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***Dissertation Report***

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# ***Parametric Study of different Levels of Detail in buildings for the estimation of Annual Heating Demand: A case study in London, UK***

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I do give permission for my dissertation to be made available to students in future years if selected as an example of good practice.

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# Abstract

In the 21st century, the importance of energy in developing countries is indisputable. In the whole wide world, the building stock is responsible for the two fifths of the total world annual energy consumption. Over recent years, the refurbishment of the existing building stock, with the purpose of being transmuted into energy efficient, and the construction of sustainable and low energy buildings, has interested the broader construction sector. Taking into account the predictions about the future climate, the need for the expeditious refurbishment of entire building blocks is essential. The Level of Detail (LoD), that it is the method used to display a project's construction details, is an important factor to consider while modelling energy at the urban scale. A parametric study regarding the data requirements for the estimation of the annual residential heat demand in city of London has been conducted for this research project. More particularly, the requirement of the observation of the actual roof type (LoD2) and the window to wall ratio (LoD3) has been examined in two different areas. The results have shown that there is a minor difference from the upgrade of lower to higher LoD, regarding these parameters. This means that the time and money – consuming procedure of observation for the roof types and calculation of windows to wall ratio of buildings at an area is not necessary, and energy performance of buildings could be estimated with an assumption from archetypes and building ages. Finally, in future work, from the energy aspect, the refurbishment date, as well as different air change rate of buildings or indoor temperatures, could be taken into consideration for more representative results, at mixed age areas, but also, from the data requirement and modelling point of view, studies could be conducted regarding the simplest way to link the required data from different surveying companies into a single dataset that could be used with ease from analysers and by this way help policy makers, regarding the reduction of the residential energy demand and carbon dioxide emissions.

Keywords: Level of Detail (LoD), Heat Demand, Parametric study, London dwelling stock, Energy Performance, QGIS, Python

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# Abbreviations

| | |
|---|---|
| **ACR** | Air Change Rate |
| **APUR** | Atelier Parisien d' Urbanisme |
| **BIM** | Building Information Modelling |
| **CO2** | Carbon Dioxide |
| **EPC** | Energy Performance Certificate |
| **EU** | European Union |
| **GHG** | GreenHouse Gas |
| **GIS** | Geographic Information System |
| **LoD** | Level of Detail |
| **RMSE** | Root Mean Squared Error |
| **UK** | United Kingdom |
| **VGI** | Volunteered Geographic Information |
| **WWR** | Window to Wall Ratio |
| **2D** | Two-Dimensional |
| **3D** | Three-Dimensional |

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# Chapter 1

# Introduction

# 1 Introduction

*This chapter introduces the background knowledge to this research study. Furthermore, it presents the aims and the objectives of the project, the methodology and the structure of the Master of Research thesis.*

## 1.1 Background

In the 21st century, the importance of energy in developing countries is indisputable [1]. The energy consumption has been augmented, presently, due to the necessities of populace, as the prosperity all over the world and the well-being depends on the energy production [1]. Nonetheless, the energy sources, universally, are limited. Hence, the rapid increase in energy consumption, makes the use of renewable energy sources inevitable [1].

In the whole wide world, the building stock is responsible for the two fifths of the total world annual energy consumption [2]. The most crucial reason for the 40% proportion of building energy consumption is that buildings require energy for lighting, air-conditioning, cooling, and heating. Without any doubt, carbon dioxide (CO2) emissions due to energy growth in buildings, simultaneously with other environmental issues, are caused by the escalation of the energy demand [2]. Consequently, over recent years, the refurbishment of the existing building stock, with the purpose of being transmuted into energy efficient, and the construction of sustainable and low or zero energy buildings, have interested the broader construction and engineering sector.

Taking into consideration the predictions about the future climate, the need for renovation and, more particularly, the expeditious refurbishment of entire building blocks or cities, are essential. Unquestionably, nowadays, one of the most important issues across the world is the climate change, as future climate scenarios state that the frequency in extreme events will increase, as well as the sea level rise and global warming are inevitable [3]. Carbon dioxide (CO2) emissions and other anthropogenic greenhouse gases, that come from the built environment, have an impact on climate change [3,4]. However, the built environment is, also, affected from the emissions of the greenhouse gases and the climate change [3,4]. Therefore, the building stock and the climate change have an interdependent relationship.

Cities are mostly related to the above matters, as the 54%, namely more than the half, of the population of the world, is concentrated in urban areas [5]. Apart from that, prognostications state that this percentage will increase to 66% by 2050 [5]. As a result of climate change, city regions are the most vulnerable to city-scale phenomena such as droughts, floods, and heat waves, putting not just human thermal comfort, but also human lives in danger [6]. Aside from that, urbanization is associated with increased industrialization and per capita energy consumption, both of which exacerbate climate change [7]. As a result, cities are both affected by and contribute to climate change, as has been stated previously for the built environment. Consequently, there is a link between urbanization and climate change, implying that urban planning is required to mitigate it. Hence, city-scale energy modelling is critical for decelerating global-scale climate change, as the rapid transformation of metropolitan regions should be done.

Without a doubt, the Level of Detail is an important factor to consider while modelling energy at the urban scale. When the term 'Level of Detail' is used, it refers to the quantity of real-world object features that are determined to be used based on the project's needs, as well as economic and computational factors [8]. In simple words, it is the method used to display a project's construction details. For example, the CityGML, which is a data model that stores 3D city and landscape models, includes four LoDs for the 3D representation of the built environment, and it is an open, multipurpose model that can be used for geographic transactions, data storage, and database modelling [9]. In particular, the LoD1 is a simple rectangular block that represents the simplest geometric representation of a building for the purpose of calculating heating demand [9]. Regarding LoD2, the roof form is added to the building level, while the location of the façade windows is also added in the LoD3 [9]. Finally, the LoD4 incorporates the modelling of the indoor space [9]. However, some engineers add a fifth LoD to the above, which is the most accurate regarding even the orientation and the location of the building [10]. As a result, the higher the LoD is, the more comprehensive the representation.

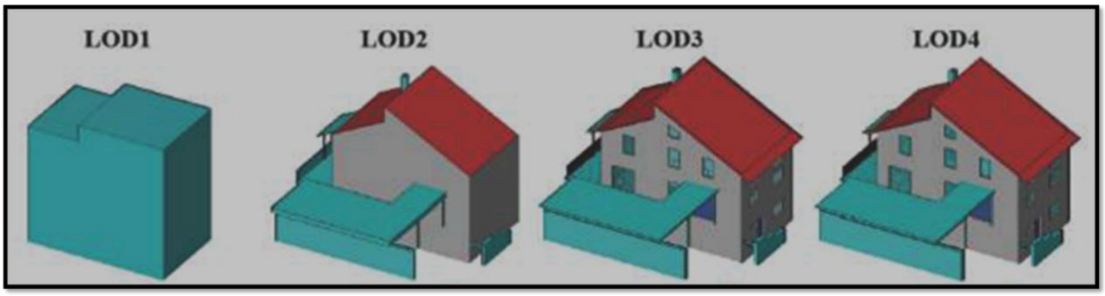



**Figure 1-1 Level of Details according to CityGML [9]**

In light of the foregoing, and for the reasons stated, the energy upgrade of cities is the most effective and efficient way to combat climate change. Therefore, a concept that explores the required Level of Detail for energy modelling at the city scale, which should be the most appropriate, is urgently needed in order to achieve both quality and accuracy, as well as economic and computational simplicity.

## 1.2 Area of Interest (AOI)

For this study the city of London, in United Kingdom (UK) has been used as the reference area. More particularly, one of the main reasons, that London has been chosen for the case study, is that data, that can be found with difficulty and with expensive and time-consuming processes, are available from “Colouring London” project and could be obtained [11]. In more details, the estimation of the annual heating demand of dwellings in London has been decided to be done.

As regards the building stock in UK, and as a consequence in London, could be described either by the type of the houses, namely their design, or by the construction of dwellings. The most frequent type of properties in UK, and especially in urban areas, are end terrace and terrace, detached and semi-detached houses, flats and apartments [12,13]. Concerning the method of construction, the vast majority of the dwellings is brick or block wall construction, and it is commonly known as the traditional construction [13]. In response to the building age, these dwellings consist of either solid walls ( 1800s – 1950) or cavity walls (1935 – now) [13]. Then, there is the non-traditional construction, which follows the traditional, and consists of metal framed, in-situ and pre-cast concrete and timber framed dwellings [13]. More particularly, the metal framed properties had been built after the Second World War, when the expeditious re-construction of buildings was an urgent need [13]. About the in-situ concrete buildings, these have been introduced from 1940s to 1970s, at the inter-war period with the intention of maintaining low-cost construction [13]. The pre-cast dwellings, on the other side, had been intended the 1920s. Their construction had been discontinued the 1930s and 1940s, and has come back the 1950s and 1960s [13]. Last but not least, the advent of the timber framed properties was in 1920s and their construction lasted for 6 decades. However, timber framed buildings came back in 1990s, but with lower demand due to their high fire risk and construction cost [13]. Finally, the majority of the non-traditional constructions, except of timber-framed properties, have an external layer of brick or tile, in order to mimic the traditional constructions.

## 1.3 Statement of Problem

As it has been stated above, for the particular project, the building stock in London city has been chosen, and more specifically, the dwellings, as the majority of them are old buildings that need rapid re-modelling. For the purpose of this study, due to climate change and other environmental issues, and the continuous increase of energy demand at the old building stock, the annual heating demand of the residential buildings in London will be evaluated. The goal is to understand, which is the least building information that is required, in order to have a proper accuracy of the calculation of the annual heating demand. After that, stakeholders could comfortably perceive the minimum Level of Detail (LoD) that is needed, as a result from the use of this knowledge for the estimation of heating demand across UK. In this way, areas with eminent heating demand could be detected and the renovation of them could be the first step to the building energy upgrade. Conclusively, from this research study the appropriate data for a good level of accuracy, regarding heating demand, will be determined, making the process of obtaining building data full speed ahead and cost effective.

## 1.4 Aims & Objectives of the Study

The main research question that this research will answer is:

How should we model, and which Level of Detail is needed in 3D city models for energy analysis?

In more detail, the aim of the project is the investigation of the most appropriate Level of Detail that is necessary, in order to determine the heating demand in buildings in urban scale, and more specifically, for this study, the annual heating demand of dwellings in London. In particular, depending on the differences of the results that will be shown from the results by changing some parameters, recommendations, about the appropriate data that should be obtained for the estimation of heating demand in city scale, will be made.

In order to achieve those aims, some steps have been taken place at this research. A brief description of the steps of the project is:

1. Critical analysis of the building stock in United Kingdom, focusing on London and on previous studies that have been done regarding the energy modelling in city scale;
2. Reviewing an existed Python script about the calculation of annual heating demand and making the appropriate changes [14];
3. Obtaining the proper data, creating the shapefile and running the Python script through the Python console in QGIS Desktop 2.18.17;

4. Critically analyze some key parameters, in order to investigate their influence in annual heating demand of dwellings and running again the Python code;
5. Bringing forward proposals, regarding the appropriate Level of Detail that is needed for energy modelling in urban scale.

Finally, the objectives of the research are listed below:

1. Understanding the data requirements for energy modelling at city scale;
2. Exploring the significance of adding details in building characteristics for the estimation of the heating demand at urban scale;
3. Formulating recommendations in terms of datasets, for forecasting the heating demand of a city, by investigating the LoD that gives satisfactory results and requires as smaller as it is possible size of data.

## 1.5 Connection to Environmental Goals

Finally, there is no doubt that there is a link between this research project and the Sustainable development goals [15]. More particularly, this research is linked to goals 7, 11 and 13 which they represent the clean energy, the sustainable cities, and the actions for the mitigation of climate change, respectively.


**Figure 1-2 Sustainable Development Goals [15]**

Apart from that, this research study is highly connected to Net Zero UK government's policy [16]. More particularly, the UK government revised the Climate Change Act, in 2019, to commit to attaining net zero emissions by 2050 [16]. This is highly opposed to the prior objective of an 80% decrease in emissions by 2050. However, in addition to this, the UK government, in April 2021, has announced that the reduction of emissions by 2035 should be no less than 78%, which is a challenging climate change goal. Therefore, the rapid energy upgrade of buildings at district scale is one solution that could contribute to the achievement of these goals.

## 1.6 Methodology Approaches

The research has been carried on by the steps that are presented below:

- <u>Background work and literature review</u>

  Literature review and encyclopaedic collection of information regarding energy use and environmental issues, climate change, the emerge for the renovation of existed building stock in urban scale and other relevant knowledge in research area were collected, studied, reviewed and recapitulated;

- Obtaining data and Modelling work

  Firstly, data about building stock should be obtained. In sequence, assumptions from past research papers and background knowledge should be made. The next step has been to create the final shapefile, that contains the whole building information. After obtaining data and creating the final shapefile, the Python script has been studied, from a previous project, in order to understand the way the annual heating demand is calculated through this [14]. Moreover, with the use of QGIS Desktop 2.18.17, the shapefile has been inserted and with QGIS 's Python console, the Python code has been run, in order to calculate the annual heating demand;
- Technical analysis and creation of the Annual Heating Demand map

  After that, changes, in several factors that are needed for the evaluation of the heating demand, have been made, in order to determine which parameters are necessary to be inserted as exact measures and not assumptions for accurate results. Then, maps regarding the annual heating demand in residential buildings in the area of interest (AOI) have been created;
- Critical Evaluation of the most appropriate LoD for energy modelling in city scale

  The next step has been to investigate the parameters that affect most the results about the heating demand with statistical analysis and to make recommendations about the acquisition of building data for energy modelling.

## 1.7 Structure of Thesis

The **first chapter** presents the background knowledge about the research topic. In addition, the area of interest is described and the problem that this study aims to solve is defined. Furthermore, the research question, the aim and the objectives are determined. Finally, at this chapter, a brief description of the methodology that has been followed for the solution of the problem is stated.

The **second chapter** makes a more comprehensive review of the relevant theory on the subject of the project and reviews past papers about the energy modelling in urban scale and parametric studies of the key factors that are needed for this. These projects could be, also, used as information and guideline for the methodology that will follow the literature review.

The **third chapter** describes the steps that have been followed for the method regarding the evaluation of the annual heating demand in residential buildings. This means that every step that has been implemented, from the collection of data to the creation of the Annual Heating Demand map are presented precisely.

The **fourth chapter** illustrates the results from the method that has been defined in the previous chapter. In addition, the findings, about the annual heating demand and the estimation of the most appropriate LoD, regarding the most impactful parameters, are discussed.

The **fifth chapter** is a digest of the entire project, concerning the estimation of the annual heating demand in dwellings. Moreover, the conclusions that have been procured from the research are pointed out. In the end, some recommendations for future studies are brought up, at this chapter.

# Chapter 2

# Literature Review

# 2 Literature Review

*This chapter presents the relevant theory regarding the subject of the project in detail. Also, at this stage of the report, studies and research projects that are related to the current dissertation are being reviewed, to give a guide to solving the research problem.*

## 2.1 Introduction

At this section, the content of the chapter is presented in a brief way.

In **section 2.2**, the theoretical framework of the subject is analyzed, covering a significant proportion on the subject, and some background knowledge is given. At the beginning, the energy and environmental issues of the recent years are pointed out. Then, the energy modelling in city scale is defined. This is followed by the definition of the Level of Detail and its contribution to the urban energy modelling. Then, a detailed description of building stock in UK is given, and particularly, for buildings in England.

In **section 2.3** the review of relevant papers and studies about the MRes dissertation theme is done. The content of this section is about methods that have been, previously, used for city energy modelling, in research studies, but also, for parametric studies that had been done, regarding the influence of building parameters on the estimation of the building energy performance.

In **section 2.4** the summary of the chapter is presented, and the research gap is determined for the area of the study.

## 2.2 Theoretical framework & Background Knowledge

### 2.2.1 Environmental issues & Energy demand

The impact of economic growth on the environment and the energy problem are topics that concern the scientific community as a whole. More precisely, global warming, which has an impact on future climate and is the cause of climate change, is a major issue, especially when combined with rising energy consumption [17]. Furthermore, the temperature of the oceans and the atmosphere has risen, according to the Intergovernmental Panel on Climate Change [18]. Apart from that, the amount of the snow and ice has decreased, whilst the level of the seas has augmented substantially [18]. In addition, statistics, as well as findings from researches, have shown that, by 2050, the world's population will have surpassed 10 billion [19]. Therefore, the population growth, will lead to the requirement of new buildings and the renovation of the existing building stock, in order to convert them into a potentially habitable environment. There is no doubt, that primary reason, for the conversion of the existing building stock, is that due to the future climate scenarios, regarding overheating, the human thermal comfort and well-being are threatened, as a result the increase in energy demand for a livable environment. In more detail, studies have proved that the 30% of the total primary energy consumption, all over the universe, comes from residential and commercial buildings [20]. Hence, as findings from past papers have evidenced, dwellings and commercial properties are responsible for a big proportion of the greenhouse gas (GHG) emissions ( ~18%), and as it is widely known GHG emissions have a significant impact on environmental issues [21]. Taking into consideration all of the above, it is obvious that the urbanization will result in raising of energy consumption, that will lead to the increase of energy demand and that will lead to the boost of the frequency of the aforementioned environmental issues and extreme weather events.

