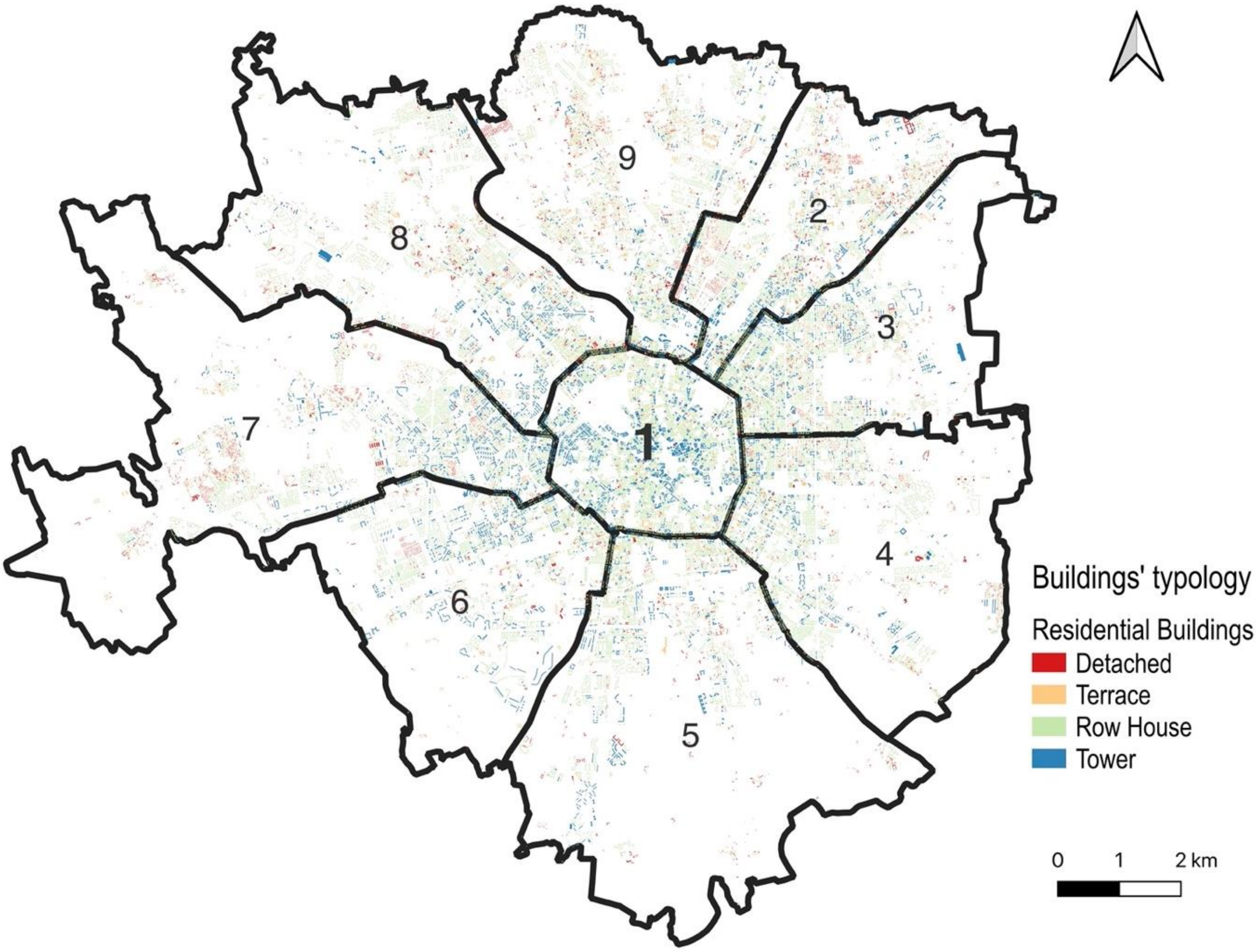

Figure 12. Buildings typology.

After that, the geometrical variables that have a strong influence on energy consumption were calculated, such as heated gross volume, heat loss surfaces, and net heated floor area. The calculation of the surface-to-volume ratio S/V required a special procedure in the QGIS software to consider the shared walls between adjacent buildings and the presence of unheated volumes. Generally, the space heating consumption increases with S/V. Based on the surface-to-volume ratio and the number of floors, different classes of buildings were identified, such as detached, terrace (maximum 3 floors), row, and tower buildings.

Only residential buildings were considered in this model, the aim is to create an energy consumption model based on various building characteristics such as the age of construction and number of inhabitants. The assumption is that residential buildings contribute the most to energy consumption in the city, while other types of buildings maintain a constant specific consumption. Since residential structures account for the majority of energy consumption, this model makes the assumption that the particular energy consumption of all other buildings is constant (Mutani and Todeschi, 2017; Mutani et al., 2016).

To better understand the distribution of domestic hot water (DHW) usage among users, the study conducted two steps. Firstly, the number of inhabitants in each census section of the city of Milan was obtained using ISTAT data, as mentioned in the pre-processing section. Secondly, The net heated surface of each census section was used to calculate the number of inhabitants in each building. By considering both of these factors, the study aimed to gain a better understanding of DHW usage patterns across the city.

As for the population, the main variables that could affect energy consumption were collected from the ISTAT database at the census section scale and processed to be assigned to each building. After the collection and pre-processing phase, a sensitivity analysis and the frequency distribution of data were performed to identify and exclude outliers. Subsequently, the two main energy-related characteristics were selected, and the buildings were grouped by period of construction and building typology (and S/V). The objective was to determine the energy performance index (EP) of non-retrofitted and retrofitted buildings for the groups of buildings with different energy-related characteristics.

The real S/V was then recalculated as mentioned before in the methodology section. (Figure 6)

4.4.Model implementation

This research aims to establish a spatially explicit representation of energy usage patterns, utilizing the power of QGIS - a robust, open-source Geographic Information System. To achieve this, the energy performance of residential buildings in Milan is analyzed using QGIS software. As with any data analysis, it is crucial to identify and correct the anomalous data, if any, to avoid potential outliers that may distort the statistical analysis. Therefore, to find the outliers, a thorough data correction procedure was performed by georeferencing and integrating these data, which involved cross-checking data from different sources and verifying the accuracy of the collected information. Furthermore, statistical analysis techniques were applied to identify the anomalous data, which were then removed or corrected as needed. By removing these outliers, a more accurate and reliable picture of the energy performance of buildings in Milan was obtained, allowing for more clear decision-making regarding energy efficiency measures and policy implementation.

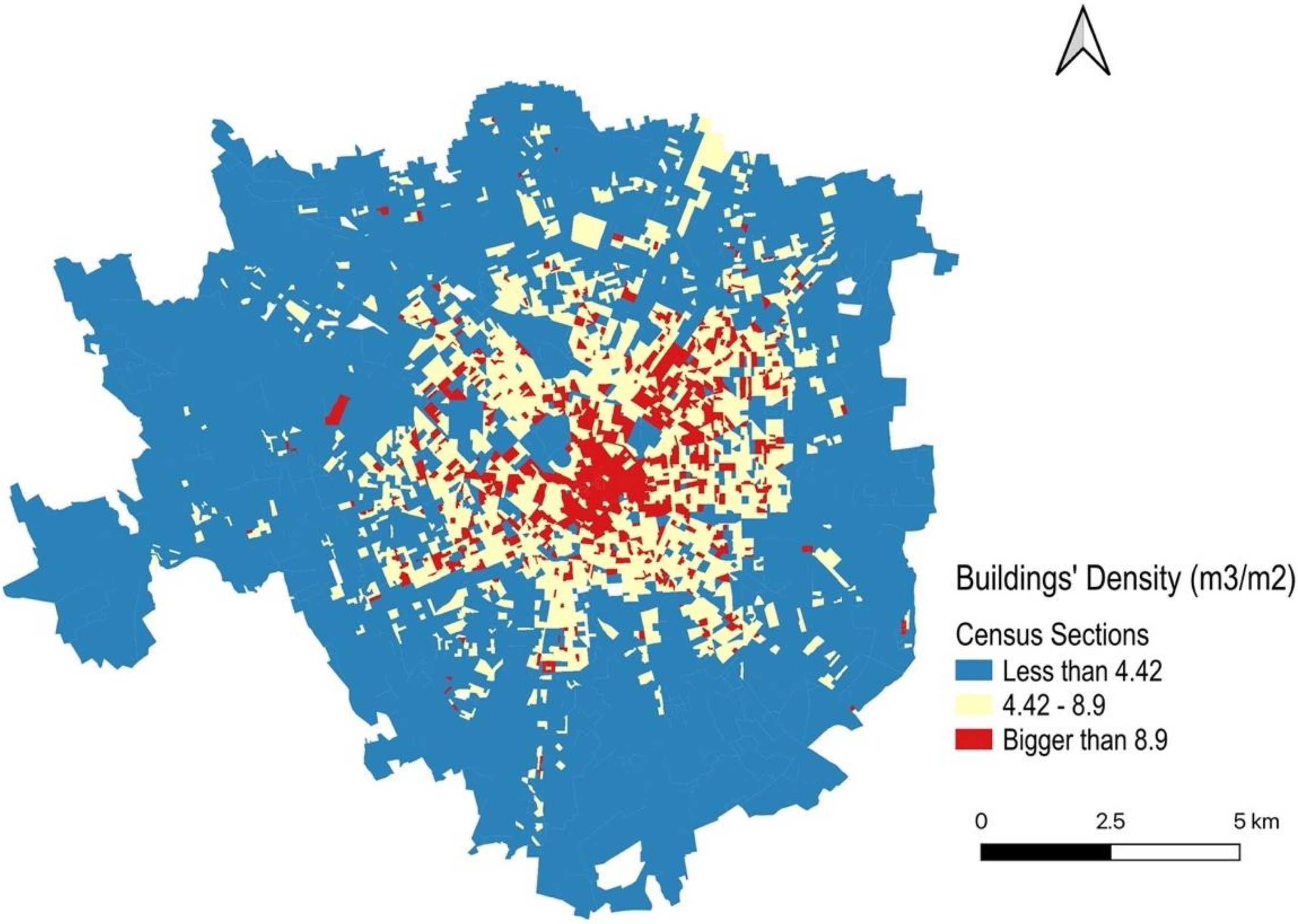

Figure 13. Buildings' density in census sections in the city of Milan.

Figure 13 illustrates the building density (BD) in the census sections context in Milan. BD is divided into three categories for low density(less than 4.42 m^3/m^2), medium density (between 4.42 and 8.9 m^3/m^2), and high density (higher than 8.9 m^3/m^2). The map was created using the georeferenced data of the EPCs assigned to the building shapefile in using QGIS tools, followed by the calculation of the density of the building in each census section. As it is shown in the map the high-density areas are mainly in the center and the majority of census sections have a low density.

The procedure continues by categorizing the EPC data in seven categories based on their period of constructions, then by dividing them on the building's density, the data was analyzed, therefore the linear regression of the energy performance index for both before and after retrofit was calculated. Figure 7 and 9 show the correlation between the energy performance index and the surface-to-volume ratio of residential buildings for non-retrofit and after retrofit interventions respectively. These linear regressions consider a range of factors that impact the energy performance of buildings in Milan, such as local climate conditions, building stock types, and energy services such as space heating and domestic hot water. Retrofit interventions have been carried out in Milan to address historical-environmental constraints and socio-economic situations. The ratio of surface area to volume (S/V) of buildings plays a significant role in determining primary energy consumption, with higher S/V ratios resulting in increased energy use. Retrofit interventions have been shown to decrease the EPgl,nren by approximately 40%, highlighting the importance of improving the energy efficiency of existing buildings. To calculate the energy consumption by fossil fuel, the EPgl,nren values were multiplied by the net heated floor area of each building and the primary energy coefficient of the fuel, primarily natural gas. The energy performance (Ep) of each building is shown by a point in correlation to the density of the buildings and the period of their construction. It is observed that older buildings have a greater inverse correlation due to their lower energy efficiency as compared to newer ones. In Figure 15 the distribution of energy performance for each period of construction is showed based on building density that are divided to thre categories; low, medium and high density. This modeling was done by classification of the data once based on period of construction and then on building density. Unfortunately, the amount of data for some of these categories were too low, for example for the period of 1971-1980. In these cases the average calculated S/V and energy performance is not reliable. In general, low building density have a higher energy performance and mainly in all period of constructions. The only period of construction oppose to this sentence is 1971-1980. The reason is as mentioned above. Also, There is an inverse relationship between the density of buildings and their energy performance in every census section. This means that as the number of buildings increases in a given area, their energy performance tends to decrease.

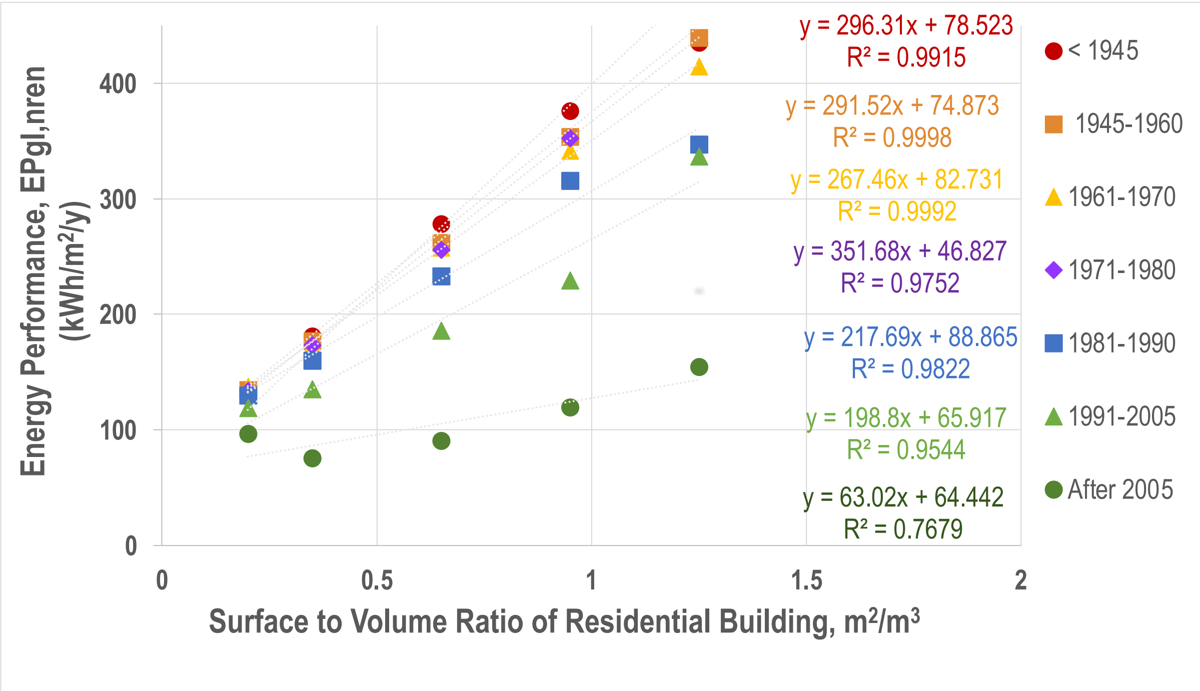

Figure 14. Energy performance EPgl,nren of residential buildings in Milan before retrofit interventions.