One solution to this major problem is to combine renewable energy sources with energy efficient building systems, as incontestably the planet’s energy reserves will not be sufficient to support the energy demand of the entire population in cities. This implies that the existing building stock should be re-modelled in order to drastically reduce energy demand. Hence, the refurbishment of whole cities is a better method to approach this scenario, not only because the need for energy update is urgent, but also because the goal for the future is not to grow the use of renewable energy sources, but to reduce the use of energy in general, with a simultaneous target the human well-being in everyday life.

Concerning the targets that the European Union (EU) has set by 2030, the greenhouse gas (GHG) emissions should be decreased by at least two fifths for the present measurements [22]. Unquestionably, this is a tough intention to achieve in view of the fact that buildings in the European Union account for 30% of $CO_2$ emissions and 40% of overall energy use [18], [23]. Moreover, according to surveys, buildings that are 50 years old or older account for 35 percent of the entire building stock [18]. This means that the rehabilitation of these old buildings is one-way path to the achievement of the environmental goals. Nonetheless, apart from that, a big proportion of new construction is not energy efficient. The percentage of this building is 75% of the whole built environment in the European Union, which makes the requirement for renovation even higher [18]. As a result, these are essential reasons to recognize that, in today's world, building construction should be done with the primary goal of reducing energy demand and upgrading the building stock of entire cities.

### 2.2.2 Energy Modelling in Urban scale

#### 2.2.2.1 Definition of Urban Building Energy Modelling

As it has been mentioned above, the reduction of greenhouse gas (GHG) emissions is a crucial concern all over the world., and as the built environment is accounted as a major part of the total energy use, from which greenhouse gasses are emitted, the improvement of built environment, especially in urban areas, is vital [24].

When the term “city building energy modelling” is mentioned, it is meant that the thermal performance of buildings is estimated, not in the individual building scale, but over a larger-scale [24,25]. Moreover, urban planning is commonly known as a technique, in other words a field that is applied, and not a science [26]. Nonetheless, urban planning is, undoubtedly, connected to the governmental domain [27]. Hence, the energy modelling in city scale plays a leading role to the choices that decision makers, such as policymakers and municipalities, make for the levelling-up of cities to smart cities [24,28].

#### 2.2.2.2 Urban Building Energy Modelling Approaches

However, there are two approaches for urban energy modelling. The first approach is the top-down approach, and the second is the bottom-up. Regarding the top-down approach, the group of buildings in the city or building block is assumed to be a single energy unit, and possible differences between buildings are not taken into account [29]. On the contrary, bottom-up models treat buildings as individual energy consumption sources, which can be grouped at the city, state, regional, or national level [29]. In the following sub-sections, a more detailed description of these two distinct approaches is done.

*2.2.2.2.1 Top-down Approach*

As it has been stated above, the top-down models illustrate the energy performance of buildings by setting up the link between the energy use sector and the related drivers, such as climate conditions, population or energy price [29]. One of the advantages that this approach is characterized by, is that the input data that is required is not as much as the input information the bottom-up approach needs [26,29–35]. Correspondingly, this technique takes into account socio-demographic and economic impacts on the energy demand, and apart from this, there is no need for detailed information about the technological aspect [29–35]. Notwithstanding, the use of past data is a disadvantage, as it is used for future decisions [29–35]. Finally, in some cases, it is tough to obtain long term historical data [29–35].

*2.2.2.2.2 Bottom-up Approach*

Regarding the bottom-up models, there are two categories of them. The first is based on physics methods and the second one is based on statistics [29].

The **physics-based method** evaluates the energy demand by taking into account every physical characteristic of a building, as well as the mechanical features of it, such as the ventilation, and the occupant's characteristics [29]. There is no doubt that the major benefit of this method is that the differences between every property are taken into consideration and the estimation of the energy performance is done at the building level [36–42]. However, the size of data that is required is vast, concerning the physical and technological attributes that are compelled [36–42]. In addition, socio-economic and demographic effects are not accounted [36–42], and also a significant amount of computing is required [36–42].

The **statistical-based method** simulates the building energy demand based on surveys, socio-demographic and socio-economic trends and billing information, and they are classified into 3 categories, the regression analysis, the conditional demand analysis and the neural network analysis [29]. Unquestionably, the fact that economic trends and demographic effects are taken into account is a significant advantage, but also, statistical-based method is an effective approach due to the consideration of differences in each building [43–47]. On the other hand, it could not missed out that bulk data is required regarding the statistical samples, simultaneously to the climate, billing and research data [43–47]. Finally, the simulation findings are strongly reliant on previous consumption trends and sometimes there can be outliers from the training data, that make results unreliable [43–47].

### 2.2.3 Level of Detail (LoD)

The Level of detail (LoD), invented by Clark in 1976 and since then it is a significant concept that is used in GIS and urban modelling to characterize the intricacy of a geographic object's representation [48]. As it has been stated in the previous chapter of this research study, the Level of Detail (LoD) relates to two constituents: the geometry or visual representation of a project and the attached data [49]. So, the Level of Detail (LoD) specifies the content of a BIM (Building Information Modeling) project at several phases of its progress [49].

In more particular, the LoDs are, commonly, classified from the LoD0 to LoD4 for 2D and 3D representation of the built environment. However, some engineers include an additional LoD, the fifth [10]. Firstly, the LoD0 is a simple flat polygon that represents the top view of a building [50]. In other words, properties in LoD0 are illustrated in two dimensional (2D) way, without height information or other building components [50]. Passing to the three-dimensional (3D) depiction of the buildings, LoD1 to LoD4 are used. The LoD1, as it has been aforesaid, is the LoD0 with the addition of the height of constructions or data about roofs [50] However, it is concerned as the BIM model that is the least comprehensive and most generic, as there are no details about the openings or other architectural components [51]. On the other hand, when referring to LoD2, a more detailed representation of the built environment is done as the type of roof is communicated with the user of the model [50]. As regards, the LoD3, this gives a more detailed information about the roofs of the buildings, and simultaneously, provides data about the façade of the properties [50]. On the subject of LoD4, modeling at this Level of Detail is commonly utilized for both the creation and completion of engineering projects [51]. In other words, this LoD contains every construction and architectural information and is the most detailed representation of a construction [51]. Finally, regarding the fifth LoD that has been aforementioned is characterized as the Level of Detail that illustrates the construction “as-built” [10]. This means that the representation of the building in terms of dimensions, form, location and orientation is precise [10].

### 2.2.4 Domestic Building stock in England, UK

At 31st of March, every year, estimates of the number of domestic properties in UK, and in each of the local authority districts, are presented by the Statistical Release. More particularly, for UK, the statistics have shown that there is a growth in the number of dwellings for a period of 17 years, and more specifically, domestic properties in UK have been risen from 25,468 to 28,993 [52]. Regarding Wales, Scotland, and Northern Ireland, especially, the increase in the number of properties for domestic use has been around 160, 300 and 100, respectively [52]. Concerning England, the number of dwellings has been gone up from 21,207 to 24,658, namely 3,500 domestic properties, approximately, all these years [53]. In the diagram below, it is obvious that over time, the growth of buildings is inevitable [53].

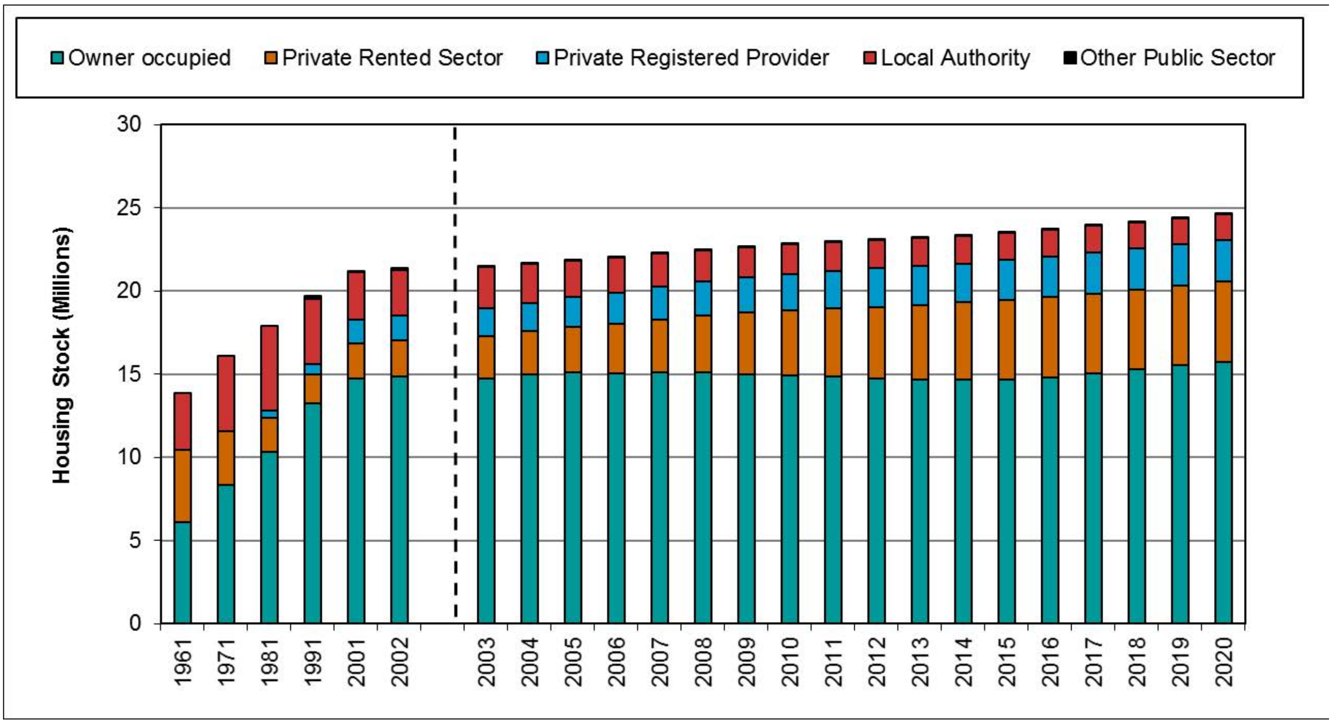



**Diagram 2-1 Dwelling Stock Estimates, England, 1961 to 2020 [38]**

This proves the fact that has been mentioned above about the urbanization and its results to the environment, as building stock affects and intensifies the environmental issues.

With reference to dwellings in England and their energy performance rating, data that has been obtained from the Energy Performance Certificates (EPCs) reveals that the new domestic buildings are more energy efficient than older constructions [54]. This is a fact that is expected, and undeniable, as new properties are mostly built under energy efficient standards. Furthermore, findings from EPCs have proved that new constructions emit less than the half carbon dioxide ($CO_2$) emissions of the old dwellings [54]. Therefore, once again, it is understandable that the need for rapid renovation of building blocks or cities is urgent.

Regarding the most common types of British buildings, there are 7 key types. The first category is the terraced house, which is a dwelling that shares its side walls with other dwellings [55]. In other words, these houses create a row of many properties. Moreover, the terraced houses are the most common preference in UK and the reason is that are cheaper than the semi-detached and detached domestic properties [55]. This means that, concerning energy demand, it is less possible these houses to be vacant, as a result the increase in energy use at these houses and the need for giving priority to their refurbishment. Furthermore, their refurbishment could be more convenient as these properties require less preservation than other homes, because of their smaller footprint. The second type of British dwellings is the semi-detached homes. In more particular, the semi-detached house is a house that shares only one side wall with another [55]. In simple words, the semi-detached houses are mirrored dwellings. Concerning their average price, these houses are more expensive than the terraced houses, but they are still affordable compared to the detached dwellings. This could lead to the conclusion, that they could be the second most possible type of UK homes that would need to be renovated. On the other hand, the detached houses are a standalone property [55]. Nonetheless, this type of constructions are not so ordinary in urban areas, they are built mostly in low density regions [55]. Therefore, not many dwellings of this type could be found in city centers, where the problem of the urbanization and the increase of energy demand occurs. Another building type for domestic use that is widespread in UK is the block of flats or apartments. These type of dwellings are the majority in city centers, with the terraced houses, and every flat is part of a larger construction [55]. The advantage of these flats is that the footprint is smaller, and their refurbishment is easier for each owner to be done for energy efficiency upgrade. Also, there are the end of terrace houses, which are like terraced, but they are based at the end of the row. The advantages regarding energy and renovation are similar to terraced dwellings, too. Finally, there are other property types in UK, such as bungalows and cottages, but these are, usually, in the countryside or rural areas and there are not so usual constructions in city centers [55].

## 2.3 Literature Review

Having said all the above, there is no doubt that the 3D city modelling is a challenging undertaking, and a shortage of data is a major issue when upgrading from LoD1 to higher Levels of Detail. Many studies have investigated the energy performance of constructions, whether at the building or city level, and some have employed a specific Level of Detail or conducted a sensitivity analysis for the investigation of the impact of specific characteristics in building thermal performance.

### 2.3.1 Sensitivity analysis for Building Energy Performance Rating

The wider construction and engineering field, has used sensitivity analysis in order to investigate building energy performance and thermal behavior in a variety of applications [56]. For instance, Wilde et al. have used sensitivity analysis method for the examination of overheating risk in buildings concerning the future climate scenarios [57]. Another similar study about the climate change, that has used sensitivity analysis methods, is one from Tian et al., where a building from University of Plymouth campus has been under-test for its thermal behavior under climate predictions [58]. Furthermore, concerning building refurbishment strategies, projects have been conducted using parametric study methods, in order to investigate the optimal retrofit standard for less heating demand and better energy performance [59].

Apart from these, sensitivity analysis could be used for the building stock and building design, too. More particularly, a research study from Hygh et al., have examined the appropriateness of sensitivity analysis, and especially of multivariate regression, for the estimation of building energy performance in early design stage [60]. In other words, at this project, 27 different building design parameters have been examined, regarding the way that they affect the energy performance of buildings. One of the most significant conclusions from this project is that sensitivity analysis method could be used in order to estimate the impact of each parameter in the thermal behavior of a building, regarding its heating or cooling loads [60]. Another study that has used parametric study, simultaneously with uncertainty analysis, has examined the way that various groups of ambiguity, and more specifically physical, design and scenario uncertainties, affect building energy efficiency rating [61]. That study, from Hopfe et al., has, also, shown that sensitivity analysis is an appropriate method to distinguish the key parameters that have an impact on cooling and heating demand of constructions [61].

From all the above, there is no doubt that sensitivity analysis is a good approach for identifying the parameters that most influence the energy performance of buildings, in order to use this knowledge not only for the design of new energy efficient properties, but also, for the calculation of the thermal behavior of the existed building stock even if there are uncertainties in some data and assumption should be done.

### 2.3.2 Impactful parameters at Energy Performance in Building Scale

As it has been mentioned above, many research studies have been done for the determination of the parameters that have a significant impact on the building energy performance in the individual building scale.

In more particular, a research study, from Ioannou et al., had evaluated the energy performance and the comfort level in building scale, by simultaneously implementing a sensitivity analysis for the occupant behavior by adding it the first time and subtracting it the second [62]. Further elaborated, the case study had been for a building in Monte Carlo, for which energy analysis had been done, assuming three different heating systems, and Class-A and Class-F dwelling [62]. The findings from this project have shown that the occupant behavior is one of the most significant parameters for calculating the energy performance in building scale, as the difference between the two runs of the model was dramatic [62]. Moreover, there is another research study from Olivero et al., that investigates the criteria that affect the building energy performance, by modelling and examining two existing public buildings, an office and a library in France and Italy, respectively [63]. The results have shown that there are some factors that are uncontrolled and unpredicted, such as the climate and the inhabitants [63]. Therefore, by connecting the study from Ioannou et al. and Olivero et al., there is no doubt that inserting the occupancy of a building is a challenging task, not only because it cannot be under control the whole lifespan of the building, but also because its impact on energy performance is major [62,63].

In addition, many other studies have examined the influence of the window to wall ratio and of the building form in energy performance. More specifically, Zhang et al. had examined the way that the shape of buildings affects their thermal performance, and in more detail how schools are influenced from the geometry factors in China [64]. The findings had shown that a window to wall ratio (WWR) of 20-40% leads to, not only an effective thermal performance, but also to the thermal comfort of occupants. However, big window to wall ratio leads to decreased lighting demand, but simultaneously, the cooling and heating demand, in higher and lower temperatures respectively, is increased [64]. One other research paper that investigated the building form had proved that buildings with more compact structure have the ability to lose less energy than structures that are incompact [65]. Same conclusions have been obtained from Hemsath and Bandhosseini and their study, where it has been seen that the most effective building form in terms of energy performance is the one that is closest to a square, and in general, that the shape influences dramatically the energy performance and the more complex it is, the more it can increase the energy demand [66]. Finally, Ghiai et al. had examined the link between the window to wall ratio and the energy consumption in Tehran, with aim the design of structures with window geometries that lead to decreased energy consumption [67]. The findings, from this research project, had shown that the window to wall ratio (WWR) is one of the most impactful parameters for the calculation of energy demand, and more particularly, that the reduction of the WWR is proportional to the reduction of energy consumption [67].