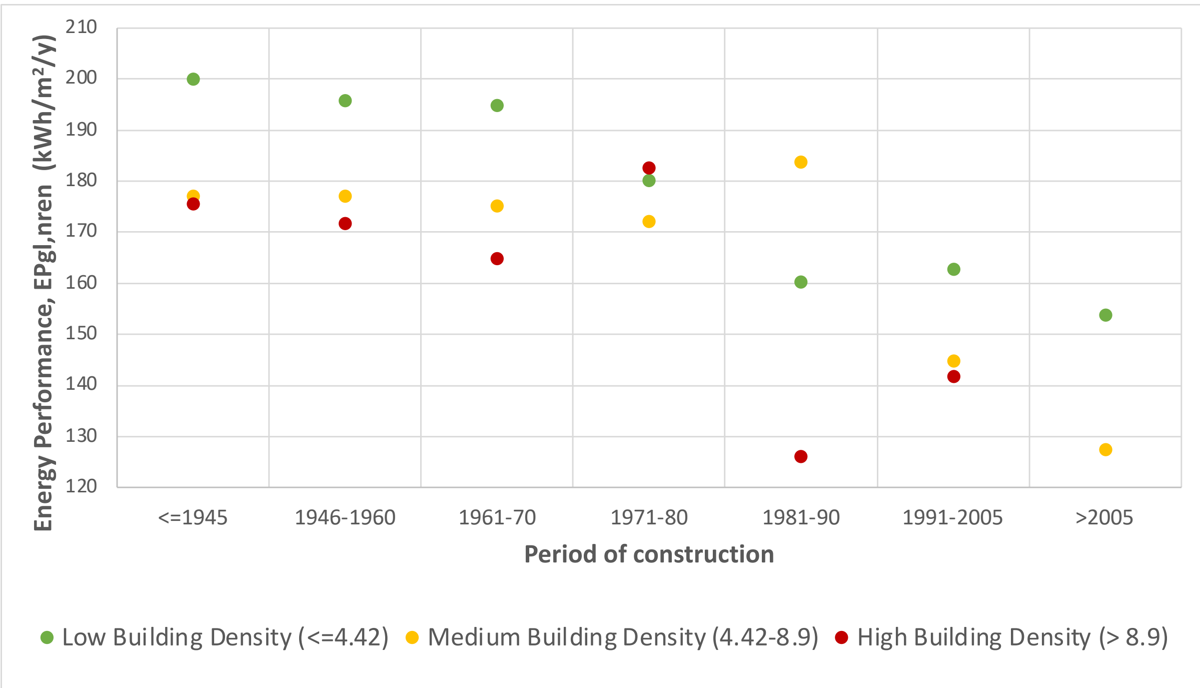

Figure 15. Energy performance EPgl,nren based on building density categories for each period of construction buildings in Milan before retrofit interventions.

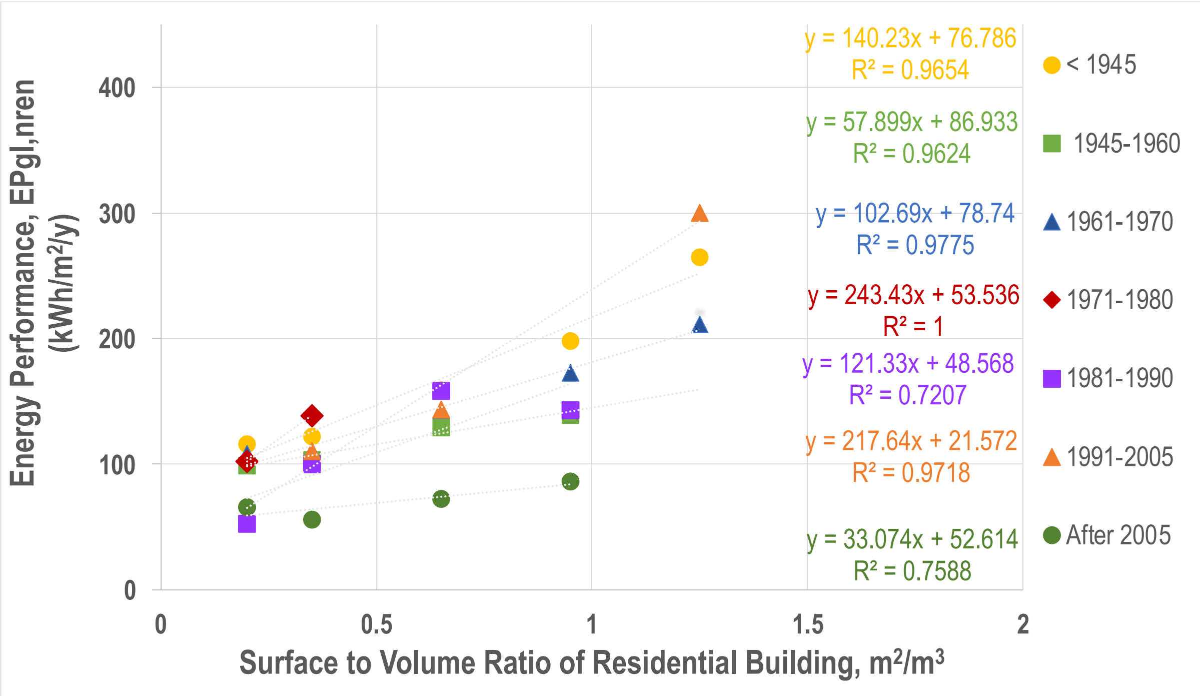

Figure 16. Energy performance EPgl,nren of residential buildings in Milan after retrofit interventions.

The EP model was then applied to the city of Milan, and the energy consumption of the existing residential building stock and the retrofitted one was calculated considering the standard climate conditions and the main characteristics of the city. The main data used in the energy-use model at the urban scale were the topography database provided by the city of Milan about residential buildings' characteristics, including the building use, footprint area, height or number of floors, gross volume, net heated surface, surface-to-volume ratio S/V, and period of construction. Additionally, data provided by the National Institute of Statistics ISTAT about population and buildings, including the number of inhabitants and families, age, nationality, working level, buildings' property, level of maintenance, empty or occupied apartments, and period of construction, were also utilized.

4.5. Calculation of domestic hot water

The formula used to calculate the daily natural gas consumption for domestic hot water (DHW) in a building is shown below (equation 2). It takes into account several factors such as the daily water usage for each individual and etc. The energy components of residential load are determined by the consumption of electricity and natural gas in single dwellings. This consumption is related to several end-use outputs such as domestic hot water, space heating, cooling, and appliances-lighting. The provincial survey database for 2017 assumes that each energy end-use is satisfied by either electricity or natural gas (Italy Energy Information | Enerdata, n.d.). The formula considers a natural gas boiler as the heat source for DHW and assumes an efficiency of 0.9 for the heat exchanger system. The calculation is based on a journal article that likely discusses energy-efficient building design and retrofitting strategies, where DHW consumption is an important factor in determining energy usage in buildings. By accurately calculating DHW consumption, building designers and policymakers can make informed decisions about DHW systems and incorporate measures to increase energy efficiency in buildings.

$$\mathbf{Q_{u,d} = V \cdot p \cdot c_p \cdot \Delta T / \eta_{DHW}}$$

Equation 2

where:

- $Q_{u,d}$ which is the daily domestic hot water consumed using natural gas,
- V is for the volume, which is the amount of water that each individual use each day which is approximately 75 liters,
- p shows the density of water which is 1kg/l,
- c_p which is 1.163 Wh/KgK, that indicates water specific heat,
- represents the temperature difference between two points. In this case, it refers to the temperature difference between the outlet of a system, assumed to be at 49°C, and the inlet, which is the temperature of the water supplied to the heater and assumed to be 11°C. The value of Δt is calculated by subtracting the inlet temperature (11°C) from the outlet temperature (49°C). So, in this scenario, the temperature difference (Δt) would be 49°C - 11°C = 38°C
- η_{DHW} refers to the efficiency of Domestic Hot Water systems that use a natural gas boiler. The value assigned to η is between 0.8-0.9.

The calculation of space heating consumption for each residential building was done by QGIS software, considering the number of inhabitants in each building.

Figure represents the annual space heating consumption for the whole city of Milan in kWh/year.

4.6 Calculation of space heating

The first step to calculating the space heating is to find the useful heated area, in order to do so, it is necessary to calculate the real S/V(surface-to-volume ratio). In this step only the heated surface are considered and the unheated parts such as stairwells, elevated shafts, and entrance halls are excluded. Using QGIS it is possible to calculate the useful heated surface of each residential buildings by first selecting each S/V (Table 7) that is calculated before and then using field calculator. And the following query:

```
CASE WHEN "S/V_a" > 0.71
THEN  "S/V_a" * 1.31
WHEN  "S/V_a" > 0.56 AND "S/V_a" <= 0.71
THEN  "S/V_a" * 1.25
WHEN  "S/V_a" > 0.32 AND "S/V_a" <= 0.56
THEN  "S/V_a" * 1.21
WHEN "S/V_a" <= 0.32
THEN  "S/V_a" * 1.08
END
```

Table 7. Buildings' tyopolgy and theirs S/V

Buildings' typology	**Surface to volume ratio –S/V [m²/m³]**	**Average multiplicative factor: S/V S/V_{real}**
Detached house	S/V > 0.71	1.31
Terrace house -row house small	0.56< S/V ≤ 0.71	1.25
Row house big	0.45 < S/V ≤ 0.56	1.21
Tower	S/V ≤ 0.45	1.08

Then the gross heated surface was calculated using the following equation:

Gross heated surface = Area * floors

Equation 3

After calculating the gross heated surface, by multiplying it by the fn factor the useful heated surface was measured. (based on each period of construction according to table 8)

Table 8. F_n factor based on period of construction

Period of construction	Wall thickness (m)
<1945	0.50
1946-80	0.30
1981-90	0.35
>1991	0.40

Finally the annual space heating for each residential building was calculated using the equation below:

Annual space heating (kWh/year) = EP * useful heated surface

Equation 4

4.7 Calculation of the electricity production with roof-integrated photovoltaic technology

To estimate the potential of photovoltaic (PV) energy, it is essential to consider different technological solutions, each with varying efficiency and panel size. These technological solutions typically include modules made of monocrystalline silicon and polycrystalline silicon. The efficiency of a PV module determines the amount of solar energy it can convert into electrical energy, while panel size refers to the physical dimensions of the PV module.

Standard parameters for photovoltaic panels include the use of the following efficiency values such as: Monocrystalline silicon: η MC=20% (0.20), Polycrystalline silicon: η PC =17% (0.17) and Thin film: η FS =10% (0.10).

Selecting a particular technology for photovoltaic installation does not only determine the required space, but also influences the associated expenses and the duration of the payback period. To calculate the amount of photovoltaic energy produced, the Šúri correlation formula is utilized based on the calculation of incident solar radiation. The formula takes into account the parameters such as the efficiency of the panels, the irradiance on the surface, and the surface area available for installation. The equation can be written as: (Šúri et al., 2007)

$$\mathbf{E = PR * Hs * S * \eta}$$

Equation 5

- E is the amount of production of electrical energy in one year (kWh/y),
- PR provides an overall evaluation of the system's effectiveness or efficiency in achieving its intended goals or objectives (≈ 0,75),
- Hs the total amount of solar energy received over the course of one year per unit area (kWh/m^2/y)),
- η quantifies the ratio of the energy produced or captured to the amount of solar energy that is incident or received:

$$\mathbf{\eta = W_p/(S * I_{stc})}$$

Equation 6

- Wp is the peak power of the panel (equal to 1 kWp that corresponds to about 6-8 m2 of PV surface S is the working surface of the panel [m2] (about 30-40% of the roof area) (Wirth, 2015)
- I_{stc} is the tested solar irradiance under standard test conditions STC (1 kW/m2, 25°C at sea level).

$$\mathbf{E_{1kWp} = PR * H_s * W_p/I_{stc}}$$

Equation 7

PR is a metric that compares the annual AC energy that is actually generated to the expected DC output of an ideal photovoltaic system that accounts for losses at the same location. The PR value, which is used in the calculation of R, is affected by a range of factors, including actual levels of solar insolation and various losses, such as shading, module efficiency, and system losses. (McKenney, 2008) Spatial models based on real data have been developed to estimate the amount of sunlight and photovoltaic (PV) potential in Italy. These models assume a performance ratio (PR) of 0.75, which takes into account factors such as actual sunlight received, PV module efficiency, and system losses when calculating the expected PV output (Mutani G. &., 2021). Solar panels typically require an installation area that is 2.5

times larger than their own surface area. This means that approximately 40% of the available suitable area needs to be allocated for the installation of PV modules. (Wirth, 2015)

The efficiency of the panel refers to the ability to convert solar energy into electrical energy, while the irradiance factor refers to the amount of solar radiation incident on the surface. The surface area available for installation is also a critical factor that determines the maximum energy output. By using this equation, it is possible to determine the potential energy production of photovoltaic installations and estimate the cost-effectiveness of different technology choices. An alternative method for determining the overall electricity production potential is used by (Castellanos, 2017). However, following Mutani G. &.,Equation (3) is utilized in this study (Mutani G. &., 2021).

The IEA Energy Technology Perspectives report (2016) utilizes a methodology that begins with parameterizing the potential for rooftop PV by population density and solar insolation. This method first calculates the rooftop area per capita, Acapita, by utilizing the population density, r, as defined in equation (1). The IEA obtained the values for the constants a and b in this equation (with values of 172.3 and 0.352, respectively) by conducting a linear regression on data from 1600 cities, which resulted in a correlation coefficient of 44% (IEA 2016).

$$\mathbf{A_{capita} = \alpha * \rho^{-\beta}}$$

Equation 8

Multiplying equation (4) by the total city population, P, gives the suitable roof area per city, A_{city}, as shown in equation (5),

$$\mathbf{A_{city} = A_{capita} * P}$$

Equation 9

The total electricity generation potential $E_{PV,IEA}$ is then calculated, as shown in equation (6),

$$\mathbf{E_{PV;IEA} = A_{city} * H_{solar;city} * \eta * PR \cdot f_{orientation}} \text{ (Castellanos, 2017)}$$

Equation 10

where $H_{solar,city}$ is the solar insolation ($kWh^{-1}\ m^{-2}\ yr^{-1}$), η is the rooftop PV system efficiency, PR is the performance ratio (assumed to be 75%, as indicated in (IEA 2016)), and $f_{orientation}$ is the orientation factor (assumed to be 1 in aggregate, as indicated in (IEA 2016)). NASA's Surface Meteorology and Solar Energy data (2014) is used to obtain the solar insolation, $H_{solar,city}$, for each city. After acquiring the necessary data, the total electricity generation potential from rooftop PV is calculated using the different methods and compared. The IEA method serves as a baseline and the percentage difference, D, between the other methods and the IEA method is calculated using the following formula:

$$\Delta = (E_{PV;IEA} - E_{PV,city\text{-}specific}) / E_{PV;IEA} * 100\%$$

Equation 11

Renewable energy deployment strategies are gaining popularity due to various factors such as the significant cost reductions in solar energy and energy storage, ease of building integration, and growing concerns about climate change risks. One of the most rapidly growing low-carbon technologies in response to these trends is solar photovoltaics (PV). (Castellanos, 2017) Over the past decade, there has been a significant increase in PV deployment, with a growth rate of 40 times its previous capacity, resulting in approximately 300 GW of installed capacity globally. (Kurtz, 2017) Projections indicate that this trend will continue, with an estimated 430 GW of installed capacity expected by 2020, as reported by the International Energy Agency (IEA) in 2015. Figure 1 shows that the solar industry has been primarily dominated by Distributed PV. However, despite this dominance, there is still a vast potential for additional deployment. In the United States alone, the estimated technical generation potential for rooftop PV systems is almost 40% of the total national electric-sector sales in 2016. (Gagnon, 2016) and (Strupeit, 2016)

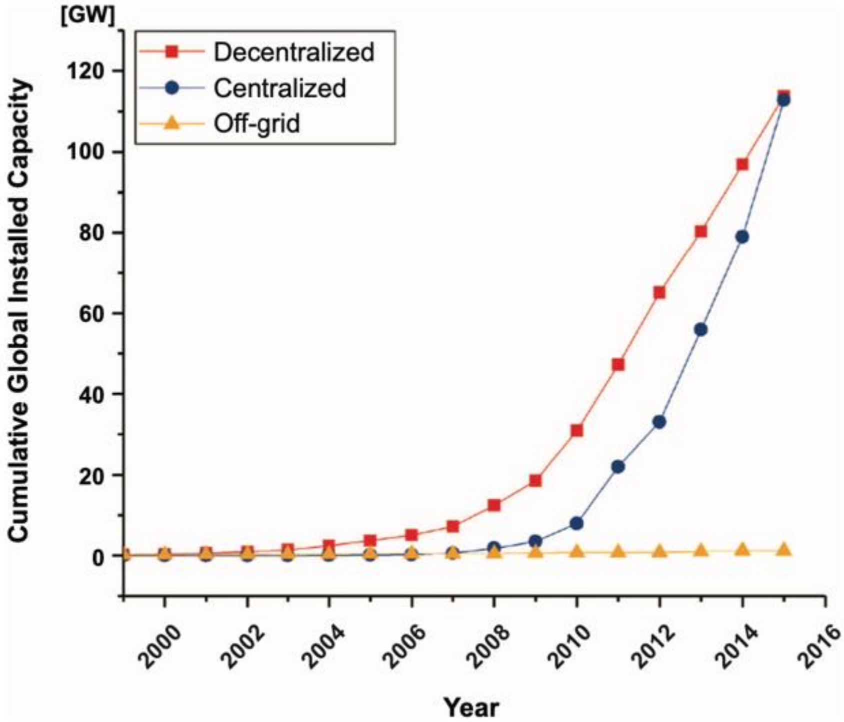

Figure 17. **“**The global installed capacity (GW) has evolved over time from 2009 to 2015, as shown by the red line (squares) representing decentralized grid-connected PV installations, the blue line (circles) representing centralized grid-connected PV systems, and the yellow line (triangles) representing off-grid PV installations. Although off-grid PV installations have smaller capacity, they are anticipated to continue expanding. (Lighting Global and Bloomberg New Energy Finance in 2016)” (Source: ternational Energy Agency 2000, 2016).

There are several barriers that have obstructed the development of distributed PV, including a lack of awareness among end-users and stakeholders, high risk aversion, concerns about system performance, and a shortage of suitable rooftop space for installations, with the combination of these obstacles being the most significant hindrance. Considerable research has been conducted to understand, address, and overcome these multiple adoption barriers. (Margolis, 2006) and (Strupeit, 2016)

To locate appropriate rooftops, researchers have focused on urban areas due to their high density of rooftops. As the world's population becomes increasingly urban, with an expected 2.5 billion people moving to urban areas by 2050 (DESA, 2014), urban areas are becoming critical locations for the deployment of distributed

PV systems. Furthermore, if current advanced laboratory-tested PV technologies are commercialized and become cost-competitive, city-integrated PV has the potential to meet the energy needs of most cities. (Kammen, 2016)

The growth of distributed PV in urban areas has been highly dependent on policy in the past, and future growth may also be influenced by policy. (Schwartz, 2017) One of the challenges in developing policies for distributed PV is accurately identifying and predicting the potential for solar energy, and effectively communicating this information to non-technical stakeholders who may be risk-averse. To overcome this challenge, it is important to have reliable and user-friendly tools for assessing distributed PV potential that can be easily understood and accessed by stakeholders. This is an essential component in the development of appropriate policies. (Castellanos, 2017)

4.8. Calculation of the Solar thermal potential

The rise in electricity access and energy consumption in developing countries has led to an increasing demand for energy-saving strategies. Consequently, Solar Thermal Systems (STS) have gained popularity in recent times owing to their low cost, ease of operation, and minimal maintenance requirements. These systems are widely used in buildings, providing the production of DHW and supplying space heating/cooling. Active solar-heating systems, of which solar collectors are the key component, absorb the sun's energy and convert its radiation into thermal energy, which is then transferred to a thermo-vector fluid (such as water). The performance of a solar collector can be assessed using an energy balance approach that considers the amount of incident solar energy Qs converted into useful heat Qu transferred to the fluid carrier, as illustrated in Figure 2. The evaluation of STS is critical for determining their feasibility and effectiveness as an alternative to traditional energy sources. This is particularly important in developing countries where energy security and sustainable development are significant concerns.

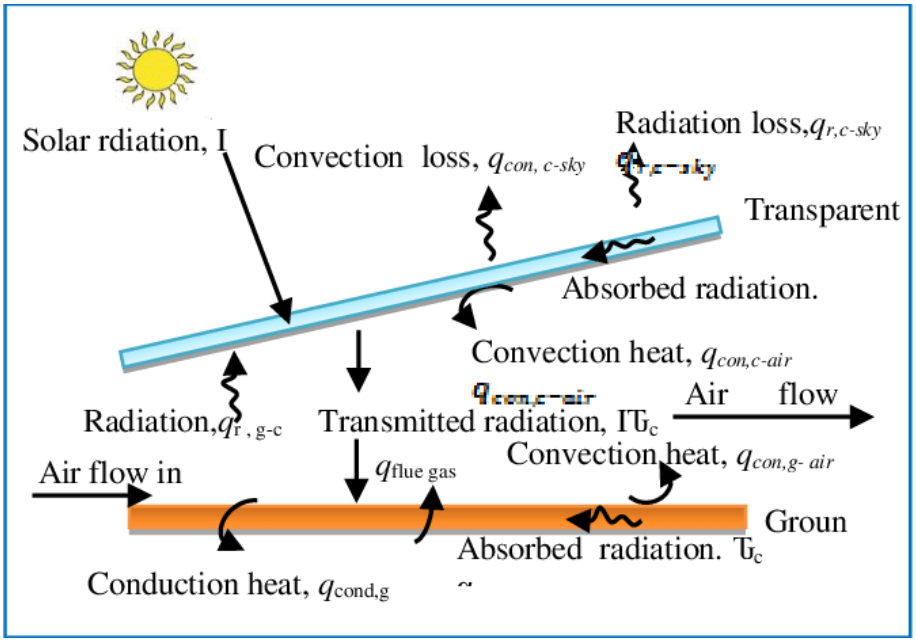

Figure 18. "The energy balance for the collector of HSCPP (High Temperature Solar Collectors for Power Production) is described using a mathematical model based on several assumptions. Firstly, the airflow inside the collector is assumed to be in a steady state. Secondly, the airflow is considered to be one-dimensional, flowing towards the center of the collector and the chimney. Thirdly, the temperature of the air at the inlet of the collector is assumed to be the same as the surrounding ambient temperature. Fourthly, any friction losses within the collector and the chimney are disregarded. Finally, it is assumed that the temperature of the external heat source (TECh) remains constant and consistent across the system."(Aurybi, 2016)

$$\eta_{coll,m} = Q_u / Q_s$$

Equation 12

Taking into account this energy balance, it becomes feasible to assess the potential of a Solar Thermal System by calculating the monthly useful thermal energy produced. This evaluation is based on the fraction of solar irradiation intensity (H_{sol}) that is converted into thermal energy for each month. The following equation illustrates this relationship:

$$Q_u = H_{sol} * A_c * \eta_{coll,m}$$ ("System Thermal Calculations," 2013)

Equation 13

- AC $[m2]$: collector gross area assumed equal to 30-40% of the surface of the roof (calculated with QGIS for each roof (Mutani G. &. 2021),
- H_{sol} $[Wh/\ m2]$: monthly incident solar irradiation intensity (calculated with QGIS for each month on each roof);
- $\eta_{coll,m}$: solar collector monthly efficiency. This equation allows us to quantify the potential of a Solar Thermal System in terms of useful thermal energy that can be produced on a monthly basis.

The most useful parameter to estimate the annual energy output and select an optimal collector based on system location and boundary conditions is the thermal efficiency of the solar collector. The European Standard EN 12975-2 is used in this study to assess the thermal efficiency.

$$\eta_{coll} = \eta_o - a_1 * x - a_2 * I * x^2$$

Equation 14

$X = (T_m - T_a)/I = \Delta T_m / I \quad (m^2K/W)$ **("System Thermal Calculations," 2013)**

Equation 15

$\eta_{coll} = \eta_o - a_1 * \Delta T_m / I - a_2 * I * (\Delta T_m / I)^2$ **("System Thermal Calculations," 2013)**

Equation 16

- ηo : optical efficiency: the fraction of the incident solar radiation energy on the glass cover which is transferred as thermal energy inside the absorber surface;
- x [$m^2K/$ W]: reduced temperature difference;
- a_1 $[W/m^2K]$: heat loss coefficient;
- a_2 [W/ m^2K]: a coefficient that represents the amount of heat that is lost from the system per unit temperature difference;
- I [$W/$ m²]: is a measure of the solar energy received per unit area:

$$I = H_{sol}/h \quad (W/m^2)$$

Equation 17

(https://re.jrc.ec.europa.eu/pvg_tools/en/#MR)

The solar collector's effectiveness relies heavily on the coefficients ηo, $a1$, and $a2$. The optical efficiency $\eta o = \tau\alpha$ represents all of the optical losses that occur during the conversion of solar radiation into thermal energy. It is independent of the average fluid temperature and is determined solely by the collector material's optical properties. As a result, it is calculated by multiplying the glazing's transmission coefficient τ and the plate's absorption coefficient α. The heat loss coefficient a_1 (W/m^2K) is another important parameter that is used to assess the collector's quality. It allows for the measurement of heat losses during conduction, convection, and infrared radiation heat transfer. It is linearly dependent on the reduced temperature difference x. This parameter is critical for determining the collector's quality, with a high-quality collector corresponding to a low $a1$ value, while a low-quality collector corresponds to a high $a1$ value. Thus, the quality of a solar collector can be improved by minimizing heat losses during the heat transfer. Finally, the last coefficient, a_2 (W/m^2K^2), is introduced due to the non-linearity of the heat transfer at high temperatures, and it has a quadratic dependency on x. Although it also aids in the detection of heat losses, its order of magnitude is lower than that of a_1. To compute the monthly efficiency $\eta_{coll,m}$ of solar collectors, the Reduced Temperature Difference must be calculated. This parameter is calculated by dividing the temperature difference between the mean fluid temperature T and the external air temperature T by the global solar irradiance I.

$$X = (T_m - T_a)/I = \Delta T_m / I \quad (m^2K/W)$$

Equation 18

To simplify the calculation, the average temperature of the fluid can be determined by taking the arithmetic mean of the inlet fluid temperature (T_{IN} = 15°C) and the outlet fluid temperature (T_{OUT} = 45°C). Consequently, the average fluid temperature is a fixed value.

$$T_m = T_{IN} + T_{OUT} = 30\ °C$$

Equation 19

Next, following the calculation mentioned above, the optical and heat losses coefficient, η_o, a_1, and a_2, are required to determine the $\eta_{coll,m}$. These values depend on the solar collector type for Vacuum Tube Solar Collectors or Flat-plate Solar Collectors. To determine the total amount of thermal energy needed by the user, the useful thermal energy required for each individual month can be added.

$$E_{th,TOT} = \sum E_{th,i} \text{ (i=1,12)}$$

Equation 20

Table 9 shows all the parameters required to calculate the efficiency of the chosen solar collectors. The specific type considered for this is the High Quality (HQ) Vacuum tube solar collector. During the calculations, the three coefficients η_0, a_1, and a_2 are considered constant. However, the value of $\Delta T_m/I$, which is the reduced temperature difference per unit of global solar irradiance, varies for each month. As a result, the efficiency of the solar collector is also evaluated on a monthly basis.

Table 9. Parameters for the evaluation of high-quality vacuum tube Solar Collector efficiency.

	Ta (°C)	Tm (°C)	Hours of sunlight (h)	H(Wh/m^2)	I (W/m^2)	n 0	a 1	a 2	x (m^{2}K/W)	x 2 (m^{2}K/W)	n coll
January	3.5	30	277.45	33963	122.41	0.7	1.15	0.011	0.22	0.046866007	0.39
February	7.1	30	287	42203	147.05	0.7	1.15	0.011	0.16	0.024251629	0.48
March	8.7	30	363.22	69106	190.26	0.7	1.15	0.011	0.11	0.012533265	0.55
April	14.6	30	399.3	62291	156	0.7	1.15	0.011	0.1	0.009745233	0.57
May	18.7	30	454.5	75411	165.92	0.7	1.15	0.011	0.07	0.004638306	0.61
June	21.1	30	462.5	98596	213.18	0.7	1.15	0.011	0.04	0.001742959	0.65
July	24.9	30	468.62	100439	214.33	0.7	1.15	0.011	0.02	0.000566206	0.67
August	24	30	432.45	84522	195.45	0.7	1.15	0.011	0.03	0.000942391	0.66
September	19.7	30	373.5	60929	163.13	0.7	1.15	0.011	0.06	0.003986638	0.62
October	12.7	30	336.87	34468	102.32	0.7	1.15	0.011	0.17	0.028587169	0.47
November	8.3	30	282.5	14800	52.39	0.7	1.15	0.011	0.41	0.17156262	0.12
December	3.6	30	267.12	21770	81.5	0.7	1.15	0.011	0.32	0.1049283	0.23

4.9. Model Validation

The calculated energy consumption for the city of Milan needs to be verified if is in line with. the actual energy consumption of residential buildings which is in sustainable energy action plan. Validating the calculated data for both domestic hot water and electricity consumption from QGIS was done using the Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE) formula. MAPE is a common metric used to assess the accuracy of a forecast or model by comparing the predicted values to the actual values (Riva, 2020).

$$MAPE = (1 / n) * \Sigma(|(Actual - Predicted) / Actual|) * 100$$

Equation 21

$$MAE = (1/n) * \Sigma|Yi - Xi|$$

Equation 22

Where:

- MAPE is the Mean Absolute Percentage Error
- n is the total number of data points
- Σ represents the summation symbol
- Actual represents the actual value
- Predicted represents the predicted value