As a result, all of the foregoing might provide an indication of the most essential factors for building energy simulations and could serve as the primary key for city-scale energy modelling.

### 2.3.3 Estimating Energy Performance in Urban Scale

Nonetheless, due to climate change, and many other reasons that have been analyzed above, in recent years a variety of city energy models has been developed, in order to estimate the energy performance in city scale. An example of these models is the CitySim platform, which has been created to assist stakeholders to handle city energy problems and make better decisions [68,69]. More particularly, in 2017, Frayssinet et al. had modelled the energy demand, both heating and cooling, for buildings at urban scale, having as target to help decision-makers create plans for the conversion of urban areas into smart cities [69]. Especially at this study, it has been concluded that the uncertainties from the input parameters can cause more uncertainties in the results than the uncertainties from model simplifications [70].

Moreover, CitySim was used in a study by Rosser et al., which was a case study regarding modelling residential buildings in two Nottingham neighborhoods for energy simulation using CityGML EnergyADE [71]. Despite the fact that numerous assumptions must be made due to the differences in geometry between the two neighborhoods, the findings suggest that a comprehensive footprint geometry is not required for estimating energy demand at district scale [71]. However, it should be noted that employing architectural typologies, as in the research study of Rosser et al., yields homogeneous results, necessitating the regular updating of survey data.

Building typologies, on the other hand, had been employed in many other research publications for city energy simulations, not just in Rosser's et al. In more detail, in 2013, Kaden and Kolbe had used statistics and semantic 3D city models to estimate the building energy consumption at a city scale [72]. This specific research study had demonstrated that this method is suitable to be used as a foundation for city energy modelling. Nonetheless, a thorough validation of the energy demand is required, particularly when recommendations for building rehabilitation are to be made [72]. Furthermore, the Atelier Parisien d' Urbanisme (APUR), a French urbanism research group, conducted a study that merged an energy simulation model with GIS 2.5D building data of Parisian structures [70]. To put it another way, this research group employed building typologies from archetypical building classes and morphological building data to estimate energy usage, as has been done in earlier research articles.

Apart from the above, another study which forecasted the heating demand at city scale, from Strzalka et al., had shown that the geometrical detail is not a significant factor to influence the results of the heating demand and that a 3D city model with a simplified geometry can be used to estimate energy demand [73]. Finally, a research study, from Dochev, had shown that the estimation of the heating demand at city scaled is feasible by using building typologies, assumptions, empirical data, and census data and that can lead in satisfactory results, as this research presents a Python script that has been validated with values taken from TABULA project webtool [14,74].

## 2.4 Summary & Research Gap

### 2.4.1 Summary

To summarize, Chapter 2 begins by providing a full overview of the theoretical background on the subject, in order to interpret several concepts that must be understood in order to comprehend the approach that will follow in the next chapter. Apart from that, at this section, the building stock of UK is described. After that, a literature review was conducted on the subject, in other words on the building energy modelling. More particularly, various papers, that had used sensitivity analysis for their projects, have been mentioned, in order to confirm the necessity of the parametric study for the determination of high-weighty factors. In addition to this, a variety of findings about impactful parameters in energy modelling at building scale have been presented. Finally, interesting findings from studies that have been conducted, regarding city energy modelling at city scales have been introduced.

### 2.4.2 Research Gap

Therefore, many studies on building energy simulations have been conducted, from the building scale to the city scale, such as Yang's et al. study in 2020, which determined the space heating energy for a city in Netherlands using geospatial and archetypical data, or Nouvel's et al. research study, which examined the accuracy of an approach that calculates the heating demand in district heating systems [75,76]. Furthermore, there are many papers that have done a parametric study for the definition of the most impactful parameters in building energy performance at the building scale, such as Coulter and Leicht's sensitivity analysis for the determination of the impact of energy modelling input parameters on the output of the energy analysis for a retrofitted building [77].

However, there are few research publications that examine the impact of various building characteristics on energy demand. For example, Ratti et al. provided recommendations for building construction by examining the impact of morphology, typology, and other building indicators on energy consumption, but most of the previous studies had either done parametric studies at building scale or used GIS data combined with other building information for city scale energy modelling, but without sensitivity analysis [78,79]. Therefore, this research study aims to examine the influence of different levels of detail in city scale energy modelling, and most specifically for London city in UK. Finally, by the term Level of Details, it is meant that the purpose of this project is to investigate whether it is necessary to use the LoD2 or LoD3 for the estimation of the heating demand in buildings.

# Chapter 3

# Methodology

# 3 Methodology

*At this chapter, the steps that have been followed for the investigation of the problem are presented.*

## 3.1 Preliminary Methodology Diagram

At this section, the diagram of the methodology, that has been constructed at the beginning of this project, is illustrated.

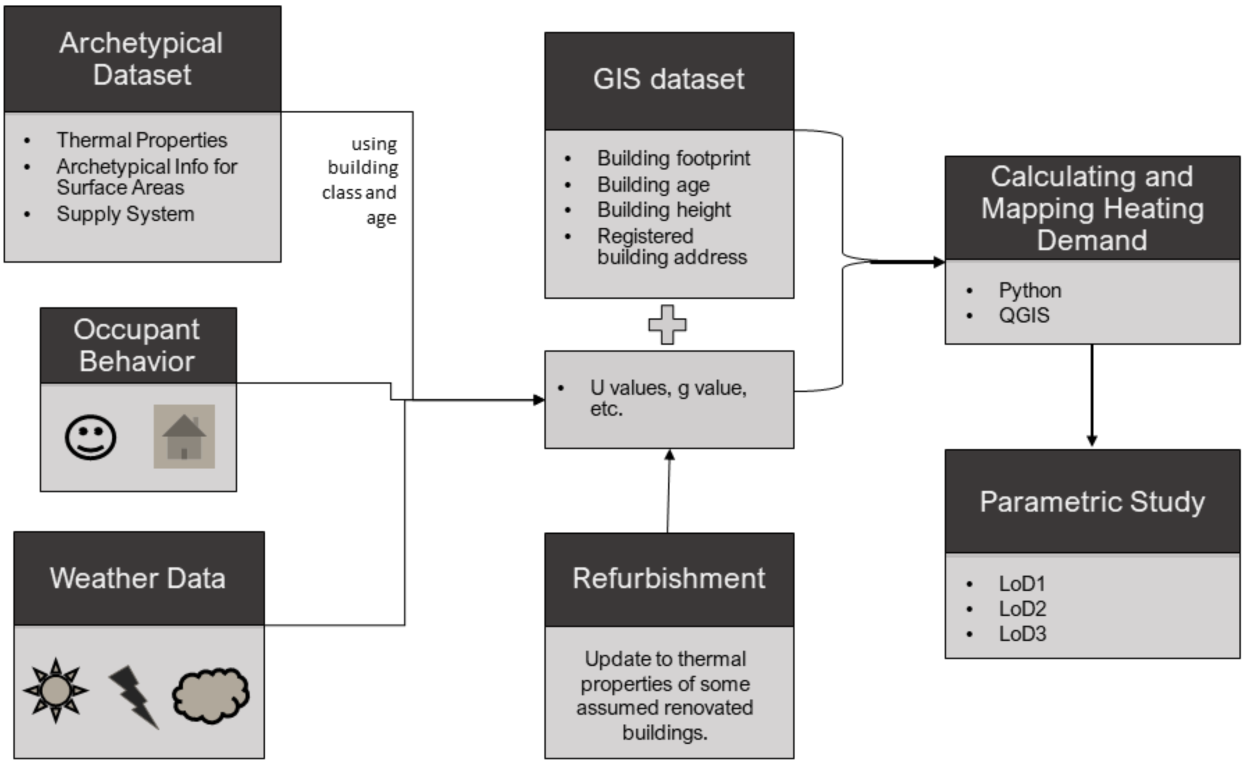



**Diagram 3-1 Methodological Design**

As it can be seen from the diagram above, the preliminary design of the methodology has included architectural typologies combined with GIS data, in order to obtain information about the buildings of the area of interest. Therefore, the archetypical dataset should include the thermal properties of the buildings, depending on the type of building and its age, and then, that information could be imported to the GIS dataset, which contains geospatial information about these buildings. Undoubtedly, the weather data should be included in order to specify the climate of the area of interest, as well as the occupant behaviour and the refurbishment rate, that play a role to the energy performance of buildings. After the construction of the big dataset, by using Python programming language, the calculation of the heat demand in buildings of the area of interest could be done with the use of the Python script adaptive from Dochev's research [14]. This code would run three times, one time for each LoD. Subsequently, the visualization of the results for every LoD would be done, and the final findings would be three different maps of the area of interest, comparing the difference on the results from upgrading from LoD1 to LoD3. Nonetheless, as in every research project, there were some obstacles that should be overpassed and the final methodology and steps have been, slightly, changed.

## 3.2 Methodology Diagram

At this section, the diagram of the final methodology, that has been followed at this project, is presented, in order to explain with a quick glance, the steps that have been followed for the implementation of the aim of the project.

At the following sections, the steps of the methodology are presented in more detail.

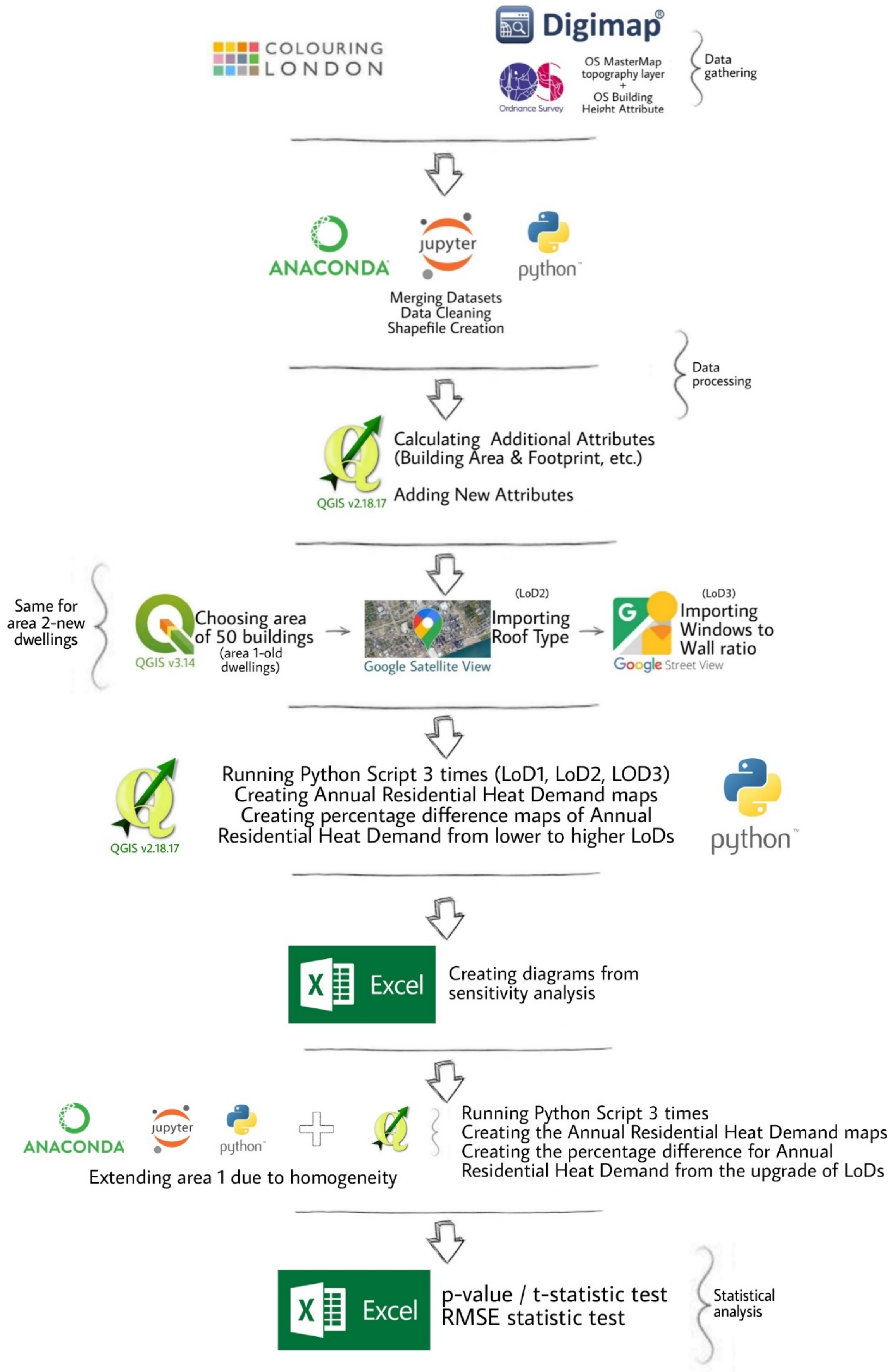



**Diagram 3-2 Technical Implementation**

## 3.3 Data gathering

### 3.3.1 ‘Colouring London’ dataset

The first step of the implementation of the methodology has been to download the dataset of ‘Colouring London’ project from UCL university, in a .csv format [11]. This platform is free and provides with open data regarding buildings, with prior target, the upgrade of London city to a more sustainable area. The extracted dataset has been the newest version, at the time that this particular research methodology has been implemented, as this platform updates its data frequently. This is happening due to the nature of the platform, in other words because ‘Colouring London’ uses Volunteered Geographic Information (VGI).

### 3.3.2 OS MasterMap Topography layer - Buildings

The next step has been to download the OS MasterMap Topography layer for London city, from Ordnance Survey and Digimap [80]. The format of this dataset is .gpkg. This dataset is the version of November 2019 and provides topographic data in detail. The OS MasterMap Topography layer is convenient due to the nine themes that is divided, such as land, rail, water and buildings. Therefore, for the aim of this specific research project, the ‘buildings’ theme has been chosen, in order to allow a clearer and more particular dataset.

### 3.3.3 OS Building Height Attribute

After these datasets, the OS Building Height Attribute has been characterized as necessary for the creation of the final dataset, so it has been downloaded from Digimap [80]. This had happened, because by cleaning the Nan/null values of the attribute with height from the dataset of ‘Colouring London’ project, many rows, namely buildings, have been deleted. Hence, OS Building Height Attribute has been a great solution.

## 3.4 Data processing

### 3.4.1 Familiarizing with data from ‘Colouring London’ project

The following step has been to use jupyter notebook online from ANACONDA, with Python programming language in order to merge the three datasets, clean from unwanted and NaN values and create the final shapefile. Hence, firstly the ‘Colouring London’ dataset as a .csv format file has been imported and read in the notebook, as it can be seen at Figure 3-1. The reading of the dataset has shown that there are 3,525,281 observations, in other words buildings in the dataset for London city, and 59 columns, namely attributes, such as the building id, the year of construction, the number of floors, etc.

**Familirising with data from "Colouring London"**

```
In [127]: import pandas as pd
          path='C:/Users/nacia/OneDrive - The University of Nottingham/Geospatial Data Science MRes/MRes Dissertation/2_WP2_Information_Sy
          df=pd.read_csv(path)
          print(df)

C:\Users\nacia\anaconda3\envs\geoenv\lib\site-packages\IPython\core\interactiveshell.py:3146: DtypeWarning: Columns (4,5,6,7,8,
9,21,34,37,39,40,55) have mixed types.Specify dtype option on import or set low_memory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,

         building_id            ref_toid   ref_osm_id  revision_id  \
0             446251  osgb5000005206506806          NaN    4997798.0
1             446253  osgb5000005206506812          NaN    4997801.0
2             446257  osgb5000005206507132          NaN    4997805.0
3             446203     osgb1000003501097          NaN    4997810.0
4             446170     osgb1000003506343          NaN    4997822.0
...              ...                   ...          ...          ...
3525277       265576     osgb1000003391390          NaN    7029291.0
3525278       446232  osgb5000005208718589          NaN    4997783.0
3525279       446243  osgb5000005206506421          NaN    4997791.0
3525280      1137761     osgb1000042080483  153045032.0    7768652.0
3525281       447942     osgb1000003088644  902364467.0    8214757.0

        location_name location_number location_street location_line_two  \
0                 NaN             NaN             NaN               NaN
1                 NaN             NaN             NaN               NaN
2                 NaN             NaN             NaN               NaN
3                 NaN             NaN             NaN               NaN
4                 NaN             NaN             NaN               NaN
...               ...             ...             ...               ...
3525277           NaN             NaN             NaN               NaN
3525278           NaN             NaN             NaN               NaN
3525279           NaN             NaN             NaN               NaN
3525280           NaN             NaN             NaN               NaN
3525281           NaN             NaN             NaN               NaN
```

**Figure 3-1 Importing and reading 'Colouring London' dataset**

### 3.4.2 Inserting OS MasterMap Topography layer

After inserting the 'Colouring London' dataset, the OS MasterMap Topography layer has been imported in the geopackage format, with the use of geopandas library and as a geodataframe. The code and result can be seen at Figure 3-2.

**Inserting OS MasterMap Topography layer geopackage**

```
In [141]: import geopandas as gpd
          pathOS='C:/Users/nacia/OneDrive - The University of Nottingham/Geospatial Data Science MRes/MRes Dissertation/2_WP2_Information_
          OSdata = gpd.read_file(pathOS)
          OSdata.head()  # Prints the first 5 rows of the loaded data to see what it looks like.

C:\Users\nacia\anaconda3\envs\geoenv\lib\site-packages\geopandas\geodataframe.py:422: RuntimeWarning: Sequential read of iterat
or was interrupted. Resetting iterator. This can negatively impact the performance.
  for feature in features_lst:

Out[141]:
```

| | fid | featurecode | version | versiondate | theme | calculatedareavalue | changedate | reasonforchange | descriptivegroup | descriptiveterm | mak |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | osgb1000001794254181 | 10053 | 2 | 2001-11-08 | Land | 18.595 | 2000-05-19 | New | General Surface | Multi Surface | Multip |
| 1 | osgb1000001794254182 | 10053 | 1 | 2001-11-07 | Land | 43.932504 | 2000-05-19 | New | General Surface | Multi Surface | Multip |
| 2 | osgb1000001794254183 | 10053 | 1 | 2001-11-07 | Land | 37.917496 | 2000-05-19 | New | General Surface | Multi Surface | Multip |
| 3 | osgb1000001794254184 | 10053 | 1 | 2001-11-07 | Land | 40.831248 | 2000-05-19 | New | General Surface | Multi Surface | Multip |
| 4 | osgb1000001794254185 | 10053 | 1 | 2001-11-07 | Land | 38.721248 | 2000-05-19 | New | General Surface | Multi Surface | Multip |

**Figure 3-2 Inserting OS MasterMap Topography layer**

Moreover, the buildings of London city from OS MasterMap Topography layer have been loaded and plotted in order to understand in a clearer way the area.

```
In [142]: #loading and plotting the buildings of London city

          OSdata.plot()

Out[142]: <AxesSubplot:>
```

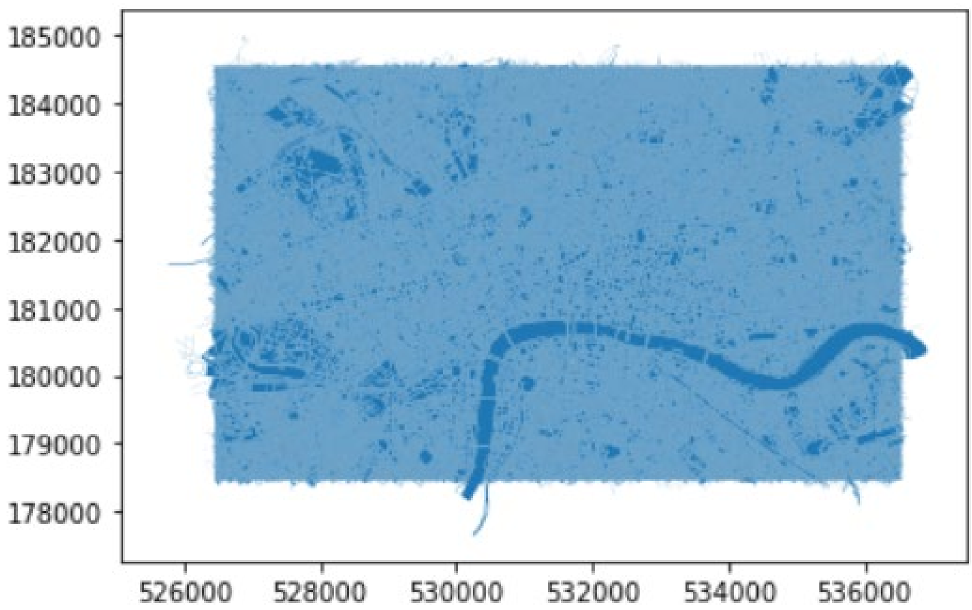



**Figure 3-3 Map of buildings in OS MasterMap Topography layer**

### 3.4.3 Joining 'Colouring London' dataset with OS MasterMap Topography layer

The next step has been to create a new dataset, that would be the join between the two aforementioned. Therefore, by using the building id of each building and, more specifically, the 'ref_toid' column from 'Colouring London' dataset and 'fid' column from OS MasterMap topography layer, which is a code of the form 'osgb5000005229422492' for instance and is called TOID, both geodataframes have been connected.

## Creating the joined dataframe

```
In [143]: #Joining the 2 dataframes
          import pandas as pd
          dfinal = df.merge(OSdata, how='inner', left_on='ref_toid', right_on='fid')
```

**Figure 3-4 Joining 'Colouring London' dataset with OS MasterMap Topography layer**

### 3.4.4 Importing OS Building Height Attribute

At this stage, the significance of the building height data that is provided by Ordnance Survey has been shown. The OS Building Height Attribute was necessary for the creation of the final dataset, because by cleaning the NaN values from the number of floors at 'Colouring London' dataset, the biggest proportion of the observations has been deleted. Therefore, it has been chosen to keep all the values and import the height of the buildings from OS Building Height Attribute. The difference from the previous datasets is that for city of London, there were six different .csv files. So, all of them have been imported to jupyter notebook, at first, and then have been merged into one at the first stage. An example of inserting the six .csv files is presented at Figure 3-5 and the merging of all of them is shown at Figure 3-6.

**Inserting OS building heights csv file**

```
In [20]: import pandas as pd
         path1='C:/Users/nacia/OneDrive - The University of Nottingham/Geospatial Data Science MRes/MRes Dissertation/2_WP2_Information_S
         dfheights1=pd.read_csv(path1)
         print(dfheights1)
```

```
                 OS_TOPO_TOID  OS_TOPO_TOID_VERSION BHA_ProcessDate TileRef  \
0      osgb1000001794885829                     2        3/9/2020  TQ2575
1      osgb1000001794885912                     3        3/9/2020  TQ2575
2      osgb1000001796345285                     5        3/9/2020  TQ2575
3      osgb1000001796407372                     1        3/9/2020  TQ2575
4      osgb1000001796407374                     1        3/9/2020  TQ2575
...                     ...                   ...             ...     ...
70571  osgb5000005259977883                     1        3/9/2020  TQ2575
70572  osgb5000005259977884                     1        3/9/2020  TQ2575
70573  osgb5000005259977886                     1        3/9/2020  TQ2575
70574  osgb5000005260189551                     1        3/9/2020  TQ2575
70575  osgb5000005260189555                     1        3/9/2020  TQ2575

       AbsHMin  AbsH2  AbsHMax  RelH2  RelHMax  BHA_Conf
0          3.9   10.5     12.7    6.6      8.8        99
1          4.2   15.9     16.3   11.7     12.1        99
2          5.8    5.8      7.8    0.0      2.0        99
3          7.8   23.6     28.5   15.8     20.7        99
4          7.3   15.5     20.0    8.2     12.7        99
...        ...    ...      ...    ...      ...       ...
70571      3.8    9.1     10.3    5.3      6.5        99
70572      3.6    5.6      5.9    2.0      2.3        99
70573      3.6   11.6     11.6    8.0      8.0        99
70574      3.8   18.5     19.2   14.7     15.4        99
70575      4.1    7.8      8.3    3.7      4.2        99

[70576 rows x 10 columns]
```

**Figure 3-5 Importing the first .csv file of OS Building Height Attribute**

**Joining all height dataframes into one**

```
In [27]: dfheights=dfheights1

In [28]: dfheights=dfheights.append(dfheights2, ignore_index=True)

In [29]: dfheights=dfheights.append(dfheights3, ignore_index=True)

In [30]: dfheights=dfheights.append(dfheights4, ignore_index=True)

In [31]: dfheights=dfheights.append(dfheights5, ignore_index=True)

In [32]: dfheights=dfheights.append(dfheights6, ignore_index=True)
```

**Figure 3-6 Joining the six datasets of OS Building Height Attribute**

### 3.4.5 Creating the big dataset

The following step has been to merge all geodataframes and create one with all buildings and attributes. Hence, the merged geodataframe, that has been created from 'Colouring London' dataset and OS MasterMap Topography layer, has been connected with OS Building Height Attribute.

**Merging the dataframe of heights with the building attributes dataframe**

```
In [35]: #Joining the 2 dataframes
         import pandas as pd
         dfinal = dfinal.merge(dfheights, how='inner', left_on='fid', right_on='OS_TOPO_TOID')
```

**Figure 3-7 Creating the joined geodataframe**

### 3.4.6 Exporting final dataset into shapefile

After that, the final dataset has been exported into a shapefile and has been inserted into QGIS, in order to check its content in a more convenient way and begin the data cleaning.

```
In [40]: gdf = gpd.GeoDataFrame(dfinal)
         gdf.to_file(driver = 'ESRI Shapefile', filename= "C:/Users/nacia/OneDrive - The University of Nottingham\Geospatial Data Science
```

**Figure 3-8 Exporting dataset as shapefile**

### 3.4.7 Keeping dwellings/residential buildings

The next step has been to clean the dataset from buildings that are not dwellings, and their land use is other than residential. Hence, the dataset has been reduced to less observations with the following code.

```
In [43]: dfinal=dfinal.loc[(dfinal['current_landuse_group']=='{Dwellings}') & (dfinal['current_landuse_order']== 'Residential')]
```

**Figure 3-9 Keeping dwellings/residential buildings – condition**

Without doubt, the condition has been checked and only the necessary buildings have been kept, as it is shown at Figure 3-10.

```
In [48]: dfinal['current_landuse_group'].unique()
Out[48]: array(['{Dwellings}'], dtype=object)

In [49]: dfinal['current_landuse_order'].unique()
Out[49]: array(['Residential'], dtype=object)
```

**Figure 3-10 Condition check**

### 3.4.8 Cleaning 'NaN' 'building age'

After keeping dwellings, the next thing that should be done has been to clean the column of building age from 'NaN' values, as the age of the construction of buildings is needed in order to insert the thermal properties of the construction materials from the architecture typology. Hence, at the dataset there have been 92,836 NaN values for building age, which have been deleted.

```
In [52]: #Checking how many NaN values are there in building age column
         dfinal['date_year'].isnull().sum()

Out[52]: 92836

In [53]: #cleaning rows where "date_year" is NaN
         df = dfinal.dropna( how='any',
                             subset=['date_year'], inplace=True)
```

**Figure 3-11 Cleaning 'NaN' values from building age column**

### 3.4.9 Cleaning 'NaN' 'building form'

For the same reason as at the above subsection, the 'NaN' values from the column that shows the form of the buildings should be deleted, as the thermal properties that would be assigned to each building, from the typology, depend on building age and building form. The 'NaN' values at the column of building form have been 31,694 and have been dropped.

```
In [57]: #Checking how many NaN values are there in'building_attachment_form' column
         dfinal['building_attachment_form'].isnull().sum()

Out[57]: 31694

In [58]: #cleaning rows where "building_attachment_form" is NaN
         df = dfinal.dropna( how='any',
                             subset=['building_attachment_form'], inplace=True)

In [59]: #checking the unique values that column "building_attachment_form" has
         dfinal['building_attachment_form'].unique()

Out[59]: array(['Mid-Terrace', 'End-Terrace', 'Semi-Detached', 'Detached'],
               dtype=object)
```

**Figure 3-12 Deleting 'NaN' values of building form and checking the unique values of residential buildings that have been left**

As it can be seen from Figure 3-12, the building forms that have been left from the dataset have been the terraced buildings (Mid-Terraced and End-Terraced) and the detached buildings (Semi-Detached and Detached). Therefore, the analysis of the project has been done for this type of buildings and the thermal properties for the envelope of these buildings have been inserted from Tabula typology [81].

### 3.4.10 Exporting dataset as a shapefile

After that, the cleaned dataset has been exported as a shapefile, in order to import it at QGIS and add some columns at attribute table.

**Exporting Shapefile**

```
In [61]: gdf = gpd.GeoDataFrame(dfinal)
         gdf.to_file(driver = 'ESRI Shapefile', filename= "C:/Users/nacia/OneDrive - The University of Nottingham\Geospatial Data Science
```

**Figure 3-13 Exporting shapefile**

### 3.4.11 Adding columns at attribute table

At first, the area and perimeter of each building have been calculated using the above shapefile and the geometry tools at QGIS. Then, the floors of the buildings have been calculated by assuming that each floor is 3m and by dividing the height of buildings with the assumed value. After that, the inhabitant attribute has been added. The calculation of the occupancy has been done by using the area of each building and the minimum area per person in London, which is equal to 32.8 $m^2$ [82]. Finally, it should be mentioned that for areas smaller than 32.8 $m^2$, it is assumed that there is only 1 occupant.

### 3.4.12 Inserting thermal properties from Tabula archetype

After adding these columns, the dataset has been inserted to jupyter notebook and the thermal properties, namely the thermal transmittance (U-value), have been assigned depending on the building age and building form. The specific values that have been inserted for both building forms, all building age ranges and for roofs, walls, floors, and windows are shown at Appendix 1 from Table 0-1 to Table 0-6. More particularly, from Table 0-1 to Table 0-4, the U-values from the year of construction are shown, but at Table 0-5 and Table 0-6, the U-values of the renovations are presented.

```
In [72]: #insert U-value of Walls

         #single-family houses ->  semi-detached and detached

         dftest.loc[np.where((((dftest['building_a'] == 'Semi-Detached') | (dftest['building_a'] == 'Detached'))
                             & (dftest['date_year'] <= 1944)))[0], 'UWalls'] = 2.1

         dftest.loc[np.where((((dftest['building_a'] == 'Semi-Detached') | (dftest['building_a'] == 'Detached'))
                             & ((dftest['date_year'] > 1944) & (dftest['date_year'] <= 2003))))[0], 'UWalls'] = 1.6

         dftest.loc[np.where((((dftest['building_a'] == 'Semi-Detached') | (dftest['building_a'] == 'Detached'))
                             & ((dftest['date_year'] > 2003) & (dftest['date_year'] <= 2009))))[0], 'UWalls'] = 0.35

         dftest.loc[np.where((((dftest['building_a'] == 'Semi-Detached') | (dftest['building_a'] == 'Detached'))
                             & (dftest['date_year'] >= 2010)))[0], 'UWalls'] = 0.28


         #terraced houses ->  Mid-Terrace and End-Terrace

         dftest.loc[np.where((((dftest['building_a'] == 'Mid-Terrace') | (dftest['building_a'] == 'End-Terrace'))
                             & (dftest['date_year'] <= 1944)))[0], 'UWalls'] = 2.1

         dftest.loc[np.where((((dftest['building_a'] == 'Mid-Terrace') | (dftest['building_a'] == 'End-Terrace'))
                             & ((dftest['date_year'] > 1944) & (dftest['date_year'] <= 2003))))[0], 'UWalls'] = 1.6

         dftest.loc[np.where((((dftest['building_a'] == 'Mid-Terrace') | (dftest['building_a'] == 'End-Terrace'))
                             & ((dftest['date_year'] > 2003) & (dftest['date_year'] <= 2009))))[0], 'UWalls'] = 0.35

         dftest.loc[np.where((((dftest['building_a'] == 'Mid-Terrace') | (dftest['building_a'] == 'End-Terrace'))
                             & (dftest['date_year'] >= 2010)))[0], 'UWalls'] = 0.28
```

**Figure 3-14 Assigning U-values for the walls of the buildings**

At the figure above, the way that the U-values had been assigned to the walls for every building is shown. At the same way, the U-values for the rest particles of the building envelope have been defined.