In order to check the accuracy of the procedure for electricity consumption, the obtained results from QGIS was compared with those computed using the PVGIS platform (with monthly and yearly deviations), accessible at (https://re.jrc.ec.europa.eu/pvg_tools/en/tools.html) This platform enables the assessment of solar radiation on horizontal or tilted surfaces and the corresponding photovoltaic energy production. The monthly and yearly relative deviations of E1kWp was determined by comparing the calculated outcomes of QGIS and PVGIS using the following formula:

$$(E_{PVGIS} - E_{calc,QGIS}) / E_{PVGIS}$$

Equation 23

4.10. Final Results

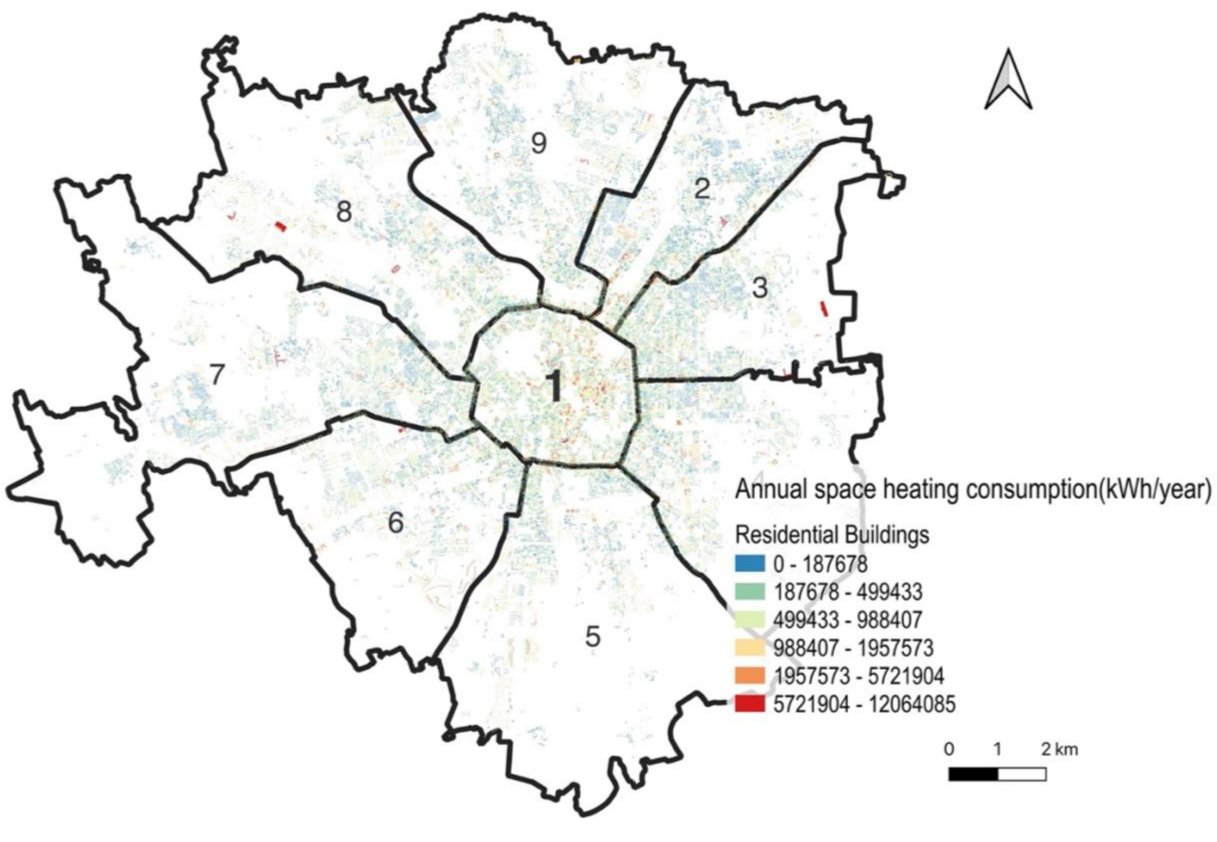

Figure 19. Annual space heating consumption for residential buildings

Figure 19 displays the energy consumption for space heating, which was determined based on the number of inhabitants in each census section and residential building. It was assumed that each person uses 50 liters of hot water per day at a temperature of 45°C. This allowed the estimation of the total DHW energy consumption for the residential buildings in Milan.(Equation 2)

After simulating monthly solar irradiation on the roofs of the buildings, the results were used to evaluate the solar renewable technologies in kWh/m2 for 12 different months. For thermal energy production, two solar technologies were simulated: flat and vacuum thermal collectors. The flat collectors had an average efficiency of 57%, ranging from 29% in December to 75% in July, while the vacuum collectors had an average efficiency of 70%, ranging from 52% in December to 69% in July. Figure 15 depicts the use of roof-integrated vacuum collectors on 20% of the available roof area. In Milan, the presence of large condominiums limits the roof area per inhabitant, thereby reducing the possibility of meeting the hot water energy demand, especially in winter.

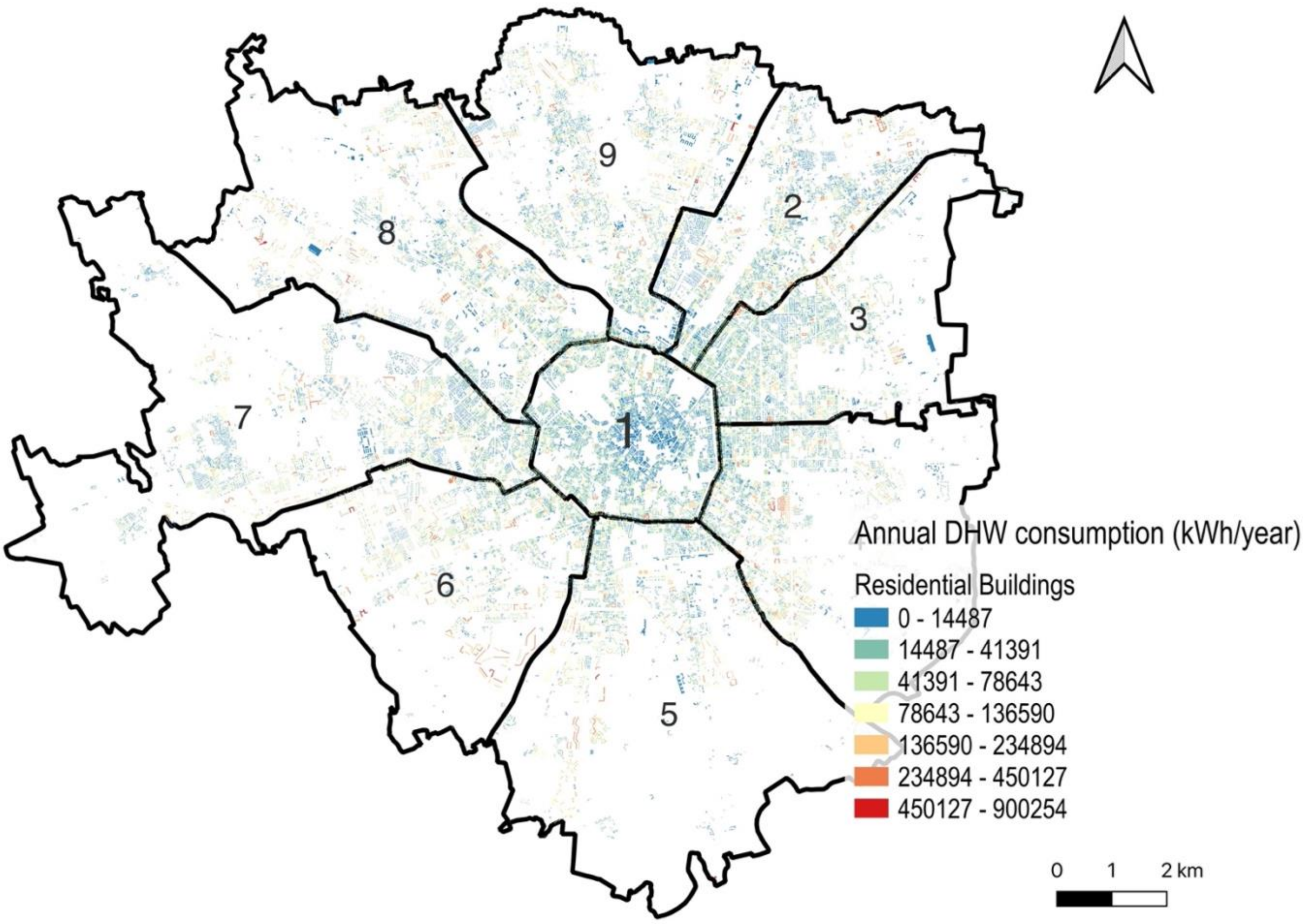

Figure 20. Annual domestic hot water consumption.

Figure 20 illustrates the dispersion of domestic hot water consumption among nine districts of Milan. As we go from the center to the outskirts the DHW consumption increases. Majority of buildings have a medium consumption of DHW.

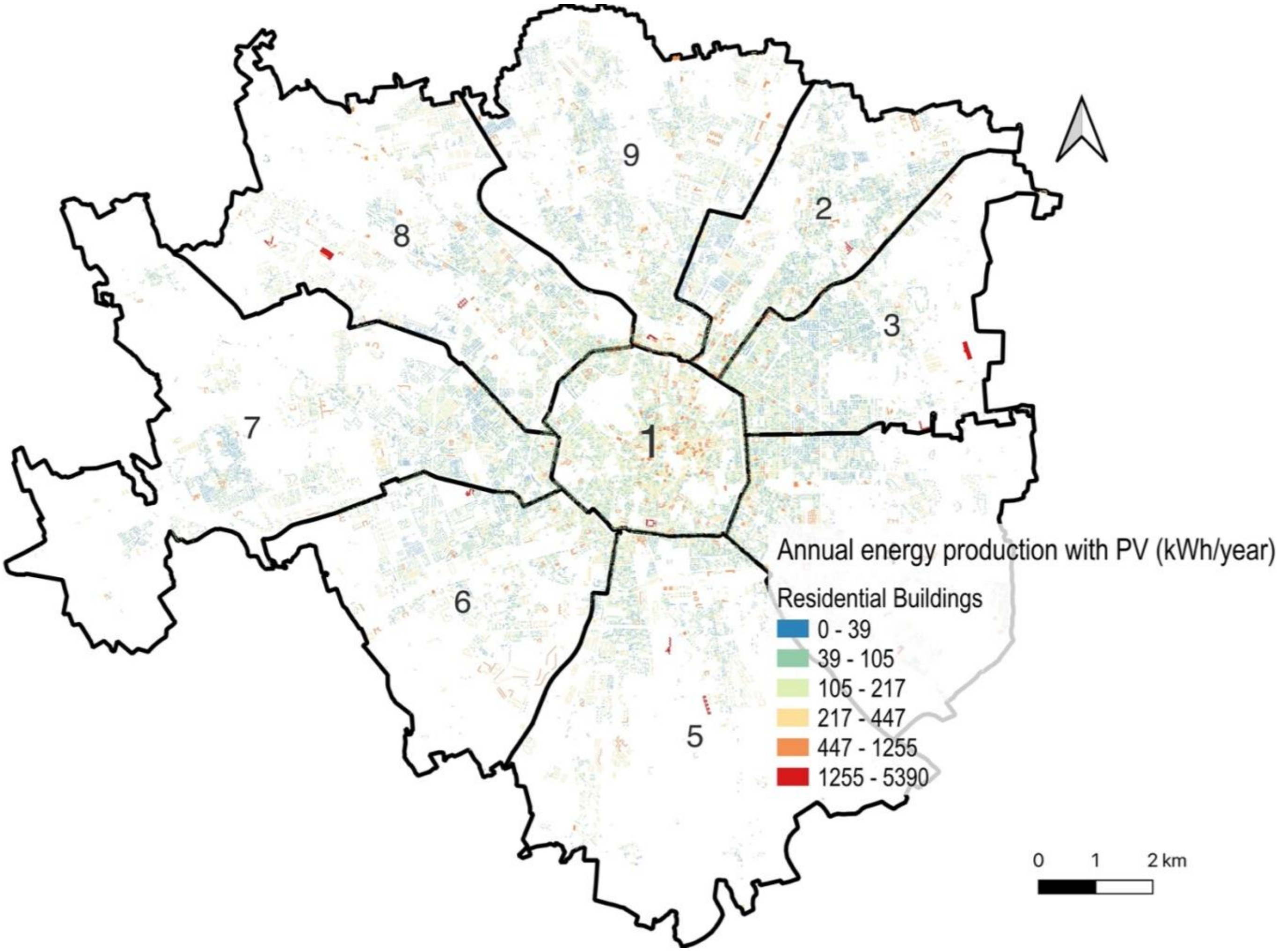

Figure 21. Annual energy production with roof-integrated Photovoltaic panels.

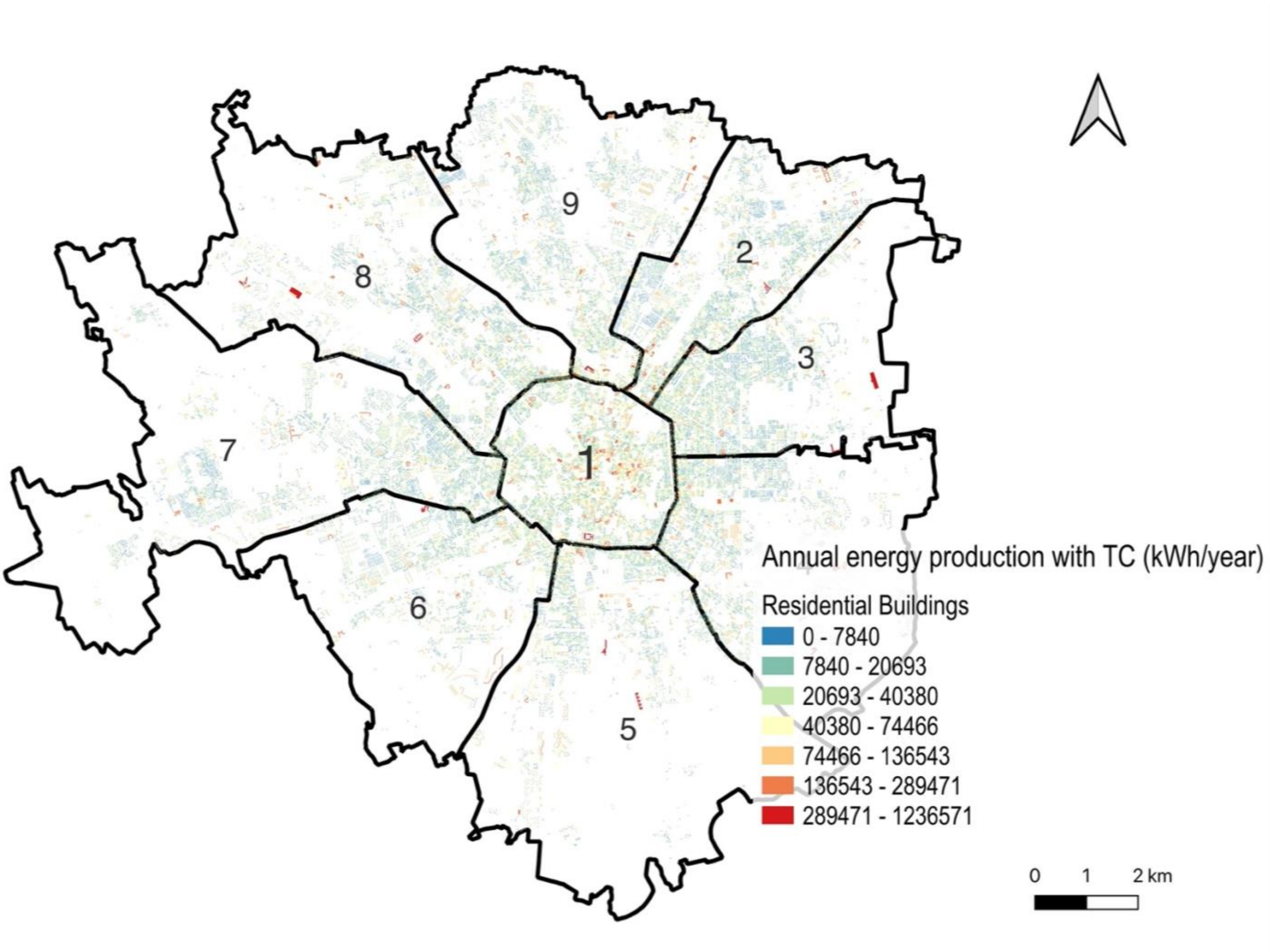

Figure 22. Annual energy production with roof-integrated solar thermal collectors.

Figure 21 and 22 illustrate the amount of energy produced using photovoltaic and solar thermal collector technologies in kWh/year.