### 3.4.13 Cleaning buildings with 'zero' floors

At this stage, the shapefile has been tested and it has been found out that there were some buildings with 'zero' floors, due to the division of the height of each building with 3m. Hence, because of that, the next step has been to assign one floor to every building that has building height under 3m.

```
In [98]: #cleaning data from floors = 0
         dftest.loc[np.where(dftest['RelHMax'] < 3)[0], 'Floors'] = 1
```

**Figure 3-15 Assigning one floor to buildings with height under 3m**

### 3.4.14 Exporting final shapefile

The last step from Python code at jupyter notebook has been to export the final shapefile in order to import it to QGIS and begin the analysis.

```
In [99]: gdftest = gpd.GeoDataFrame(dftest)
         gdftest.to_file(driver = 'ESRI Shapefile', filename= "C:/Users/nacia/OneDrive - The University of Nottingham\Geospatial Data Sci
```

**Figure 3-16 Exporting final shapefile**

## 3.5 Analysis

### 3.5.1 Adding final columns to shapefile using QGIS attribute table

After exporting the final shapefile from jupyter notebook, this has been imported to QGIS in order to import some other values to parameters that are necessary for the calculation of the heat demand. The first column that has been added has been the internal gains, that have been assumed equal to 3 W/m$^2$, from Tabula [81]. After that, the window to wall ratio (WWR) for LoD1 has been assumed equal to 20%, based on empirical data and Dochev 's research, and the roof type for LoD1 has been assumed as hip, as the majority of these type of buildings have pitched roof based on Tabula [14,81]. Moreover, the air change rate (ACR) has been taken equal to 0.6 and the heat volume coefficient equal to 0.8 based on an average floor height of 3 meters [14,81]. Furthermore, the inside temperature of the buildings has been assumed as a uniform value for this case study, which is equal to 19.5~20℃, as from Public Health England a temperature range between 18-21℃ is the minimum range of the inside temperature in buildings in UK for a healthy indoor environment [83]. Finally, the percentage of the facade in walls and windows that are renovated has been assumed as zero, as in UK the 'patch' renovation is not applied as in Bulgaria, that the model of Dochev has been, first, applied and tested.

### 3.5.2 Adding the climate data for London city

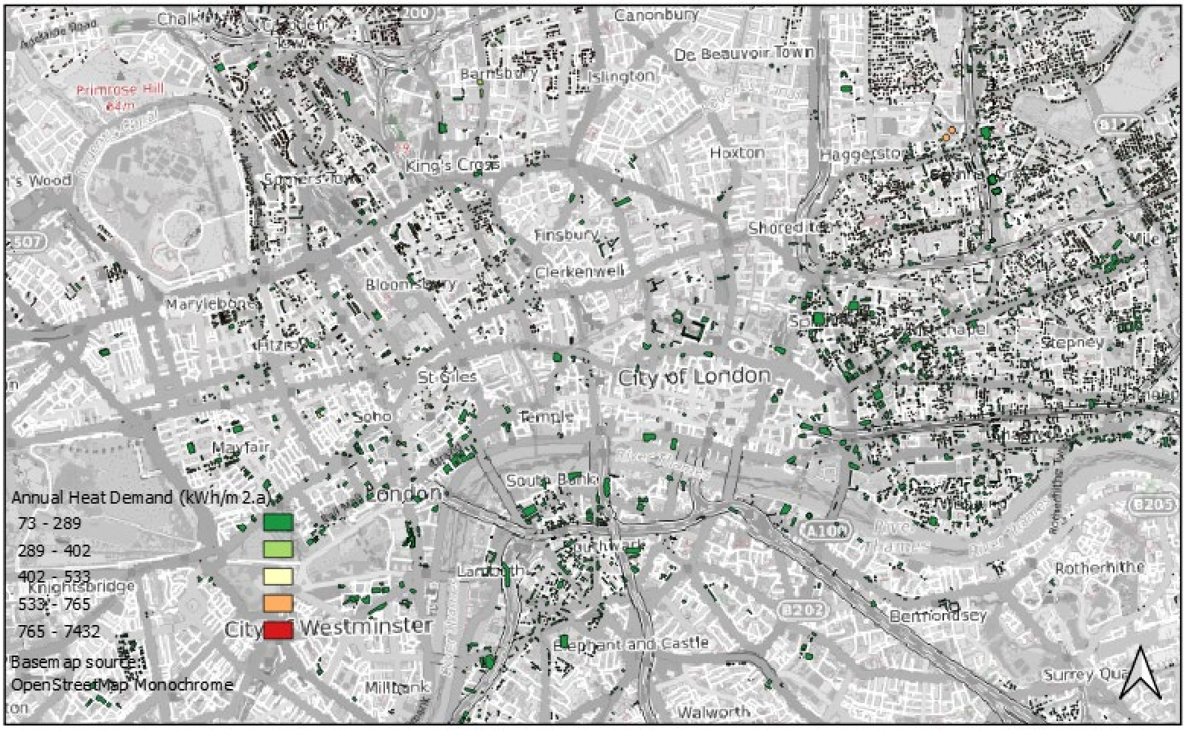
The final step, in order to check that the model runs smoothly and gives results, has been to change the climate data in the Python script that calculates the annual heat demand. Therefore, it has been necessary to find out the monthly temperature and the solar radiation for the heating season, that the case study examines. The climate data for the area of interest have been gathered from PHPP software, which provides with validated weather data from NASA. A screenshot from the specific excel spreadsheet with climate data from PHPP software is presented at Appendix 2, Figure 0-1. At the table above the values for the heating season are illustrated.

**Table 3-1 PHPP climate data for the area of interest**

| *Heating season/ Months* | *Average Temperature (℃)* | *Solar Radiation North ($W.m^{-2}$)* | *Solar Radiation East ($W.m^{-2}$)* | *Solar Radiation West ($W.m^{-2}$)* | *Solar Radiation South ($W.m^{-2}$)* | *Solar Radiation Horizontal ($W.m^{-2}$)* |
|---|---|---|---|---|---|---|
| *Jan* | 0.4 | 10 | 13 | 14 | 29 | 21 |
| *Feb* | 1.3 | 15 | 26 | 28 | 59 | 40 |
| *Mar* | 4.4 | 26 | 41 | 44 | 66 | 65 |
| *Oct* | 9.4 | 18 | 32 | 34 | 63 | 50 |
| *Nov* | 4.7 | 10 | 15 | 16 | 32 | 23 |
| *Dec* | 1.6 | 7 | 9 | 10 | 21 | 15 |

### 3.5.3 Checking that model runs

The following step has been to check that the model runs as expected. Hence, the big final dataset that has been created, which consists of 13,722 buildings has been analyzed in LoD1. This means that the dataset has been remained with the assumed roof type and windows to wall ratio (WWR) and the Python script of Dochev 's research has been run in order to confirm that the dataset is ready to be used for the next LoDs. At the figure below, it can be seen that the model has run successfully, and it has given as output the annual heat demand map in dwellings of London city for LoD1.




**Annual Heat Demand in dwellings of London city**

**Figure 3-17 Output of the model for big dataset for LoD1**

Therefore, as this model for the calculation of annual heat demand is validated from Dochev ‘s research and the particular dataset that has been created for this case study works, the following step has been to find out the roof type for LoD2 and the WWR for LoD3, in order to apply the parametric study.

### 3.5.4 Choice of smaller areas

As in every research, there have been some obstacles that should be overcome. At this research, the lack of data and, in particular, the lack of roof type of buildings and windows to wall ratio (WWR) have driven the method from city of London to two smaller areas, in order to assign manually for each building both the roof type and the WWR. The first area is an area of 49 old buildings and the second one is an area of 49 new buildings from 2003 onwards, in order to examine if the building age is a parameter that could affect the results.

### 3.5.5 Assigning the roof type for each building

As it has been mentioned above, the roof type of buildings has missed from the dataset. Hence, another way should be found in order to upgrade the analysis from LoD1 to LoD2. Therefore, with the use of QGIS v3.14 and Google Satellite View, the roof type for each building has been inserted manually, for both areas.

### 3.5.6 Assigning the WWR for each building

In order to assign the WWR for each building, for the upgrade from LoD2 to LoD3, the method is slightly more complicated than above. The softwares that have been used are QGIS v3.14, the Google Street View add-in, the Google Street View at browser and the IC Measure software. Taking as an example one building, the first step that has been done was to investigate the street that is located, with the use of Google Street View add-in (Figure 3-18).

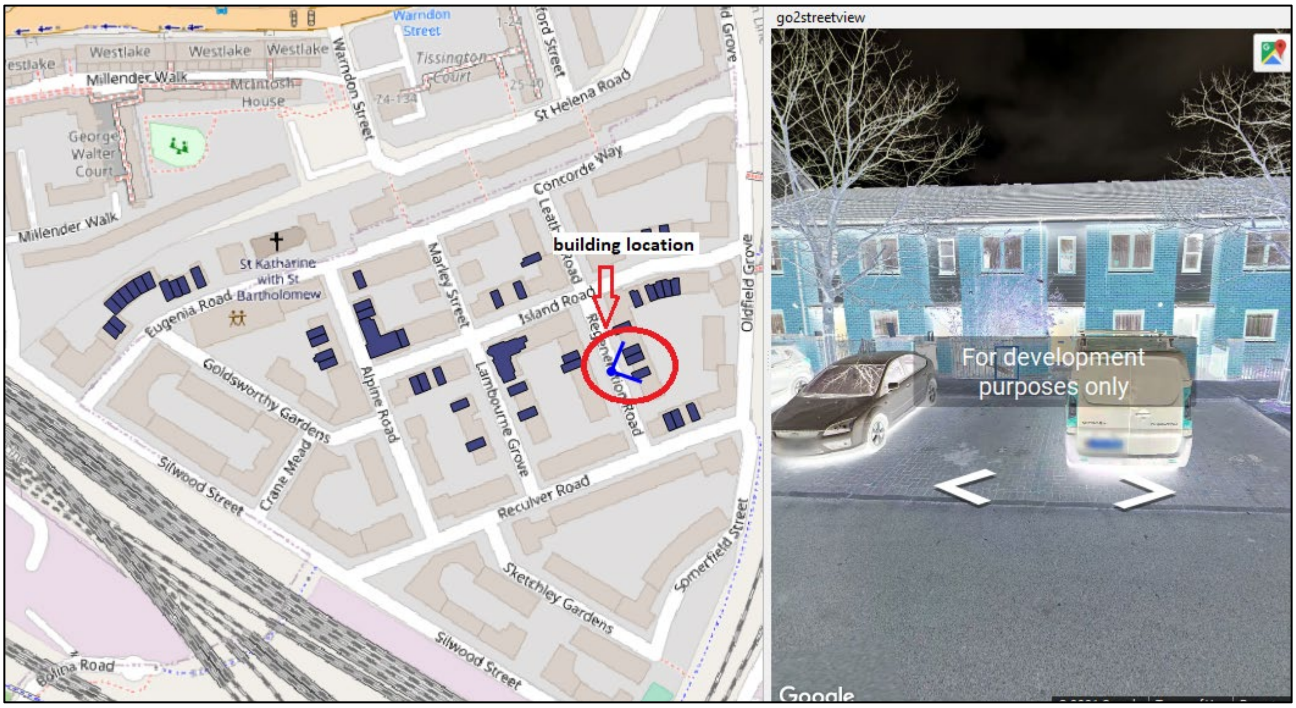



**Figure 3-18 Building of interest – Location**

After that, Google Street View has been opened in external browser, in order to take a clearer screenshot of the building of interest.

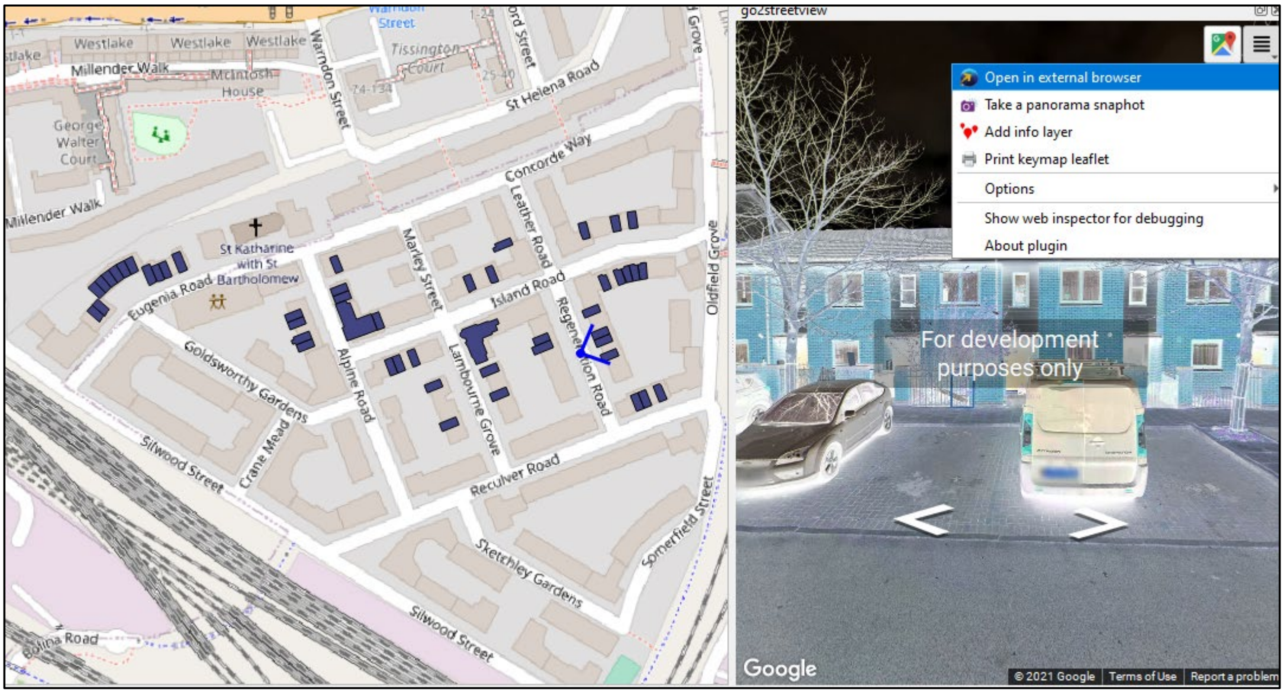



**Figure 3-19 Opening Google Street View in external browser**

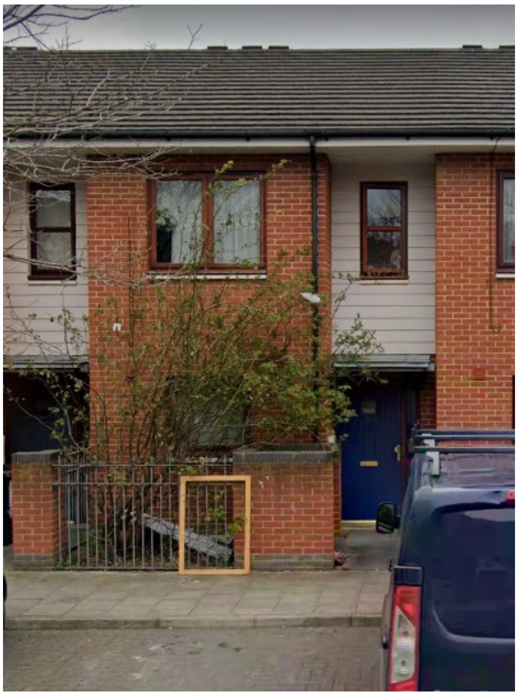


**Figure 3-20 Screenshot of the building of interest**

At Figure 3-20, the screenshot from the external browser of the building of interest is illustrated.

Therefore, by importing this image to IC Measure software, the windows and façade of the building could be measured, as it is shown in Figure 3-21.

Finally, having measured all these areas, the windows to walls ratio (WWR) could be calculated with a simple division.

These steps have been followed for both areas and for each building, in order to upgrade the datasets from LoD1 to LoD2.

Nonetheless, it is recognised that the results from this technique are approximate values. However, this technique is a step forward than the assumption at LoD1, where a uniform value is taken for all buildings.

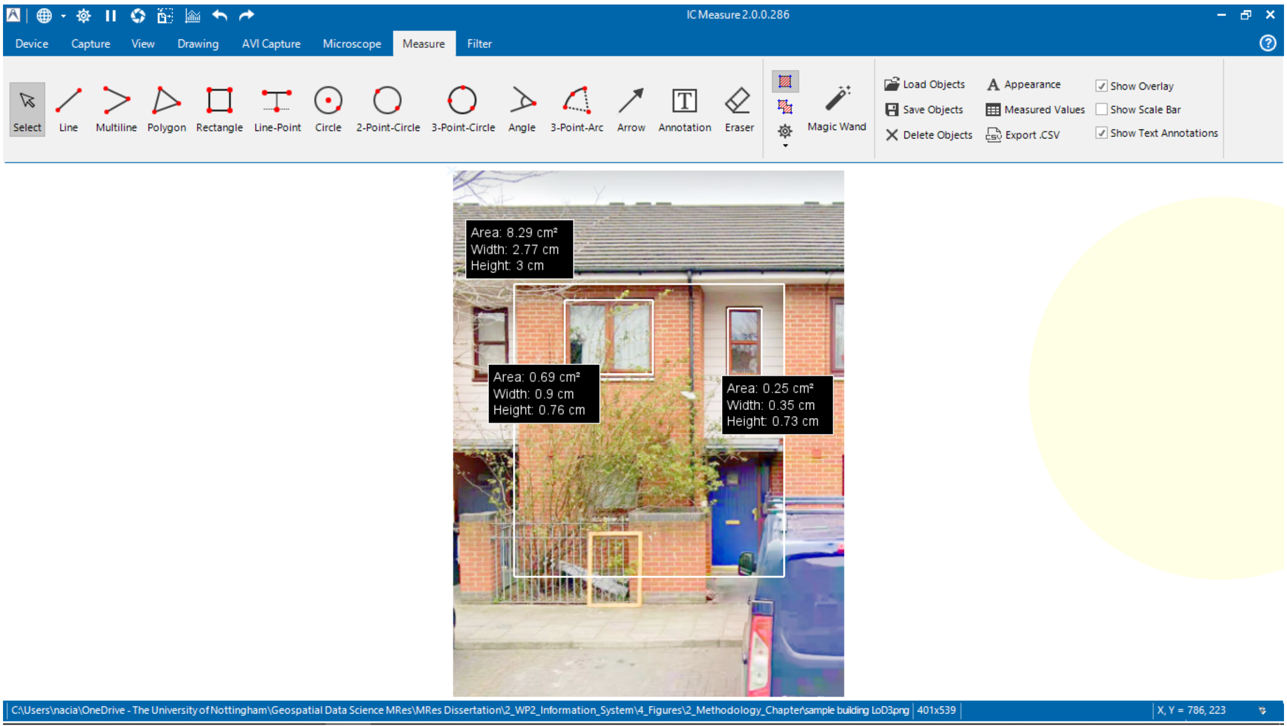



**Figure 3-21 Measured areas from IC Measure software for the building of interest**

## 3.6 Parametric Study

### 3.6.1 <u>Calculating Annual Heat Demand</u>

After completing the measurements regarding the roof type and the WWR for the two datasets (old and new buildings datasets), the next step has been to run the model three times for each dataset. More particularly, the first time, the model has run for LoD1, where assumptions have been made for roof type and WWR. The second time, the model has run for LoD2, where the information about the roof type has been added. And the third time, the model has run for LoD3, where information about the WWR has been added, too.

For the calculation of the heat demand as it has been mentioned above the Python script from Github repo of Dochev ‘s research has been used, by changing the climate data [14]. At this stage, it should be mentioned that in order the code to run successfully, QGIS v2.18.17 should be used in combination with Python console add-in.

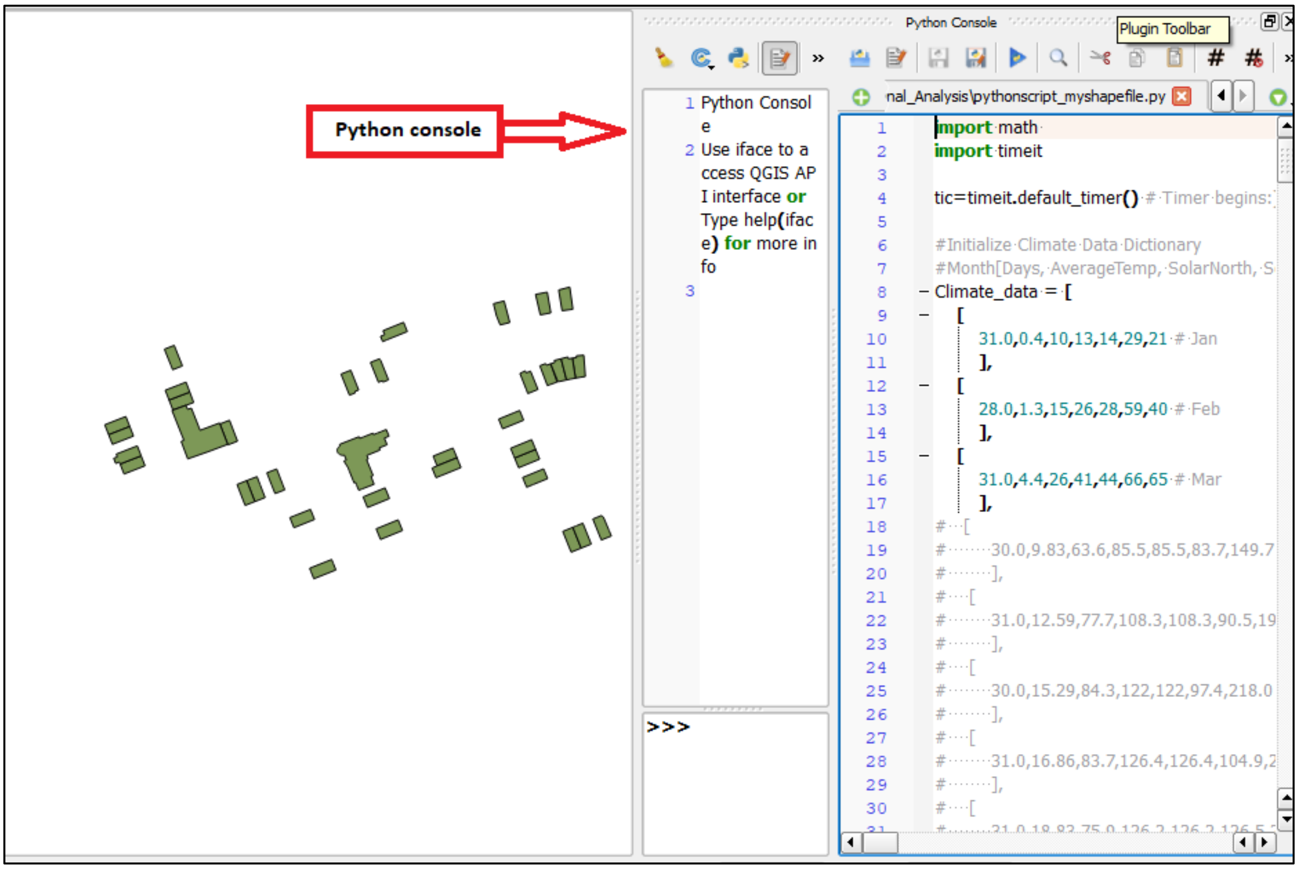



**Figure 3-22 Python console and Python script in QGIS v2.17.18**

At the following section the Python code from Dochev I. is described [14].

### 3.6.2 Python code description

First of all, the whole code idea is based on energy balance equations for buildings, which means that it is a physics-based approach.

The code starts by importing the required Python libraries, which are the ‘math’ and ‘timeit’, the first for mathematical equations and the second for timing the durations that the code runs. After that, the weather data is inserted to the code, by using Python dictionaries for each month. In more detail, each dictionary for each month contains the number of days, the average outdoor temperature, the solar radiation in North, East, South and West and, finally, the horizontal radiation.

After that, all the attributes from the attribute table on QGIS are archived in the code as Python variables. For instance, the height of each building has been in the column ‘HEIGHT’ at QGIS attribute table, so the column ‘HEIGHT’ has been inserted in a Python parameter called Height. The same has been done for every column at QGIS attribute table.

The next step has been the creation of functions for the equations that should be used for the energy balances calculations, specifically for the energy losses and gains. For example, the equation for the internal gains has been inserted into a Python function, which takes as input parameters the number of floors of each building, the floor area and the internal gain coefficient (The internal gain coefficient has been taken as a constant from Passive House standard.). The same has been done for all the energy balance equations.

Consequently, the most interesting step has been to classify the buildings into attached and detached, in order to take into consideration common walls between buildings, which in theory do not have any heat losses [14]. Therefore, a spatial check is done to understand if buildings are connected. If their geometry is not intersecting with another, then the geometry, namely the building, is free and is detached, otherwise the building is attached. Then, a spatial check is done, in order to find out, which parts of the walls are connected, and for these parts of walls no heat loss is calculated. Undoubtedly, if the height of the building under test is higher than the adjacent building, the area of the wall that is not part of both buildings is taken into account for thermal losses.

The following step has been to calculate the area of the walls, so each segment of the building footprint has been multiplied by the height of the building and then, the window area has been applied. All the above steps have been done in order to 'describe' the building geometry as simple as it could be done.

So, the monthly energy performance rating for each building follows the above steps, by using the functions of the energy balance equations that have been created. Hence, the monthly energy losses for each building are calculated, in which the roof type is taken into consideration. More specifically, it has been assumed that if the roof type is flat, the major possibility is a heated space to border the outdoor air, but if the roof type is hip, it is more possible an unheated space to border the outside air. Therefore, monthly energy losses, ventilation losses, solar gains and internal gains are computed for the building and after that, the total heat demand is calculated for the whole year.

Finally, the steps that have been described above for the individual building are implemented for all the buildings by using a loop at the code for the whole dataset [14].

### 3.6.3 Calculating the percentage difference – Creating graphs

The following step, after the calculation of the annual heat demand has been to export the attribute tables from the above parametric studies, into .csv files. Then, with the use of Microsoft Excel software, the percentage difference of the results from the upgrade from lower LoD to higher LoD have been calculated and diagrams have been plotted in order to show this difference.

## 3.7 Mapping the percentage difference

The idea of the project has been to, mainly, present the percentage difference of the results of the annual heat demand from the upgrade from a lower LoD to a higher. Therefore, in order to understand this difference and make the results more obvious, a spatial analysis of this difference should be made, and maps of the areas should be created that would show the findings in a convenient way for the audience. At the next subsections the steps of the creation of map are shown for area 1 (old buildings) as an example.

### 3.7.1 Creating a .csv file with findings

Hence, at the next stage of the project a .csv file has been created with the following columns:

1. building_id, where the unique id of each building has been inserted;
2. ref_toid, where the unique building identifier from Ordnance Survey (OS) has been imported;
3. heat_demand_LoD1, where the annual heat demand at LoD1 has been shown;

4. heat_demand_LoD2, where the annual heat demand at LoD2 has been shown;
5. heat_demand_LoD3, where the annual heat demand at LoD3 has been shown;
6. LoD1-LoD2-Dif, where the percentage difference of the results of annual heat demand from LoD1 to the upgrade of LoD2 has been calculated;
7. LoD2-LoD3-Dif, where the percentage difference of the results of annual heat demand from LoD2 to the upgrade of LoD3 has been calculated;
8. LoD1-LoD3-Dif, where the percentage difference of the results of annual heat demand from LoD1 to the upgrade of LoD3 has been calculated.

### 3.7.2 Creating the shapefile for QGIS

For the creation of the shapefile that would contain the percentage differences of the results, Python programming at jupyter notebook with the use of anaconda, should be applied. The first step has been to import the .csv file that has been made into jupyter notebook (Figure 3-23).

```
In [1]: #importing the csv file with differences for area 1 (old buildings)
        import numpy as np
        import pandas as pd
        pathtest='C:/Users/nacia/OneDrive - The University of Nottingham/Geospatial Data Science MRes/MRes Dissertation/3_WP3_Analytics/
        dfarea1=pd.read_csv(pathtest)
        print(dfarea1)
```

**Figure 3-23 Importing .csv file**

After that, the OS MasterMap Topography layer has been inserted in order to obtain spatial information for the buildings from the geometry column (Figure 3-24).

```
In [2]: #importing OS topography layer in order to connect it to csv file and take the geometry column
        import geopandas as gpd
        pathOS='C:/Users/nacia/OneDrive - The University of Nottingham/Geospatial Data Science MRes/MRes Dissertation/2_WP2_Information_
        OSdata = gpd.read_file(pathOS)
```

**Figure 3-24 Importing OS MasterMap Topography layer**

After that, a new geodataframe has been created, which consisted of the geometry column (‘geometry’) and the TOIDs of buildings (‘fid’) (Figure 3-25).

```
In [4]: dfgeom = OSdata[['geometry','fid']]
        dfgeom
```

Out[4]:

| | geometry | fid |
|---|---|---|
| 0 | POLYGON ((526485.800 178495.100, 526488.100 17... | osgb1000001794254181 |
| 1 | POLYGON ((526456.450 178511.700, 526456.700 17... | osgb1000001794254182 |
| 2 | POLYGON ((526460.800 178514.700, 526464.750 17... | osgb1000001794254183 |
| 3 | POLYGON ((526468.900 178520.350, 526473.400 17... | osgb1000001794254184 |
| 4 | POLYGON ((526464.750 178517.500, 526466.700 17... | osgb1000001794254185 |
| ... | ... | ... |

**Figure 3-25 Creation of geodataframe with spatial information of each building**

The following step has been to merge the two geodataframes, create the final dataset and delete the extra ‘fid’ column (Figure 3-26 and Figure 3-27).

```
In [5]: #Inserting geometry column
        import pandas as pd
        dfarea1 = dfarea1.merge(dfgeom, how='inner', left_on='ref_toid', right_on='fid')
        dfarea1
```

Out[5]:

| | building_i | ref_toid | Heat Demand-LoD1 | Heat Demand-LoD2 | Heat Demand-LoD3 | LoD1 to LoD2-Dif | LoD2 to LoD3-Dif | LoD1 to LoD3-Dif | geometry | fid |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1948730 | osgb1000001769621447 | 385.216232 | 398.888580 | 394.966939 | 0.035493 | 0.009831 | 0.025312 | POLYGON ((535485.580 178525.390, 535483.850 17... | osgb1000001769621447 |
| 1 | 1985033 | osgb1000001769641015 | 410.569482 | 425.074074 | 418.547930 | 0.035328 | 0.015353 | 0.019433 | POLYGON ((535363.190 178531.960, 535370.000 17... | osgb1000001769641015 |
| 2 | 1948875 | osgb1000001769621209 | 495.852125 | 513.317172 | 509.712659 | 0.035222 | 0.007022 | 0.027953 | POLYGON ((535508.620 178551.950, 535505.040 17... | osgb1000001769621209 |
| 3 | 1985210 | osgb1000001769621469 | 443.664442 | 459.295919 | 448.357451 | 0.035233 | 0.023816 | 0.010578 | POLYGON ((535483.050 178504.580, 535486.590 17... | osgb1000001769621469 |

**Figure 3-26 Creation of final dataset**

```
In [6]: dfarea1.drop(['fid'], axis='columns', inplace=True)
```

**Figure 3-27 Deleting the extra column of 'fid'**

Finally, the dataset has been exported as a shapefile, in order to use it for the spatial analysis.

```
In [8]: #exporting to shapefile
        gdfarea1 = gpd.GeoDataFrame(dfarea1)
        gdfarea1.to_file(driver = 'ESRI Shapefile', filename= "C:/Users/nacia/OneDrive - The University of Nottingham\Geospatial Data Sc
```

**Figure 3-28 Exporting final dataset as a shapefile**

### 3.7.3 Importing shapefile to QGIS v3.14 for the creation of the maps

The last step has been to import the shapefile to QGIS v3.14, in order to create three different maps that would show the percentage difference from the upgrade of lower LoD to a higher LoD.

The above method has been followed for the area 2 of new buildings, where another three maps have been exported as output.

## 3.8 Extending the area 1 (old buildings)

After mapping the area of the old buildings, it has been observed that the specific area consisted of the same type of buildings in terms of building form. Moreover, after a virtual 'walk' to this location with the use of Google Street View, it has been found out that the actual buildings have the same appearance as the buildings that have been kept in the previous dataset with the known building age and form. Hence, it has been decided to extend this area, by adding some buildings that their building age could be assumed from the homogeneity of the area. More specifically, the dwellings that have been inserted to the small dataset, are residential buildings, that in the big dataset had NaN values at the building age and building form. Therefore, their building age has been assumed from their neighbouring buildings and the building form has been imported from the quick virtual 'walk' to the area. With this technique, dwellings that have been deleted from area 1 first dataset by filtering the null values, at this dataset exist and fill some gaps in the initial map.

Finally, for area 2 (new buildings), the same technique could not be applied, in order to fill the map. This happens due to the inhomogeneity of this area, that does not allow to assume, with high confidence level, the building age, and the building form. At Figure 3-29, a screenshot of the inhomogeneity of the area, from QGIS software, can be seen.