The utilization of solar thermal collectors can help reduce the dependence of residential buildings on conventional heating systems that commonly rely on fossil fuels. These collectors can ensure the uninterrupted provision of hot water or space heating during power outages or natural disasters, and contribute to the reduction of carbon footprints, thus enhancing the building's resilience and sustainability. As presented in Table 10 the yearly energy usage for space heating and domestic hot water, along with the energy generated through solar thermal collectors, is illustrated based on district-wise analysis. Table 10 indicates that the amount of energy consumed annually for domestic hot water is nearly equivalent to the energy generated through solar collectors. However, in central district 1, which has a lower population density, energy production is four times greater than consumption.

Table 10. Annual energy use for space heating and DHW, and solar energy production for the different districts in Milan.

District No.	Energy-use for Space Heating (kWh)	Energy-use Domestic Hot Water (kWh)	Energy Production with PV (kWh)	Energy Production with TC (kWh)	Main Period of Construction
1	2,159,760,482	26,880,471	489,894	112,564,570	Before 1919
2	1,385,778,981	71,038,722	350,234	80,519,641	1919 - 1945
3	1,554,205,534	56,027,955	340,931	78,361,483	1919 - 1945
4	1,411,604,896	54,943,131	328,607	75,521,774	1946 - 1960
5	1,069,742,649	41,455,477	264,363	60,753,303	1946 - 1960
6	1,193,039,955	46,626,220	269,170	61,881,836	1946 - 1960
7	1,497,747,450	71,188,523	363,334	83,509,355	1946 - 1960
8	1,613,617,212	64,080,611	381,051	87,588,255	1946 - 1960
9	1,524,246,655	73,134,804	379,513	87,273,754	1961 - 1970

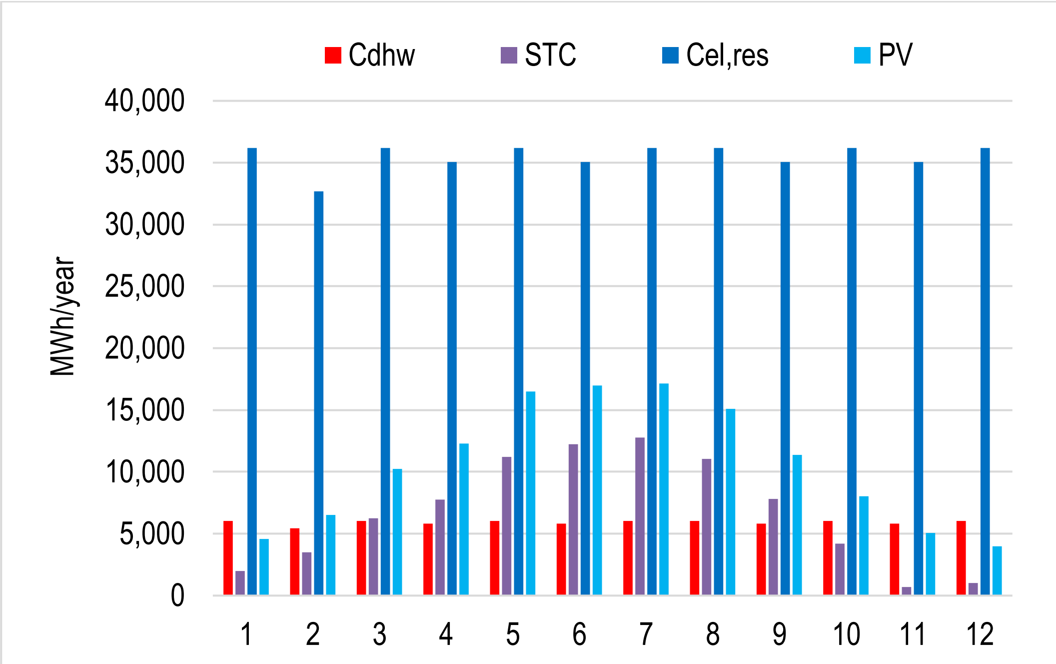

Figure 23. Monthly energy consumption and production with solar thermal collectors (STC) and photovoltaic modules (PV).

Figure 23 displays the monthly data for district 2 regarding the energy produced by STC and PV, as well as the consumption of DHW and electricity. The consumption of DHW and electricity remains relatively stable throughout the year, with only slight variations due to the differences in the number of days in each month. STC production using 20% of the roof area and an average efficiency of 62% shows a high level of self-sufficiency during the summer months, but lower levels during the winter months, particularly in November, as solar irradiance varies seasonally. The annual self-sufficiency index for STC, which is the ratio of self-consumption to consumption, is 70%, with a range of 17-211% throughout the year. The same analysis was performed for roof-integrated photovoltaic modules with an efficiency of 20%. Also, Figure 23 illustrates the relative monthly production of electricity using 30% of available roofs, compared to the consumptions. The annual self-sufficiency index for PV panels is 30%, with a monthly range of 11-48%. It is important to assess the self-consumption level before implementing any STC or PV plants by evaluating the relationship between demand and production to achieve higher levels of self-consumption for end-users and avoid overproduction. The optimal panel efficiency should also be chosen considering the demand profile and global irradiation. This can be achieved through a demand/production assessment that considers the specific user profile and solar irradiation values for the case study.

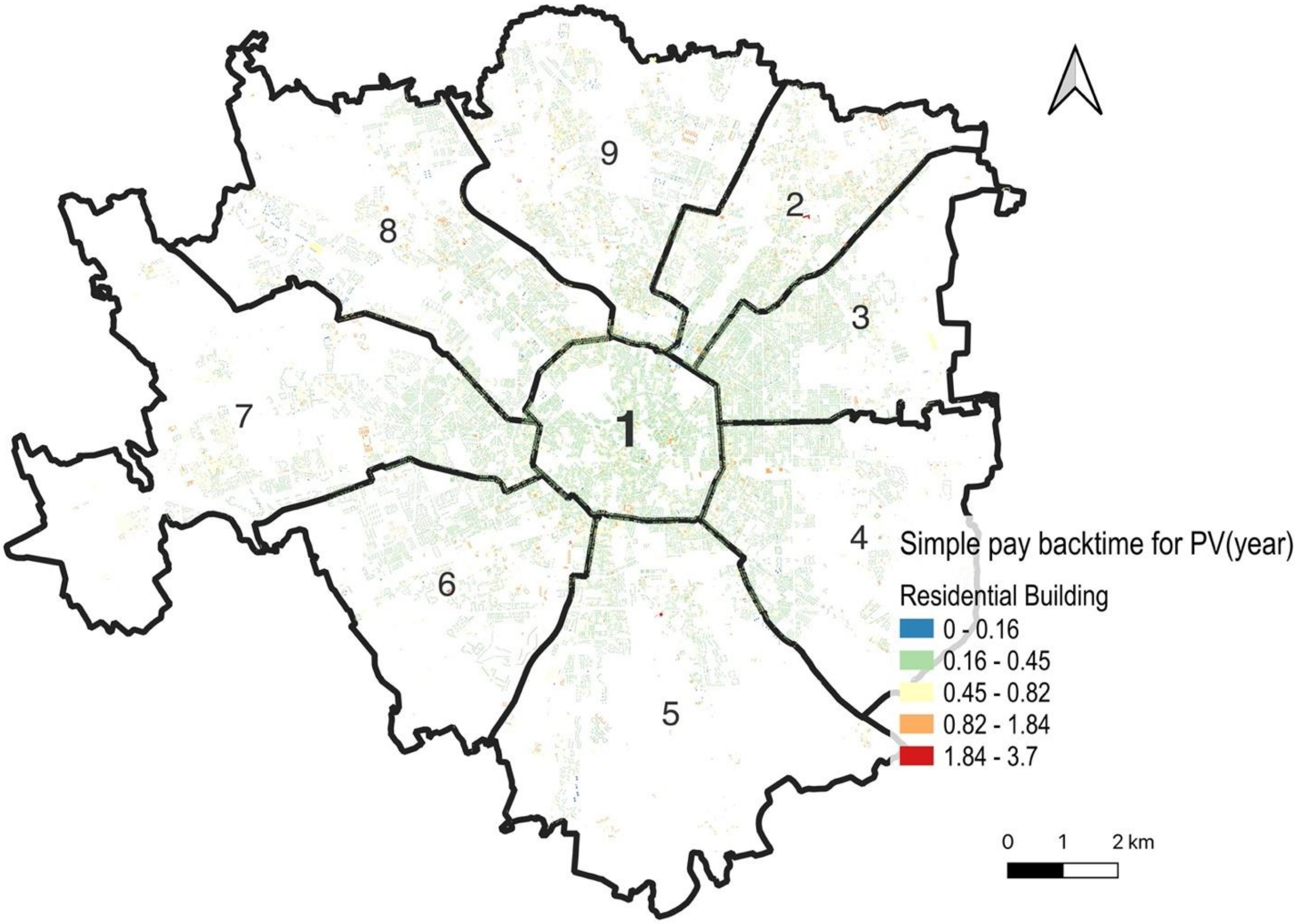

Figure 24. the simple payback time for photovoltaic technology.

Figure 24 is the map of Simple Payback Time (SPT) for photovoltaics. It shows the amount of time in years required to recover the investment cost for PV systems in different districts of Milan. The SPT is calculated by dividing the investment cost by the yearly revenues generated by the PV system. The majority of the buildings have a payback less than one year. The highest payback is 3.7 years which allows almost all of the buildings to be more profitable by investing in PV systems.

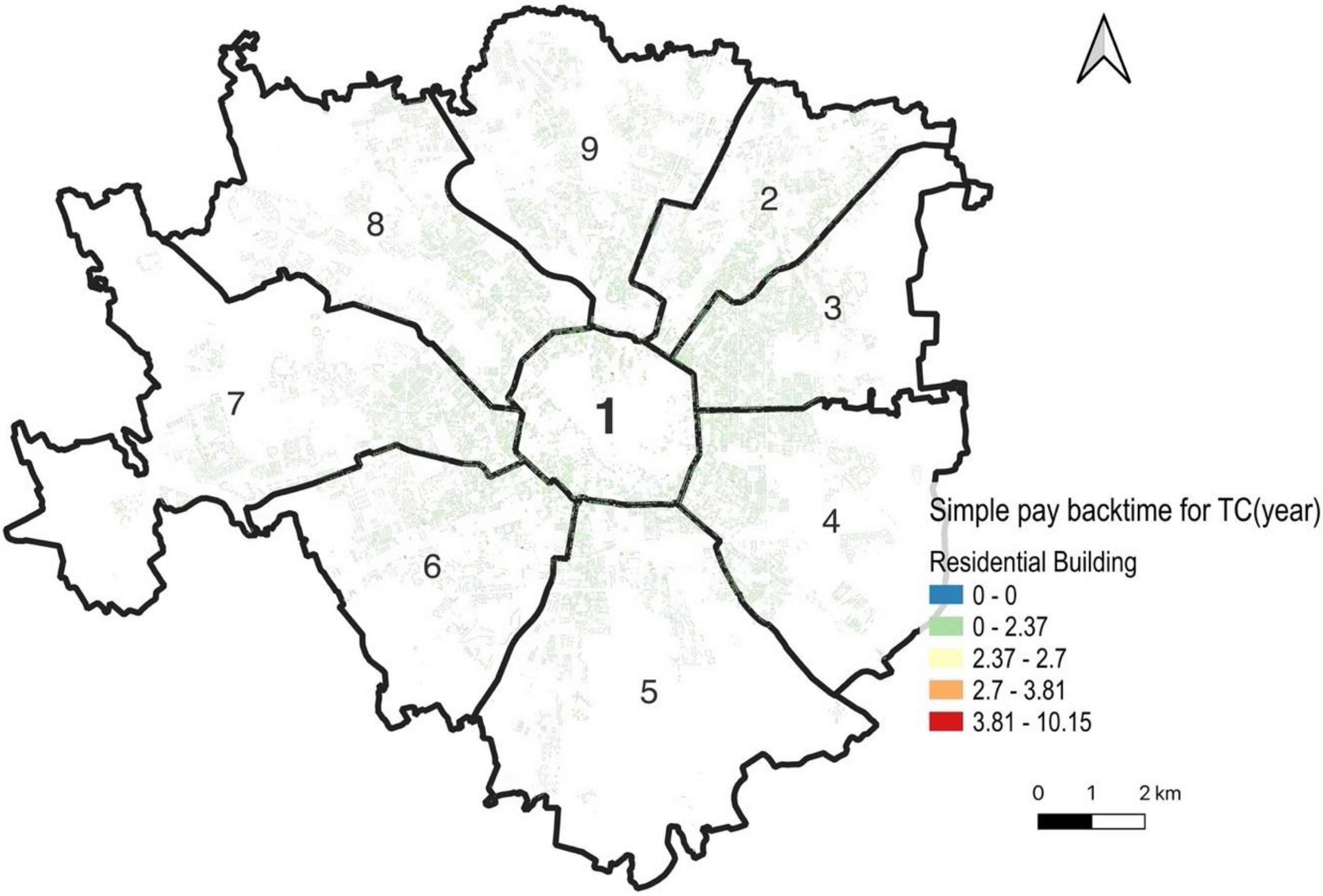

Figure 25. Simple payback time for solar thermal collector technology.

Figure 25 shows the Simple Payback Time (SPT) for solar thermal collectors. It indicates that the majority of the buildings have a payback period between 0 and 2.3 years. The highest payback time is nearly 10 years. This means that investing in solar thermal collectors can be highly profitable for many buildings in the area, with a significant return on investment within a relatively short period. The SPT is calculated as the ratio between the investment cost and the yearly revenues, and it does not consider discount cash flow methods.

Chapter five

Conclusion

The present study aimed to analyze the energy consumption and production of residential buildings in Milan, Italy, and investigate the potential of using solar technologies to reduce the dependence on conventional heating systems that rely on fossil fuels. The study employed a GIS-based approach and open-source data to analyze the energy consumption and potential of solar technologies. The results indicated that the energy consumption for domestic hot water and space heating is high, and the use of solar technologies can significantly reduce this energy consumption. The study also found that the majority of buildings in Milan have a payback period of less than one year for investing in photovoltaic systems, while investing in solar thermal collectors can be highly profitable, with a significant return on investment within a relatively short period The study also highlights that the greater the volume, the higher the energy consumption required to maintain comfortable indoor temperatures.

The analysis simulated monthly solar irradiation on the roofs of the buildings, which was used to evaluate the solar renewable technologies in kWh/m^2 for 12 different months. The results showed that the flat collectors had an average efficiency of 57%, ranging from 29% in December to 75% in July, while the vacuum collectors had an average efficiency of 70%, ranging from 52% in December to 69% in July. The study also found that the presence of large condominiums limits the roof area per inhabitant, thereby reducing the possibility of meeting the hot water energy demand, especially in winter.

The study's findings also revealed that the consumption of DHW and electricity remains relatively stable throughout the year, with only slight variations due to the differences in the number of days in each month. The self-sufficiency index for PV panels is 30%, with a monthly range of 11-48%. Furthermore, the optimal panel efficiency should be chosen considering the demand profile and global irradiation. The utilization of solar thermal collectors can help reduce the dependence of residential buildings on conventional heating systems, ensure the uninterrupted provision of hot water or space heating during power outages or natural disasters, and contribute to the reduction of carbon footprints, thus enhancing the building's resilience and sustainability.

According to Figure 26, the trend line for the use of photovoltaic technology in Milan shows an annual increase of 90% in the considered surface area, which corresponds to 30% of the roof area for each residential building. Following this trend, and based on the calculations of installed power shown in Figure 27, the goal will be achieved by the year 2056, as indicated in Figure 28.

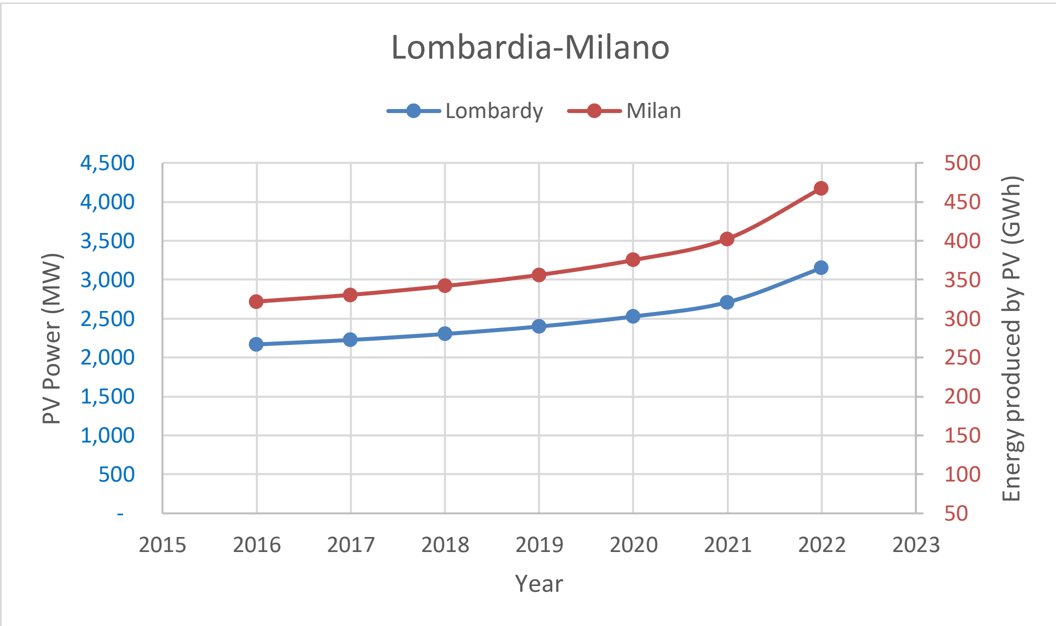

Figure 26. Trends in Lombardy's PV power and energy production by PV technology.

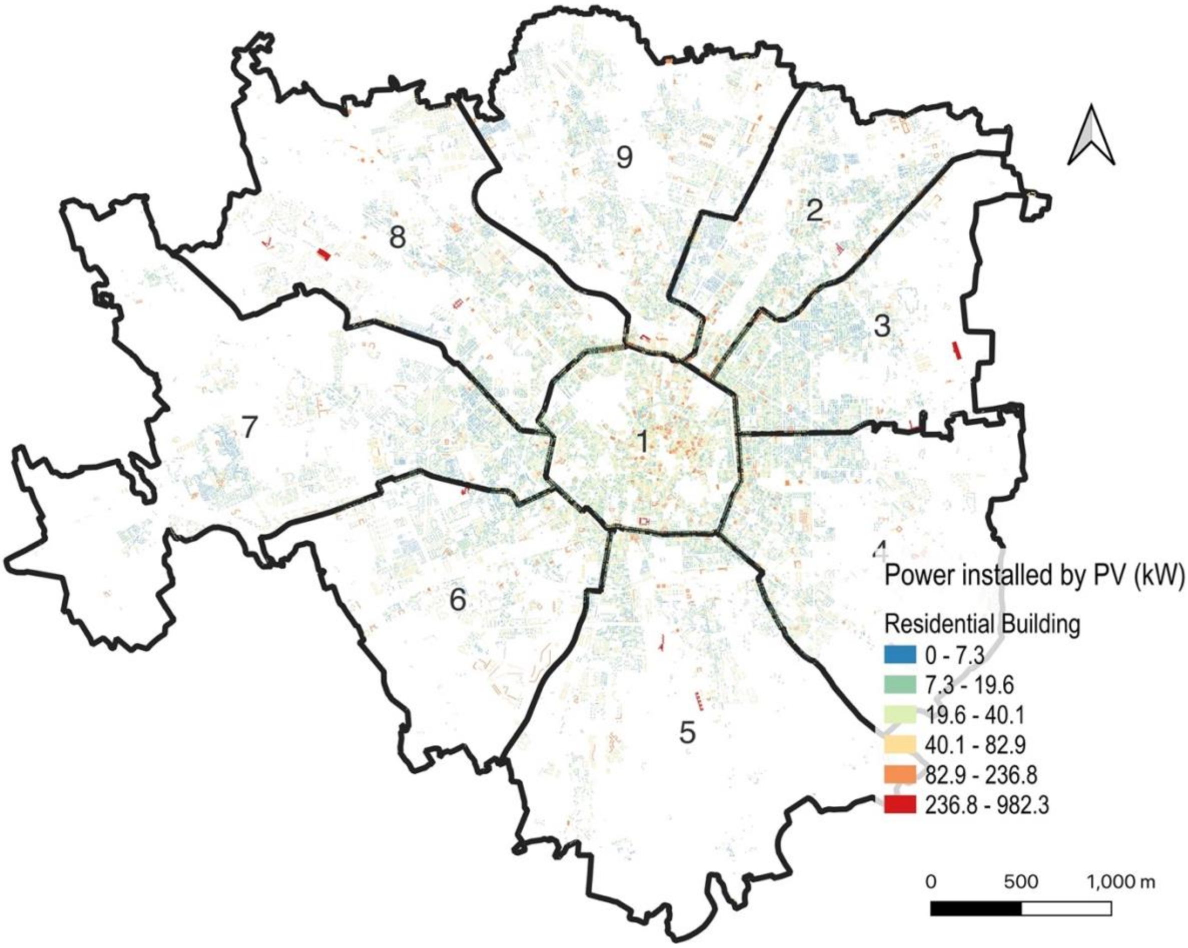

Figure 27. Power installed by PV (kWh).

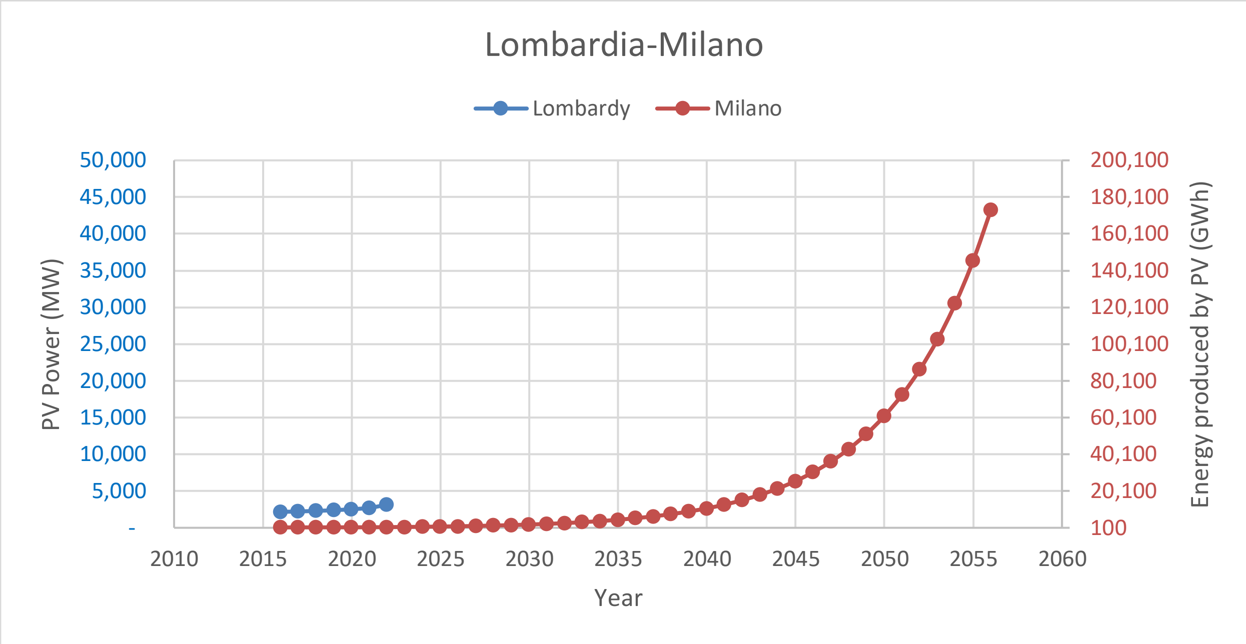

Figure 28. Estimated trend lines in Lombardy's PV power and energy production by PV technology.

In conclusion, this study demonstrates the potential of solar technologies to mitigate energy consumption in residential buildings in Milan, Italy. The findings emphasize the economic viability of investing in photovoltaic systems and highlight the importance of considering solar thermal collectors for enhanced energy efficiency. By leveraging solar technologies, buildings can contribute to a cleaner and more sustainable future, reducing reliance on fossil fuels and promoting environmental resilience.

Bibliography

(http://www.inuedizioni.com/it/prodotti/rivista/n-027-urbanistica-dossier).

1. A. Foucquier, S. Robert, F. Suard, L. Stéphan, A. Jay, (2013) State of the art in building modelling and energy performances prediction: a review, Renewable and Sustainable Energy Reviews, 23, 272–288
2. Adam, A.A. and Badea, A., 2017, October. Top-down model for the calculation of energy savings. In 2017 International Conference on ENERGY and ENVIRONMENT (CIEM) (pp. 211-215). IEEE. https://doi.org/10.1109/CIEM.2017.8120856
3. Alhamwi, A., Medjroubi, W., Vogt, T., & Agert, C. (2017). GIS-based urban energy systems models and tools: Introducing a model for the optimization of flexibilization technologies in urban areas. Applied Energy, 191, 1-9. https://doi.org/10.1016/j.apenergy.2017.01.048
4. Ali, K., Jianguo, D., & Kirikkaleli, D. (2022). Modeling the natural resources and financial inclusion on ecological footprint: The role of economic governance institutions. Evidence from ECOWAS economies. Resources Policy, 79, 103115. https://doi.org/10.1016/j.resourpol.2022.103115
5. Ali, U., Shamsi, M. H., Hoare, C., Mangina, E., & O'Donnell, J. (2021). Review of urban building energy modeling (UBEM) approaches, methods and tools using qualitative and quantitative analysis. Energy and Buildings, 246, 111073. https://doi.org/10.1016/j.enbuild.2021.111073
6. Alliance for Sustainable Energy, LLC, «URBANopt» 2019. [Online]. Available: https://docs.urbanopt.net/. [Accessed on 19 March 2023]
7. Arnette, A. N. (2013). Integrating rooftop solar into a multi-source energy planning optimization model. Applied Energy, 111, 456-467. https://doi.org/10.1016/j.apenergy.2013.05.003
8. ARPA Lombardia, Atmospheric Emissions Inventory INEMAR (INventario EMissioni ARia), https://www.inemar.eu/xwiki/bin/view/InemarDatiWeb/Risultati+Regionali (accessed June 2022)
9. Aurybi, M. A., Al-Kayeim, H. H., Gilani, S. I., & Ismaeel, A. A. (2006). Mathematical modeling to evaluate the performance enhancement of solar updraft power plant by an external heat source. ARPN Journal of Engineering and Applied Sciences, 11. http://scholars.utp.edu.my/id/eprint/25471
10. Baeldung. (n.d.). MAPE vs WAPE vs WMAPE. Baeldung. Retrieved from https://www.baeldung.com/cs/mape-vs-wape-vs-wmape

11. Bergamasco, L., & Asinari, P. (2011). Scalable methodology for the photovoltaic solar energy potential assessment based on available roof surface area: Application to Piedmont Region (Italy). Solar energy, 85(5), 1041-1055. https://doi.org/10.1016/j.solener.2011.02.022
12. C40 Cities, URL: https://www.c40.org [Online; accessed 21-Mar-2023].
13. Caputo, P., & Pasetti, G. (2017). GIS tools towards a renovation of the building heritage. Energy Procedia, 133, 435-443. https://doi.org/10.1016/j.egypro.2017.09.388
14. Carozza, M., Mutani, G., Coccolo, S., & Kaempf, J. (2017). Introducing a hybrid energy-use model at the urban scale: the case study of Turin (IT). In Proceedings of 3rd Building Simulations Application Conference BSA 2017, 8-10 February 2017, Bolzano, Italy. 8-10 February 2017. https://arodes.hes-so.ch/record/7721
15. Castellanos, S., Sunter, D. A., & Kammen, D. M. (2017). Rooftop solar photovoltaic potential in cities: how scalable are assessment approaches?. Environmental Research Letters, 12(12), 125005. https://iopscience.iop.org/article/10.1088/1748-9326/aa7857/meta
16. Charfi, W., Chaabane, M., Mhiri, H., & Bournot, P. (2018). Performance evaluation of a solar photovoltaic system. Energy Reports, 4, 400-406. https://doi.org/10.1016/j.egyr.2018.06.004
17. Council, G.W.E., 2017. GWEC Global Wind Report 2019. Global Wind Energy Council: Bonn, Germany. https://gwec.net/wp-content/uploads/2021/03/GWEC-Global-Wind-Report-2021.pdf
18. Covenant of Mayors, Sustainable Energy Action Plan 2018, https://www.covenantofmayors.eu/about/covenant-community/signatories/action-plan.html?scity_id=11832 (accessed June 2022)
19. De Vries, F.T., Thébault, E., Liiri, M., Birkhofer, K., Tsiafouli, M.A., Bjørnlund, L., Bracht Jørgensen, H., Brady, M.V., Christensen, S., De Ruiter, P.C. and d'Hertefeldt, T., 2013. Soil food web properties explain ecosystem services across European land use systems. Proceedings of the National Academy of Sciences, 110(35), pp.14296-14301. https://doi.org/10.1073/pnas.1305198110
20. Delmastro, C., Mutani, G., Schranz, L., & Vicentini, G. (2015). The role of urban form and socio-economic variables for estimating the building energy savings potential at the urban scale. Int J Heat Technol, 33(4), 91–100. https://core.ac.uk/download/pdf/234908797.pdf
21. DESA, U. (2014). Department of Economic and Social Affairs, Population Division, United Nations (2014). World Urbanization Prospects: The 2014 Revision, CD-ROM Edition. https://www.un.org/en/development/desa/publications/2014-revision-world-urbanization-prospects.html
22. Dogan, T., & Reinhart, C. (2017). Shoeboxer: An algorithm for abstracted rapid multi-zone urban building energy model generation and simulation.