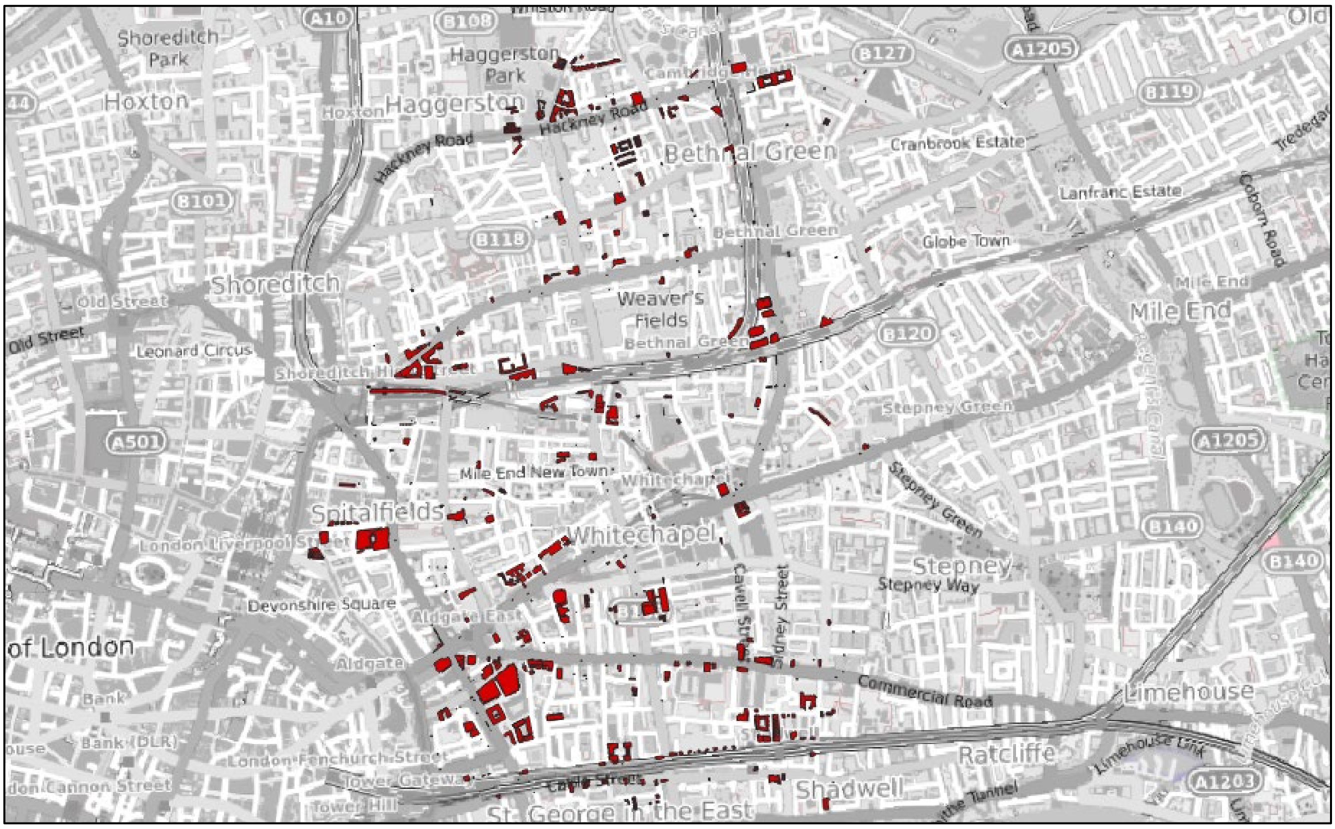



**Figure 3-29 Extended area 2 (new buildings)**

## 3.9 Statistical Analysis

### 3.9.1 Dependent T-Test for significance level of the difference on Annual Residential Heat Demand

For the investigation of the level of significance of the difference between the output of the annual residential heat demand from a lower to a higher LoD, the Dependent T-Test has been chosen to be used, as it compares the means.

Nonetheless, before the implementation of the process, the data should meet some requirements. In other words, in order for the Dependent T-Test to give valid results, the following assumptions should be applied for the data.

The first assumption is that the dependent variable, which is the annual residential heat demand should be a continuous value, that it is as it is measured in kWh/ ($m^2$.a).

The second assumption is that the independent variable should be consisted of two 'related groups' or two categorical. In this case, at first, the independent variable is the roof type, and secondly, the WWR, which are both categorical variables.

The third assumption is that the sample should not consist of significant outliers. Therefore, the sample of the research has been checked and any significant outlier has been subtracted from it.

The fourth, and last, assumption is that the differences in the dependent variable, namely the annual residential heat demand, should be distributed normally.

Hence, after checking that the sample is valid for the Dependent T-Test, the calculations have been done through Data Analysis Tools in Excel software, and more particularly, through 't-Test: Paired Two Sample for Means'.

### 3.9.2 Pearson correlation / t-statistic test (percentage difference – building age and building form)

As an additional step for the specific project, a brief statistical analysis has been done, in order to check whether the building age or building form influence the percentage difference from the upgrade of a lower LoD to a higher LoD. In other words, from the statistical test, it could be investigated, for instance, if older buildings have greater difference at the result of the annual heat demand than the newer buildings and the inversed. More particularly, a Pearson correlation test has been applied, which is defined as a statistical test that determines the association between two variables. Therefore, for the specific topic the associations that have been tested are the below:

1. The building age with the percentage difference from LoD1 to LoD2;
2. the building age with the percentage difference from LoD2 to LoD3;
3. the building age with the percentage difference from LoD1 to LoD3;
4. the building form with the percentage difference from LoD1 to LoD2;
5. the building form with the percentage difference from LoD2 to LoD3;
6. the building form with the percentage difference from LoD1 to LoD3.

The calculations have been done by using the Microsoft Excel software. At first, the null hypothesis has been defined, which is that there is a strong dependence between the difference percentage from the upgrade of LoDs and the building age or building form. The next step has been to calculate the Pearson correlation coefficient (r), from the 'PEARSON' formula of Microsoft Excel, which can define the strength of the association of the two variables. Hence, if r is equal to -/+1, there is a perfect negative/positive association and if it is equal to 0 there is no association. After that, the t-statistic has been defined from the coefficient value. The formula for its calculation is the below:

$$t = \frac{r * \sqrt{n-2}}{\sqrt{1-r^2}}$$

, where n is the number of the observation of the analysis, namely the number of buildings.

In sequence, the p-value from the t-statistic has been calculated from TDIST function of Microsoft Excel software. Finally, a small p-value (≤0.05) means that there is evidence to reject the null hypothesis, whereas a large p-value (>0.05) indicates weak evidence to reject it. If the p-value is close to 0.05, the value is marginal and everybody at an audience could draw his own conclusions.

#### 3.9.3 RMSE statistic test (percentage difference – building age and building form)

Finally, the RMSE (Root Mean Squared Error) has been estimated for the difference of the annual heat demand from the upgrade of lower to higher LoD. The calculation has been done by using the Microsoft Excel software. The first step has been to calculate the difference from LoD1 to LoD2, LoD2 to LoD3 and LoD1 to LoD3. Then, the following formula has been used in order to calculate the RMSE.

$$RMSE = \sqrt{\frac{\Sigma(Pi - Oi)^2}{n}}$$

, where Σ means the sum of the parenthesis, Pi is the predicted value and Oi is the observed value for the $i^{th}$ observation in the dataset and n is the sample size.

Therefore, after calculating the RMSE for every upgrade, the significance of the addition of the roof type (LoD2) and the WWR (LoD3) can be seen, as the RMSE is always the same units as the dataset values.

### 3.10 Assumptions & Simplifications during modelling

There is no doubt that the bigger and more challenging a project is, the more assumptions and simplifications might be made, in order to obtain some findings. Firstly, for this project, the biggest assumption that has been made, is that all dwellings are assumed non-renovated, as it has been mentioned above. This means that the annual heat demand that has been calculated, it might not be the current annual heat demand for some of the dwellings, as some of them might be refurbished from the date that have been constructed. Hence, for future studies it would be a step forward to find out, which buildings are renovated and include the renovated thermal transmittance values (U-values) to the dataset. Nonetheless, from the data requirement aspect, namely for the comparison of the results from LoD1 to LoD2 and LoD3, it is not necessary to have the exact value, as proportions are taken into account. However, from the energy aspect is a highly significant information that should be considered. Apart from that, the simplification regarding the air change rate (ACR) should be taken into consideration, as at this case study, a uniform value has been assumed from Tabula typology, but, in reality, each building has its own air change rate. The same occurs for the inside temperature, where the average of the minimum range of indoor temperature regarding Public Health England has been inserted to the model. Nevertheless, for district or city scale these parameters could be assumed as uniform for the buildings, as the differences to the holistic findings are minor. Finally, regarding the window to wall ratio (WWR), that has been calculated for every building, in order to calculate the annual heat demand at LoD3, it should be mentioned that even this WWR is an approximate value. One reason that this happens is that the ratio has been calculated at the façade that is visible to the street, due to the use of Google Street View. Therefore, it has been assumed that this ratio is the same for the whole building. Another reason is that in some buildings the street view is not so clear due to obstacles, such as cars or trees. This means that some areas have been measured approximately. In spite of everything, for the update to LoD3, this is a detail, as we talk about a percentage/ ratio and using Google Street View is a good approach at this level.

# Chapter 4

# Results & Discussion

# 4 Results & Discussion

*At this chapter, the results that have been obtained are presented. Furthermore, simultaneously with the illustration of the results, a discussion about them is done.*

## 4.1 Annual Residential Heat Demand

### 4.1.1 Plausibility check

The results regarding the LoD1, LoD2 and LoD3 are presented at this section. More particularly, as it has been aforementioned, the final Python script that calculates the annual heat demand is validated from the research study of Dochev, so at this stage there was no need for validation [14].

Nonetheless, an approximate validation, specifically, for the city of London has been done. More particularly, from the live tables on Energy Performance of Buildings Certificates from GOV.UK, information regarding the energy demand of domestic buildings from 2008/04 until 2021/02, has been obtained [84]. Then, the average from all these years, from 55,510 buildings, has been calculated and found equal to 273.45 kWh/ (m$^2$.a). After that the average of the heat demand from the 225 dwellings from the sample of this study has been estimated for every LoD. The results are shown at the following table.

**Table 4-1 Plausible check**

| | *LoD1* | *LoD2* | *LoD3* | *AVG-LoDs* | *GOV.UK* |
|---|---|---|---|---|---|
| *Energy Demand kWh/ (m2.a)* | 313.84 | 314.58 | 312.99 | 313.80 | 273.45 |
| *Difference with GOV.UK* | 40.39 | 41.13 | 39.54 | **40.35** | |

As it can be seen from Table 4-1, the average difference from the calculated results and the value from GOV.UK is 40 kWh/ (m$^2$.a), approximately. This difference is acceptably small (~12%), as concerning the sample size there is a huge difference. This means that the sample size of dwellings from GOV.UK is more representative than the 225 dwellings from the study's sample. Apart from that, the value from GOV.UK represents both heating and cooling period of the year. This means that the average energy demand is logic to be slightly decreased from the calculated, as the model takes into consideration only the heating period of the year. Finally, at this research study, it has been assumed that none of the buildings has been renovated, due to lack of data. Therefore, undoubtedly, the estimated heating demand would be slightly higher as in many buildings there is no energy upgrade, whereas in reality there is.

At the following maps, Figure 4-1 to Figure 4-6, the results regarding the annual residential heat demand for LoD1 to LoD3, are illustrated, respectively, for both areas.

### 4.1.2 Annual Residential Heat Demand maps for area 1 – old buildings

At this subsection, the maps show the annual heat demand in an area of London that consists of older buildings. At Figure 4-1, the heat demand has been calculated at LoD1, namely by assuming the roof type and the WWR. The assumed roof type is the 'hip', as from Tabula typology, it is shown that this type of roof is more common to UK dwellings [81].


**Figure 4-1 Annual Residential Heat Demand with LoD1 for area 1 (old buildings)**

There is no doubt that the calculated heat demand is high as expected. This happens because the thermal envelope of the majority of old dwellings does not consist of thermal insulation or consists of thermal insulation construction materials with high thermal transmittance (U-value), which means that these properties cannot be high energy effective.

Similar, results have been obtained for LoD2, where the exact roof type of each building has been inserted to the dataset, with the use of Google Satellite view. As it is obvious, the illustration of the map is the same as for LoD1, except of one building that has been moved to a class that represents a higher heat demand.


**Figure 4-2 Annual Residential Heat Demand with LoD2 for area 1 (old buildings)**

The same occurs for LoD3, where an estimation of the window to wall (WWR) ratio has been inserted to the dataset, by using the Google Street view and IC measure software. Nonetheless, as it is clear from the maps, the illustration of the map for LoD3 (Figure 4-3) is insignificantly different to the above maps. Finally, only a few buildings can be seen that have changed and classified to a higher annual residential heat demand class. For this reason, it has been decided to check another area of dwellings in London, where the construction could be newer than the above.

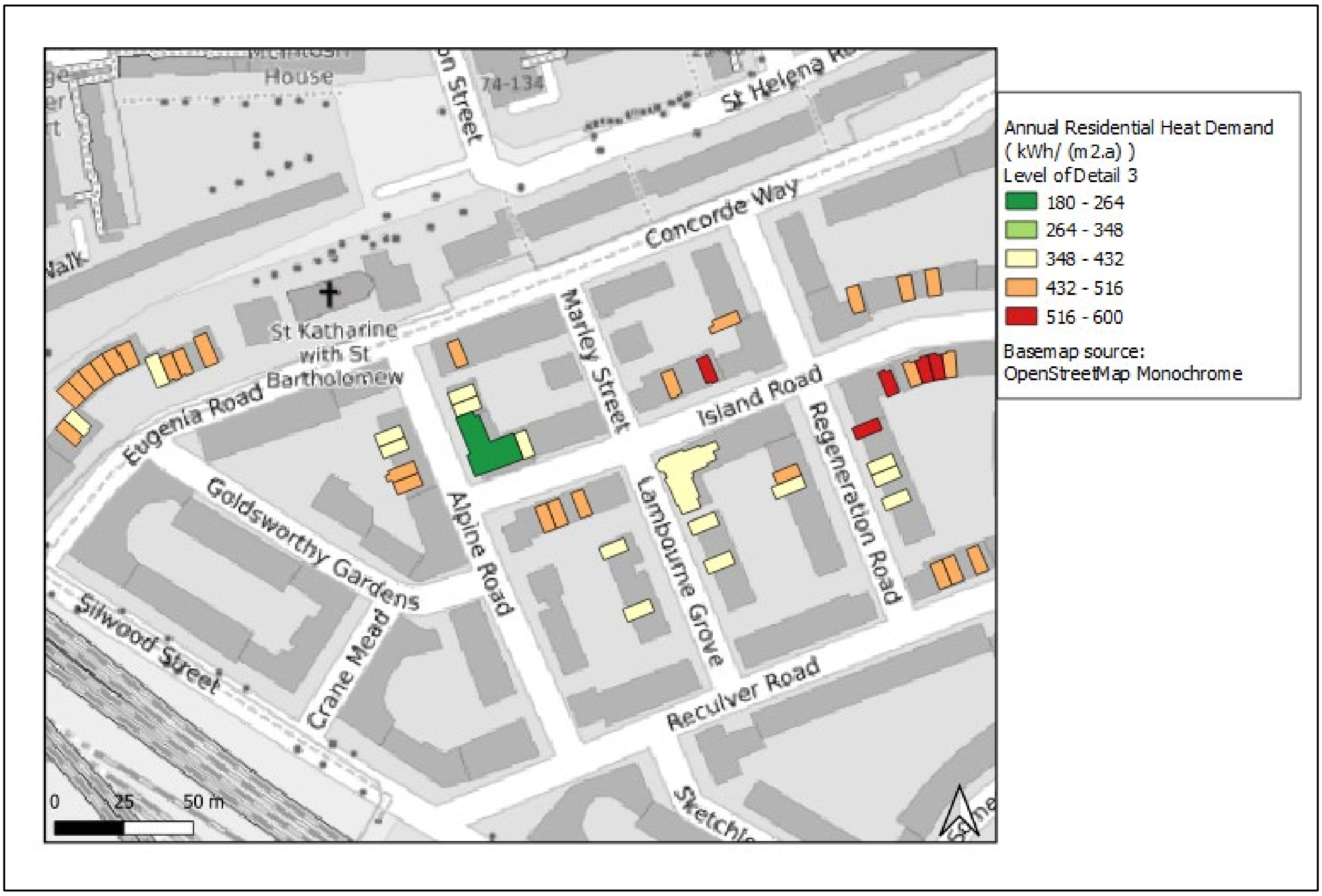



**Figure 4-3 Annual Residential Heat Demand with LoD3 for area 1 (old buildings)**

### 4.1.3 Annual Residential Heat Demand maps for area 2 – new buildings

The results from the area with newer dwellings are presented at the maps below (Figure 4-4 to Figure 4-6). As it is obvious the illustration of the results is the same again for all LoDs. More particularly, from the legend, it can be seen that the annual heat demand at the area of London with newest dwellings (construction year > 2003) is extremely lower than the annual heat demand of older buildings. These results could be foreseen, as high energy effective construction materials with lower thermal transmittance are commonly chosen for buildings at recent years.

Despite that, from LoD1 to LoD2 there is no difference at the results of the annual heat demand, as it is shown from the maps below, and only for LoD3 there is a small difference. However, the difference is too small, especially, if taking into consideration the time consumed for the calculation of the WWR than assuming a logic and average value.

Undoubtedly, for the convenience of the comparison of annual heat demand, some graphs have been plotted, for both areas, and are illustrated at subsection 4.1.4.