Energy and Buildings, 140, 140-153. https://doi.org/10.1016/j.enbuild.2017.01.030

23. Duffle, J., & Beckman, W. (1980). Solar Engineering of Thermal Processes, John Wiley & Sons Inc.
24. Energy for Europe by European Commission, https://ec.europa.eu/energy/en [Online; accessed 21-Mar-2023]
25. Ferroukhi, R., Renner, M., García-Baños, C., Elsayed, S. and Khalid, A., 2020. Renewable Energy and Jobs: Annual Review 2020. https://www.irena.org//media/Files/IRENA/Agency/Publication/2019/May/IRENA_Renewable-energy-and-jobs_Annual-review_2019.pdf
26. Foucquier, A., Robert, S., Suard, F., Stéphan, L., & Jay, A. (2013). State of the art in building modelling and energy performances prediction: A review. Renewable and Sustainable Energy Reviews, 23, 272-288. https://doi.org/10.1016/j.rser.2013.03.004
27. Fuso Nerini, F., Tomei, J., To, L. S., Bisaga, I., Parikh, P., Black, M., ... & Mulugetta, Y. (2018). Mapping synergies and trade-offs between energy and the Sustainable Development Goals. Nature Energy, 3(1), 10-15. https://doi.org/10.1016/j.enpol.2020.112028
28. Gagnon, P., Margolis, R., Melius, J., Phillips, C., & Elmore, R. (2016). Rooftop solar photovoltaic technical potential in the United States. A detailed assessment (No. NREL/TP-6A20-65298). National Renewable Energy Lab.(NREL), Golden, CO (United States). https://doi.org/10.2172/1236153
29. Gobakis, K., & Kolokotsa, D. (2017). Coupling building energy simulation software with microclimatic simulation for the evaluation of the impact of urban outdoor conditions on the energy consumption and indoor environmental quality. Energy and Buildings, 157, 101–115. https://doi.org/10.1016/j.enbuild.2017.02.020
30. Google 2017 Project Sunroof Data Explorer https://sunroof.withgoogle.com/data-explorer/ (Accessed: 23 March 2023)
31. Hofierka, J., & Kaňuk, J. (2009). Assessment of photovoltaic potential in urban areas using open-source solar radiation tools. Renewable energy, 34(10), 2206-2214. https://doi.org/10.1016/j.renene.2009.02.021
32. Hong, T., Chen, Y., Luo, X., Luo, N. and Lee, S.H., 2020. Ten questions on urban building energy modeling. Building and Environment, 168, p.106508. https://doi.org/10.1016/j.buildenv.2019.106508
33. Hong, T., Lee, M., Koo, C., Jeong, K., & Kim, J. (2017). Development of a method for estimating the rooftop solar photovoltaic (PV) potential by analyzing the available rooftop area using Hillshade analysis. Applied Energy, 194, 320-332. https://doi.org/10.1016/j.apenergy.2016.07.001
34. Hong, T., Piette, M. A., Chen, Y., Lee, S. H., Taylor-Lange, S. C., Zhang, R., ... & Price, P. (2015). Commercial building energy saver: An energy retrofit analysis toolkit. Applied Energy, 159, 298-309. https://doi.org/10.1016/j.apenergy.2015.09.002

https://doi.org/10.1016/j.rser.2013.03.004

35. IEA, 2019. Renewables 2019 analysis and forecast to 2024 executive summary. https://www.iea.org/reports/renewables-2019
36. IEA. (2019). Perspectives for the clean energy transition. The critical role of buildings, IEA, Paris; www.iea.org/publications/reports/PerspectivesfortheCleanEnergyTransition/.
37. In focus: Energy efficiency in buildings (Dogan & Reinhart, 2017), http://www.eesi.org/, [Online; accessed 21-Mar-2023].
38. International Energy Agency (IEA) 2016 Trends in Photovoltaic Applications—Survey Report of Selected IEA Countries between 1992 and 2015 https://iea-pvps.org/wp-content/uploads/2020/01/Trends_2016_-_mr.pdf
39. Italy Energy Information at EnerData, [Online]. https://www.enerdata.net/estore/energy-market/italy/ [Accessed on 23 March 2023].
40. Jakubiec, J. A., & Reinhart, C. F. (2013). A method for predicting city-wide electricity gains from photovoltaic panels based on LiDAR and GIS data combined with hourly Daysim simulations. Solar Energy, 93, 127-143. https://doi.org/10.1016/j.solener.2013.03.022
41. Jebaraj, S., & Iniyan, S. (2006). A review of energy models. Renewable and sustainable energy reviews, 10(4), 281-311. https://doi.org/10.1016/j.rser.2004.09.004
42. K, I., & Shetty, R. (2023, May 11). Renewable Energy Efficiency in the End-User Segment. Regain Paradise. Retrieved from https://www.regainparadise.org/energy/renewable-energy-efficiency-end-user-segment.html
43. Kalogirou, S. A. (2013). Solar energy engineering: processes and systems. Academic press.
44. Kammen, D. M., & Sunter, D. A. (2016). City-integrated renewable energy for urban sustainability. Science, 352(6288), 922-928. https://www.science.org/doi/full/10.1126/science.aad9302
45. Kavgic, M., Mavrogianni, A., Mumovic, D., Summerfield, A., Stevanovic, Z. and Djurovic-Petrovic, M., 2010. A review of bottom-up building stock models for energy consumption in the residential sector. Building and environment, 45(7), pp.1683-1697. https://doi.org/10.1016/j.buildenv.2010.01.021
46. Kirikkaleli, D., & Adebayo, T. S. (2021). Do renewable energy consumption and financial development matter for environmental sustainability? New global evidence. Sustainable Development, 29(4), 583-594. https://doi.org/10.1002/sd.2159
47. Kumar, A. K., & Sharma, S. (2017). Recent updates on different methods of pretreatment of lignocellulosic feedstocks: a review. Bioresources and bioprocessing, 4(1), 1-19.

https://bioresourcesbioprocessing.springeropen.com/articles/10.1186/s40643-017-0137-9
48. Kurtz, S., Haegel, N., Sinton, R., & Margolis, R. (2017). A new era for solar. Nature photonics, 11(1), 3-5. https://www.nature.com/articles/nphoton.2016.232
49. Lauzet, N., Rodler, A., Musy, M., Azam, M. H., Guernouti, S., Mauree, D., & Colinart, T. (2019). How building energy models take the local climate into account in an urban context–A review. Renewable and Sustainable Energy Reviews, 116, 109390. https://doi.org/10.1016/j.rser.2019.109390
50. Li, W., Zhou, Y., Cetin, K., Eom, J., Wang, Y., Chen, G., & Zhang, X. (2017). Modeling urban building energy use: A review of modeling approaches and procedures. Energy, 141, 2445-2457. https://doi.org/10.1016/j.energy.2017.11.071
51. Li, X., & Wen, J. (2014). Review of building energy modeling for control and operation. Renewable and Sustainable Energy Reviews, 37, 517-537. https://doi.org/10.1016/j.rser.2014.05.056
52. Liu, Z., Deng, Z., He, G., Wang, H., Zhang, X., Lin, J., ... & Liang, X. (2022). Challenges and opportunities for carbon neutrality in China. Nature Reviews Earth & Environment, 3(2), 141-155. https://www.nature.com/articles/s43017-021-00244-x
53. Lund, H. (2007). Renewable energy strategies for sustainable development. energy, 32(6), 912-919. https://doi.org/10.1016/j.energy.2006.10.017
54. Lund, H. (2014). Renewable energy systems: a smart energy systems approach to the choice and modeling of 100% renewable solutions. Academic Press.
55. Mapdwell 2023 Mapdwell Solar https://mapdwell.com/en (Accessed: 23 March 2023)
56. Margolis, R., & Zuboy, J. (2006). Nontechnical barriers to solar energy use: review of recent literature. https://doi.org/10.2172/893639
57. McKenney, D. W., Pelland, S., Poissant, Y., Morris, R., Hutchinson, M., Papadopol, P., ... & Campbell, K. (2008). Spatial insolation models for photovoltaic energy in Canada. Solar Energy, 82(11), 1049-1061. https://doi.org/10.1016/j.solener.2008.04.008
58. Meha, D., Novosel, T. and Duić, N., 2020. Bottom-up and top-down heat demand mapping methods for small municipalities, case Gllogoc. Energy, 199, p.117429. https://doi.org/10.1016/j.energy.2020.117429
59. Moghadam, S. T., Delmastro, C., Corgnati, S. P., & Lombardi, P. (2017). Urban energy planning procedure for sustainable development in the built environment: A review of available spatial approaches. Journal of Cleaner Production, 165, 811-827. https://doi.org/10.1016/j.jclepro.2017.07.142
60. Muhammad, Y., Saini, P., Knobloch, K., Frandsen, H. L., & Engelbrecht, K. (2023). Rock bed thermal energy storage coupled with solar thermal collectors in an industrial application: Simulation, experimental and

parametric analysis. Journal of Energy Storage, 67, 107349. https://doi.org/10.1016/j.est.2023.107349

61. Mutani, G. (2023) Energy planning of the territory and energy communities. Models, databases, tools and applications. In "CONTENUTI E STRUMENTI DELLA PIANIFICAZIONE URBANA E TERRITORIALE. dalla Lezione di Giampiero Vigliano alle Prospettive del Greennew deal. (Vol. 27, pp. 106-109)
62. Mutani, G., & Todeschi, V. (2018). Energy resilience, vulnerability and risk in urban spaces. Journal of Sustainable Development of Energy, Water and Environment Systems, 6(4), 694-709. https://doi.org/10.13044/j.sdewes.d6.0203
63. Mutani, G., & Todeschi, V. (2020). Building energy modeling at neighborhood scale. Energy Efficiency, 13(7), 1353-1386. https://link.springer.com/article/10.1007/s12053-020-09882-4
64. Mutani, G., & Todeschi, V. (2021). GIS-based urban energy modelling and energy efficiency scenarios using the energy performance certificate database. Energy Efficiency, 14(5), 47. https://link.springer.com/article/10.1007/s12053-021-09962-z
65. Mutani, G., & Todeschi, V. (2021). Roof-Integrated green technologies, energy saving and outdoor thermal comfort: insights from a case study in urban environment. Planning, International Journal of Sustainable Development and Planning 16(1), 13-23. https://doi.org/10.18280/ijsdp.160102
66. Mutani, G., and Todeschi. V., (2017): "Space heating models at urban scale for buildings in the city of Turin (Italy)." Energy Procedia 122 841-846. https://doi.org/10.1016/j.egypro.2017.07.445
67. Mutani, G., Delmastro, C., Gargiulo, M., & Corgnati, S. P. (2016). Characterization of building thermal energy consumption at the urban scale. Energy Procedia, 101, 384-391. https://doi.org/10.1016/j.egypro.2016.11.049
68. Mutani, G., Todeschi, V. and Beltramino, S., 2020. Energy consumption models at urban scale to measure energy resilience. Sustainability, 12(14), p.5678. https://doi.org/10.3390/su12145678
69. Mutani, G., Todeschi, V., Kämpf, J., Coors, V., & Fitzky, M. (2018, October). Building energy consumption modeling at urban scale: Three case studies in Europe for residential buildings. In 2018 IEEE International Telecommunications Energy Conference (INTELEC) (pp. 1-8). IEEE. https://doi.org/10.1109/INTLEC.2018.8612382
70. Mutani, G., Vocale, P., & Javanroodi, K. (2023). Toward Improved Urban Building Energy Modeling Using a Place-Based Approach. Energies, 16(9), 3944.
71. N. van Beck, «Classification of energy models» Tilburg University & Eindhoven University of Technology, 1999.

https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=6769671f4db43bc0edfcf74acb58f1d27dac74e7

72. Nageler, P., Zahrer, G., Heimrath, R., Mach, T., Mauthner, F., Leusbrock, I., ... & Hochenauer, C. (2017). Novel validated method for GIS based automated dynamic urban building energy simulations. Energy, 139, 142-154. https://doi.org/10.1016/j.energy.2017.07.151
73. Official Journal of The European Union. (2018). Directive (EU) 2018/844 of the European Parliament and of the Council of 30 May 2018 Amending Directive 2010/31/EU on the Energy Performance of Buildings Directive 2012/27/EU on Energy Efficiency; L156/75.
74. Padovani, C., & Salvaggio C., (2023) Strategy for environmental sustainability and urban resilience in the Pgt of the city of Milan: the Air-Climate Plan. In "CONTENUTI E STRUMENTI DELLA PIANIFICAZIONE URBANA E TERRITORIALE. dalla Lezione di Giampiero Vigliano alle Prospettive del Greennew deal. (Vol. 27, pp. 93-99)
75. Palmer, D., Koumpli, E., Cole, I., Gottschalg, R., & Betts, T. (2018). A GIS-based method for identification of wide area rooftop suitability for minimum size PV systems using LiDAR data and photogrammetry. Energies, 11(12), 3506. https://doi.org/10.3390/en11123506
76. Prina, M. G., Manzolini, G., Moser, D., Nastasi, B., & Sparber, W. (2020). Classification and challenges of bottom-up energy system models-A review. Renewable and Sustainable Energy Reviews, 129, 109917. https://doi.org/10.1016/j.rser.2020.109917
77. Puglisi, G., Zanghirella, F., Ungaro, P., & Cammarata, G. (2016). A methodology for the generation of energy consumption profiles in the residential sector. Int J Heat Technol, 34(3), 491–497. https://doi.org/10.18280/ijht.340320.
78. Rau, C. (2016). Supporting carbon neutrality in urban environments using positive energy buildings. Urban Regeneration & Sustainability, 224.
79. RegainParadise. (2023, May 11). Renewable Energy Efficiency in the End-User Segment. Retrieved from https://www.regainparadise.org/energy/renewable-energy-efficiency-end-user-segment.html
80. Reinhart, C. F., & Davila, C. C. (2016). Urban building energy modeling–A review of a nascent field. Building and Environment, 97, 196-202. https://doi.org/10.1016/j.buildenv.2015.12.001
81. Roulet, C. A. (2002). prEN-ISO 13790-A simplified method to assess the annual heating energy use in buildings. TRANSACTIONS-AMERICAN SOCIETY OF HEATING REFRIGERATING AND AIR CONDITIONING ENGINEERS, 108(2), 911-918.
82. Ryan, E. M., & Sanquist, T. F. (2012). Validation of building energy modeling tools under idealized and realistic conditions. Energy and buildings, 47, 375-382. https://doi.org/10.1016/j.enbuild.2011.12.020

83. Santamouris, M. (2013). On the built environment—the urban influence. In Energy and climate in the urban built environment (pp. 3-18). Routledge London, UK.
84. Schwartz, L., Wei, M., Morrow, W., Deason, J., Schiller, S. R., Leventis, G., ... & Zhou, Y. (2017). Electricity end uses, energy efficiency, and distributed energy resources baseline. https://escholarship.org/content/qt0n32c92z/qt0n32c92z.pdf
85. Sharif, A., Baris-Tuzemen, O., Uzuner, G., Ozturk, I., & Sinha, A. (2020). Revisiting the role of renewable and non-renewable energy consumption on Turkey's ecological footprint: Evidence from Quantile ARDL approach. Sustainable Cities and Society, 57, 102138. https://doi.org/10.1016/j.scs.2020.102138
86. Shi, Z., Fonseca, J. A., & Schlueter, A. (2017). A review of simulation-based urban form generation and optimization for energy-driven urban design. Building and Environment, 121, 119-129. https://doi.org/10.1016/j.buildenv.2017.05.006
87. Shkurti, A., 2018. Energy consumption modeling in the western balkan countries using a top-down approach. Academic Journal of Interdisciplinary Studies, 7(3), p.35.
88. Singh, R., & Banerjee, R. (2015). Estimation of rooftop solar photovoltaic potential of a city. Solar Energy, 115, 589-602. https://doi.org/10.1016/j.solener.2015.03.016
89. Sokol, J., Davila, C. C., & Reinhart, C. F. (2017). Validation of a Bayesian-based method for defining residential archetypes in urban building energy models. Energy and Buildings, 134, 11-24. https://doi.org/10.1016/j.enbuild.2016.10.050
90. Statistics explained, (2022) Eurostat [Online]. Available: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy_statistics_-_an_overview [Accessed on 18 March 2023].
91. Strupeit, L., & Palm, A. (2016). Overcoming barriers to renewable energy diffusion: business models for customer-sited solar photovoltaics in Japan, Germany and the United States. Journal of Cleaner Production, 123, 124-136. https://doi.org/10.1016/j.jclepro.2015.06.120
92. Suganthi, L., & Samuel, A. A. (2012). Energy models for demand forecasting—A review. Renewable and sustainable energy reviews, 16(2), 1223-1240. https://doi.org/10.1016/j.rser.2011.08.014
93. Summerfield, A.J., Lowe, R.J. and Oreszczyn, T., 2010. Two models for benchmarking UK domestic delivered energy. Building Research & Information, 38(1), pp.12-24. https://doi.org/10.1080/09613210903399025
94. Šúri, M., Huld, T. A., Dunlop, E. D., & Ossenbrink, H. A. (2007). Potential of solar electricity generation in the European Union member states and candidate countries. Solar energy, 81(10), 1295-1305. https://doi.org/10.1016/j.solener.2006.12.007

95. Swan, L.G. and Ugursal, V.I., 2009. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. Renewable and sustainable energy reviews, 13(8), pp.1819-1835. https://doi.org/10.1016/j.rser.2008.09.033
96. Taghizadeh-Hesary, F., Zakari, A., Yoshino, N., & Khan, I. (2022). Leveraging on energy security to alleviate poverty in Asian economies. The Singapore Economic Review, 1-28. https://doi.org/10.1142/S0217590822440015
97. Takebayashi, H., Ishii, E., Moriyama, M., Sakaki, A., Nakajima, S., & Ueda, H. (2015). Study to examine the potential for solar energy utilization based on the relationship between urban morphology and solar radiation gain on building rooftops and wall surfaces. Solar Energy, 119, 362-369. https://doi.org/10.1016/j.solener.2015.05.039
98. Tootkaboni, M. P., Ballarini, I., & Corrado, V. (2021). Analysing the future energy performance of residential buildings in the most populated Italian climatic zone: A study of climate change impacts. Energy Reports, 7, 8548-8560. https://doi.org/10.1016/j.egyr.2021.04.012
99. UNEP. (2018). The Emissions Gap Report. https://www.unenvironment.org/resources/emissions-gap-report-2018.
100. United Nation, https://www.un.org/ [Online; accessed 21-Mar-2023].
101. United Nations Statistics Division. (2022). Goal 7: Ensure access to affordable, reliable, sustainable, and modern energy for all. In United Nations Statistics Division (Ed.), The Sustainable Development Goals Report 2022. URL: https://unstats.un.org/sdgs/report/2022/Goal-07/ [Online; accessed 25-Apr-2023].
102. United Nations. (2022). Goal 11: Sustainable cities and communities. United Nations Sustainable Development Goals. URL: https://sdgs.un.org/goals/goal11 [Online; accessed 25-Apr-2023].
103. United Nations. (2022). Goal 13: Climate action. United Nations Sustainable Development Goals. URL: https://sdgs.un.org/goals/goal13 [Online; accessed 25-Apr-2023].
104. United Nations. (2022). Sustainable Development Goals. United Nations Sustainable Development Goals. Retrieved from https://sdgs.un.org/goals [Online; accessed 25-Apr-2023].
105. Wang, L., Liu, Y., & Lin, B. (2018). Review of City Energy and Carbon Emission Policies in China: Analysis and Comparison with U.S. Policies. Energies, 11(3), 529. https://www.nature.com/articles/s43017-021-00244-x
106. Wang, W., Wu, Y., & Choguill, C. (2021). Prosperity and inclusion: The impact of public housing supply on urban inclusive growth in China. Land Use Policy, 105, 105399. https://doi.org/10.1016/j.landusepol.2021.105399
107. Weyant, J. P. (1985). General economic equilibrium as a unifying concept in energy-economic modeling. Management Science, 31(5), 548-563. https://doi.org/10.1287/mnsc.31.5.548

108. Wirth, H., & Schneider, K. (2015). Recent facts about photovoltaics in Germany. Fraunhofer Ise, 92. https://www.kompozit.org.tr/wp-content/uploads/2021/04/recent-facts-about-photovoltaics-in-germany.pdf

Appendices

8.1 Energy Performance Certificate (EPC) Data

In the context of sustainable urban development, the Energy Performance Certificate (EPC) provides valuable information on the energy efficiency of buildings. The EPC data can be used to assess the energy performance of buildings, compare the energy efficiency of different buildings, and identify energy-saving opportunities. Therefore, EPC data can play a critical role in developing strategies for improving the energy efficiency of buildings and achieving sustainability goals.

To support research and analysis related to EPC data, the Lombardy region of Italy has made available a public database called "Database CENED 2 - Certificazione ENergetica degli EDifici". This database contains information on the energy performance of buildings in the Lombardy region, including the energy rating, energy consumption, CO_2 emissions, and other relevant information. The database includes information on both residential and non-residential buildings and covers a wide range of building types.

Researchers and practitioners interested in the energy performance of buildings in the Lombardy region can use this database to conduct statistical analysis, develop energy models, and identify patterns and trends related to energy performance. This data can also be used to evaluate the effectiveness of energy policies and regulations related to building energy efficiency.

Therefore, the Lombardy region's EPC database is a valuable resource for researchers and practitioners interested in sustainable urban development and building energy efficiency. The database can provide insights into the energy performance of buildings in the region and support the development of effective strategies for improving energy efficiency and reducing carbon emissions.

It is a mandatory requirement in Italy for all residential, commercial, and public buildings that are put on the market for sale or rent. The validity of the EPC is ten years, and it must be issued by a certified energy certifier. The process of obtaining an EPC in Italy involves an assessment of the building's energy performance by a certified energy certifier. The certifier examines several factors, including the construction materials, heating and cooling systems, lighting, and other elements that may impact the building's energy consumption. The certifier uses specific software to analyze the building's energy performance and assigns it an energy rating on a scale from A to G, with A being the most energy-efficient and G being the least efficient.

The results of the energy analysis are then used to generate an EPC, which includes information on the building's energy rating, energy consumption, CO_2 emissions, and recommendations for enhancing its energy efficiency. The EPC must be displayed in a visible place within the building, and a copy must be provided to the prospective buyer or tenant.

8.2 Energy statistics

In the year 2020, the European Union witnessed a reduction in the gross available energy as compared to 2019, which declined by 8.1%. Despite a persistent long-term downward trend, crude oil and petroleum products continued to be the primary energy source for the European economy, followed by natural gas, which ranked second. However, both oil and natural gas exhibited a decline in 2020, with a decrease of 12.6% and 2.4%, respectively. On the other hand, renewable energy sources observed a continual increase, surpassing solid fossil fuels in 2018 and 2019, and gaining further ground in 2020. Solid fossil fuels experienced a decline of 18.4% in 2020, reaching the lowest value since 1990. This shift toward renewable energy sources signifies a significant transformation in the energy landscape of the European Union, albeit there are still considerable challenges to overcome (*Energy Statistics - an Overview*, 2022).

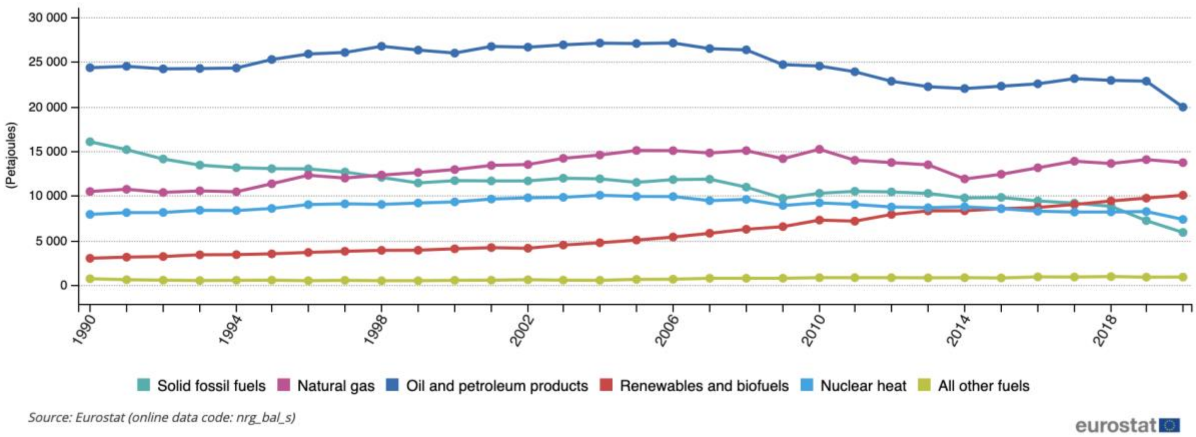

Figure 29. "Gross available energy, EU, 1990-2020", Source: Eurostat (online data code: nrg_bal_s).

"In 2020, the primary production of energy in the European Union (EU) was lower than in the previous year, amounting to 24,027 petajoules (PJ), a decline of 7.1%. The most significant downward trends were observed in the production of solid fossil fuels (-16.5%), natural gas (-21.2%), and oil and petroleum products (-5.2%). Nuclear heat production also decreased sharply (-10.7%) after remaining relatively stable for several years. However, there was an increase in renewable energies (+3.0%) and non-renewable waste (+1.6%). "Renewable energies accounted for the highest share in primary energy production in the EU in 2020 (40.8%), followed by nuclear heat (30.5%), solid fossil fuels (14.6%), natural gas (7.2%), oil and petroleum products (3.7%), and non-renewable waste (2.4%)" (*Energy Statistics - an Overview*, 2022).

“Looking at the past decade (2010-2020), the trend in primary energy production has been negative for solid fossil fuels, oil, natural gas, and nuclear energy. Natural gas production saw the most significant decline (-62.4%), followed by solid fossil fuels and oil and petroleum products, which experienced drops of 43.0% and 35.1%, respectively. On the other hand, renewable energies saw a clear positive trend over the same period, with a 39.2% increase (excluding 2011). Non-renewable waste also experienced an increase in production, rising by 30.2%. These trends reflect the EU's ongoing efforts to shift towards a more sustainable energy mix and reduce its reliance on fossil fuels” (*Energy Statistics - an Overview*, 2022).

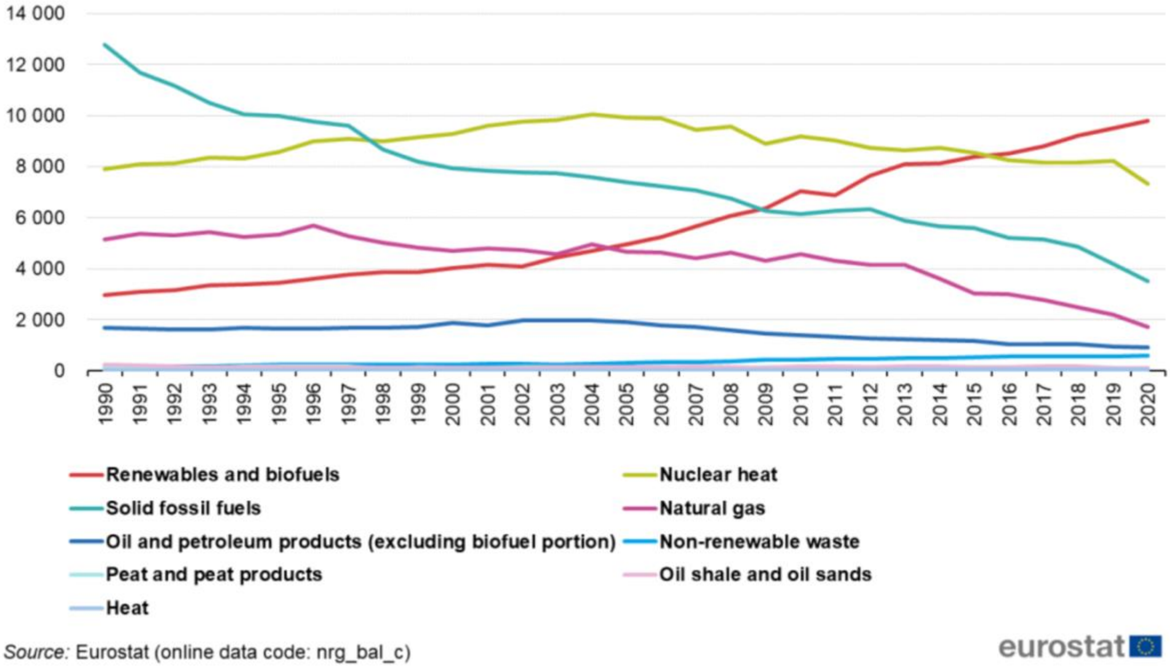

Figure 30. Primary energy production by fuel, EU, in selected years 1990-2020 (petajoule) Source: Eurostat (nrg_bal_c)

“The largest portion of energy consumption in the year 2020 in the EU was utilized in energy transformation, as shown in Figure 3, followed by the transportation sector, households, and the industrial sector, with percentages of 24.2%, 18.8%, 18.5%, and 17.2%, respectively. The services sector accounted for

9.1% of the energy consumption, while non-energy use and other sectors accounted for 6.7% and 5.5%, respectively" (Eurostat, 2022).

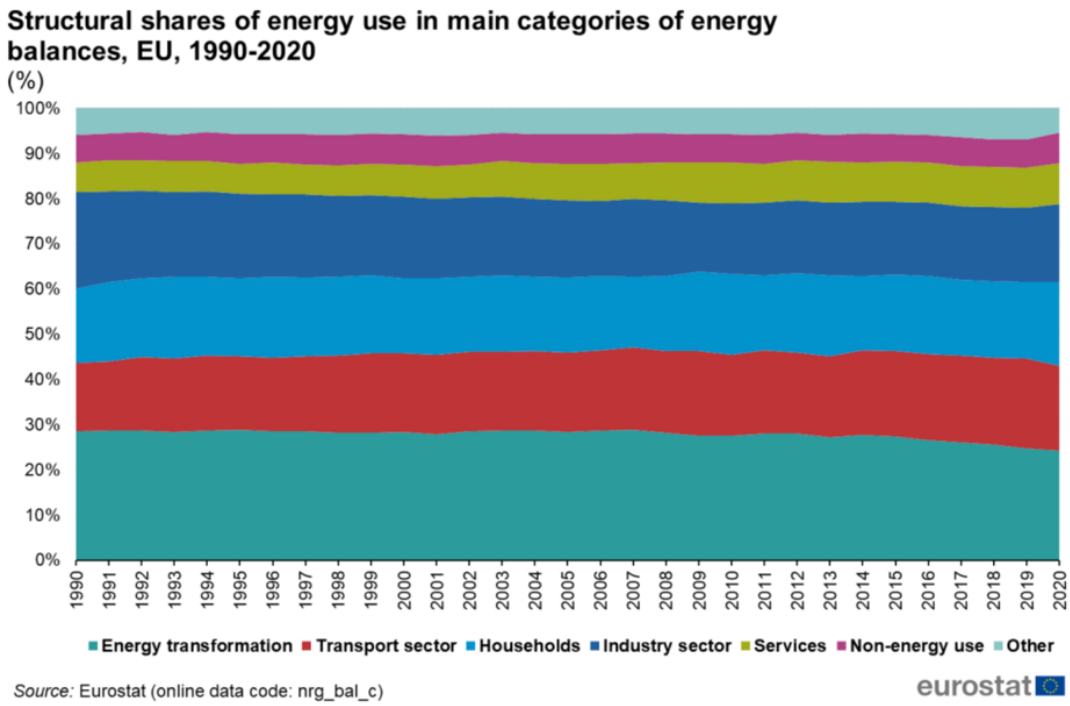

Figure 31. Structural shares of energy use in main categories of energy balances, EU, 1990-2020 (%) Source: Eurostat (nrg_bal_c)