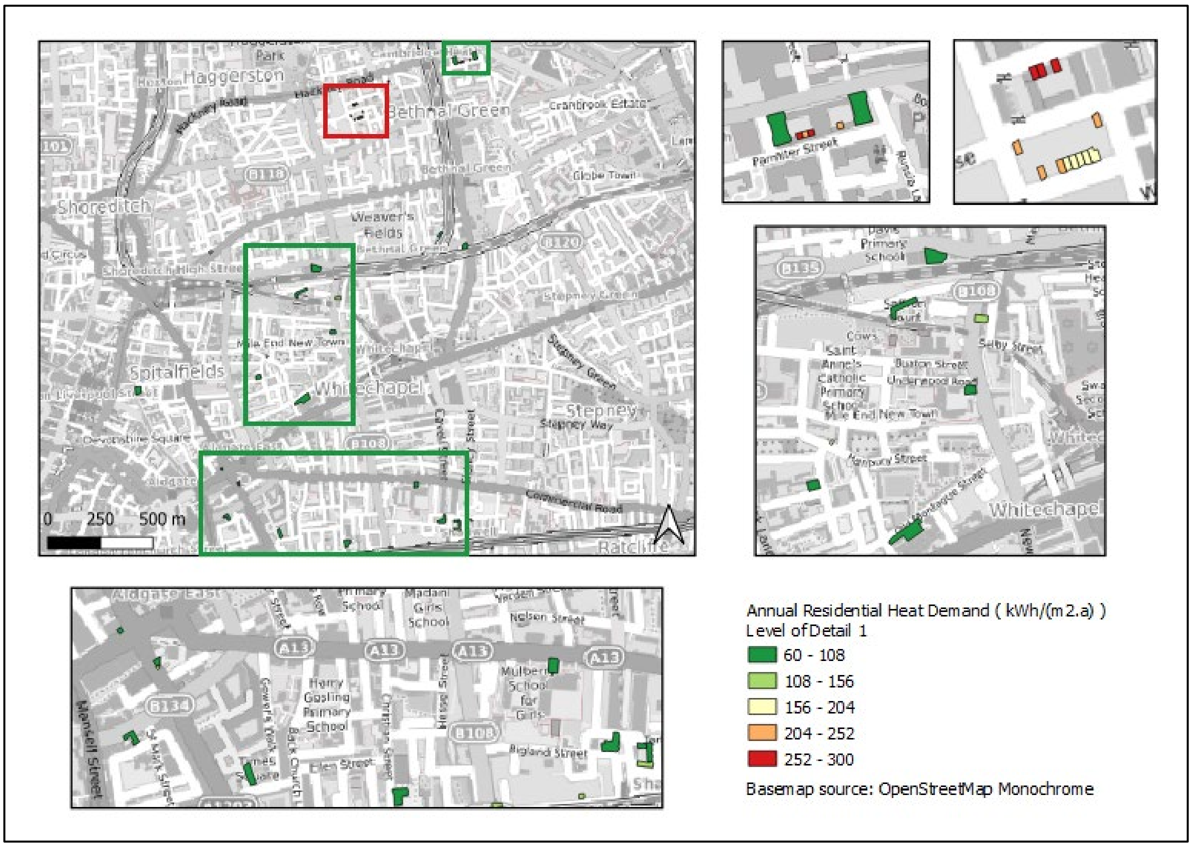



**Figure 4-4 Annual Residential Heat Demand with LoD1 for area 2 (new buildings)**

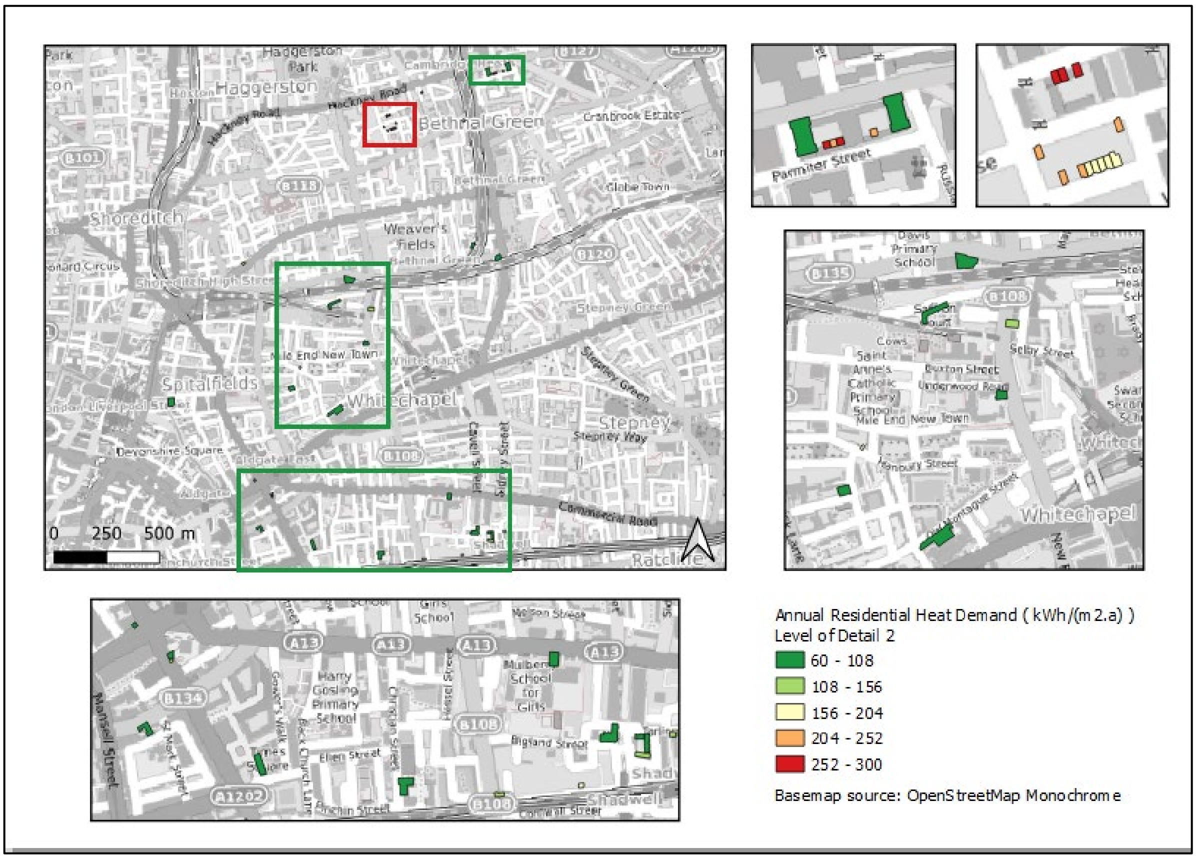



**Figure 4-5 Annual Residential Heat Demand with LoD2 for area 2 (new buildings)**

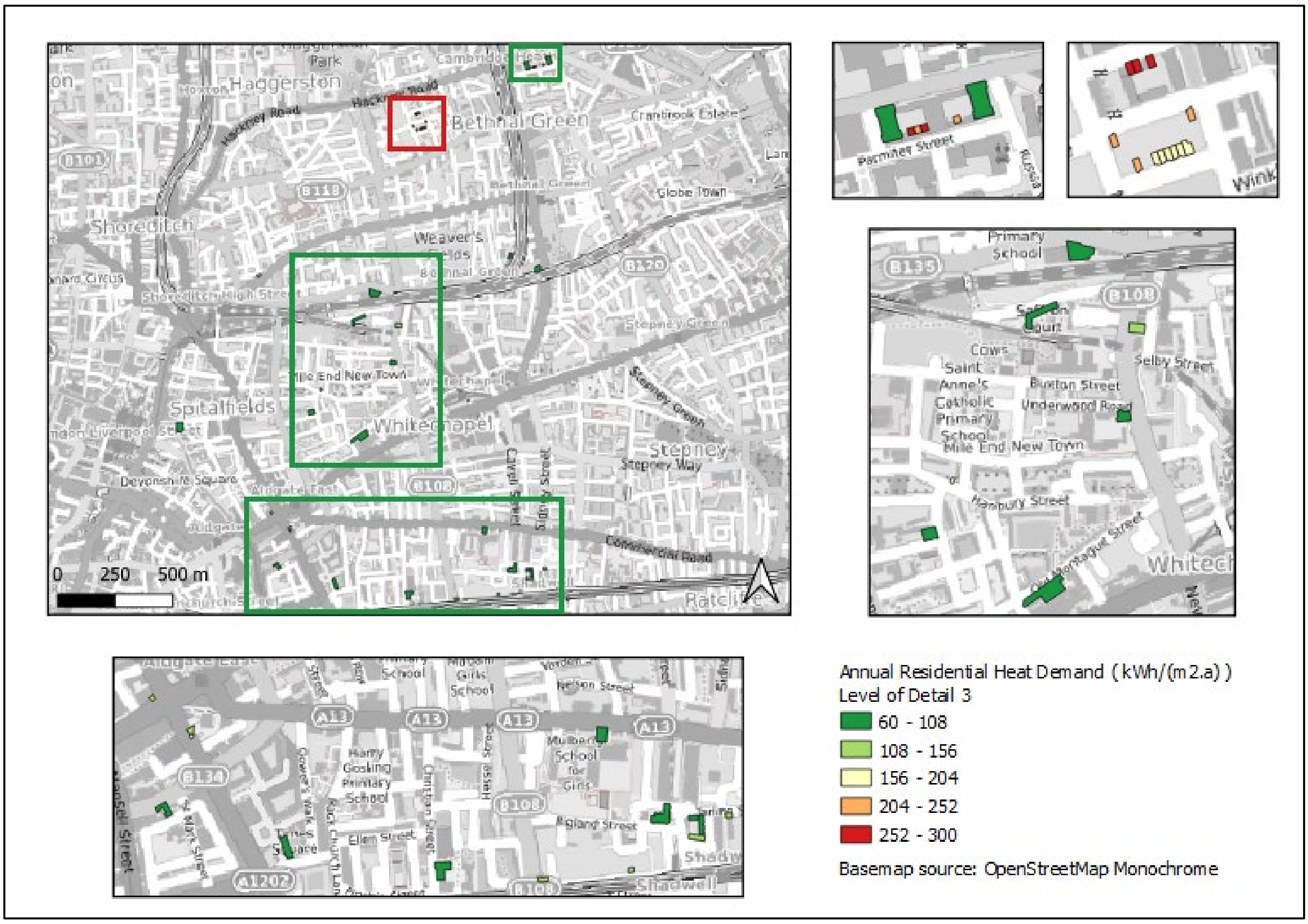



**Figure 4-6 Annual Residential Heat Demand with LoD3 for area 2 (new buildings)**

### 4.1.4 <u>Annual Residential Heat Demand diagrams for both areas</u>

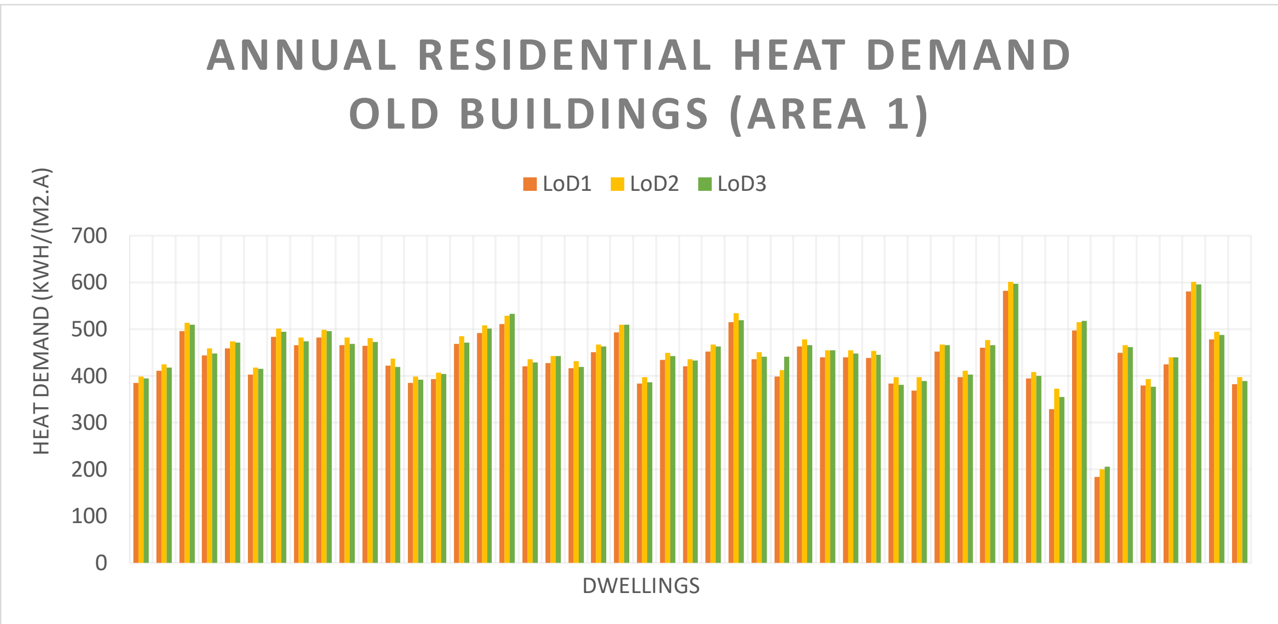



**Diagram 4-1 Comparison of Annual Residential Heat Demand for Area 1 (old buildings) from LoD1, LoD2 and LoD3**

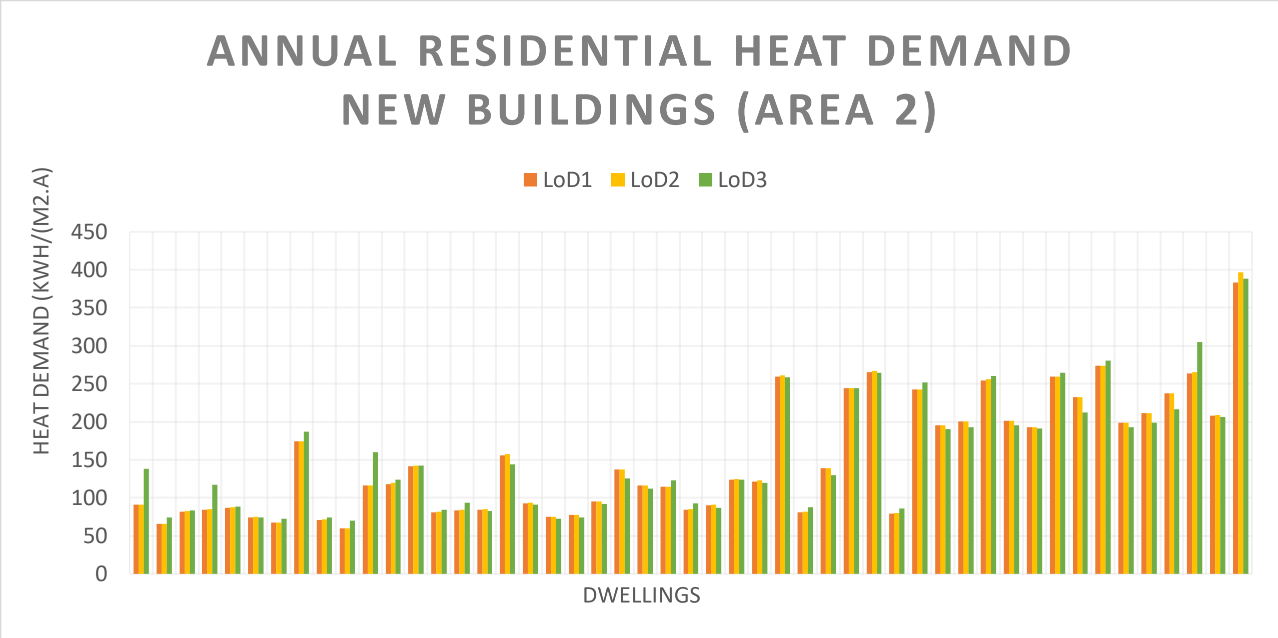



**Diagram 4-2 Comparison of Annual Residential Heat Demand for Area 2 (new buildings) from LoD1, LoD2 and LoD3**

At the above graph, the three different columns represent the result of annual heat demand for each Level of Detail. As it can be seen, at both graphs the difference between the height of the three columns is minor, except of three buildings at the area 2 (new buildings). This could have happened, because some new buildings in London are constructed with glazing facades, instead of the common facades for dwellings. Therefore, the window to wall ratio cannot be the average and most common and the results of the annual heat demand with the assumed value of WWR end up being different.

Consequently, the percentage difference from LoD1 to LoD2 and then, to LoD3 has been calculated, in order to compare the findings and conclude.

## 4.2 Percentage difference of the results

At this section, the percentage difference of the annual residential heat demand is presented, as it has been calculated for a more convenient comparison between the results from the different LoDs.

Diagram 4-3 and Diagram 4-4 show the percentage difference that has been estimated. At these diagrams, the three columns represent the percentage difference of the annual heat demand for each building. In other words, the first column represents the percentage difference from the upgrade of the results from LoD1 to LoD2, the second column represents the percentage difference of the upgrade from LoD2 to LoD3, and finally, the third column represents the upgrade from LoD1 to LoD3.

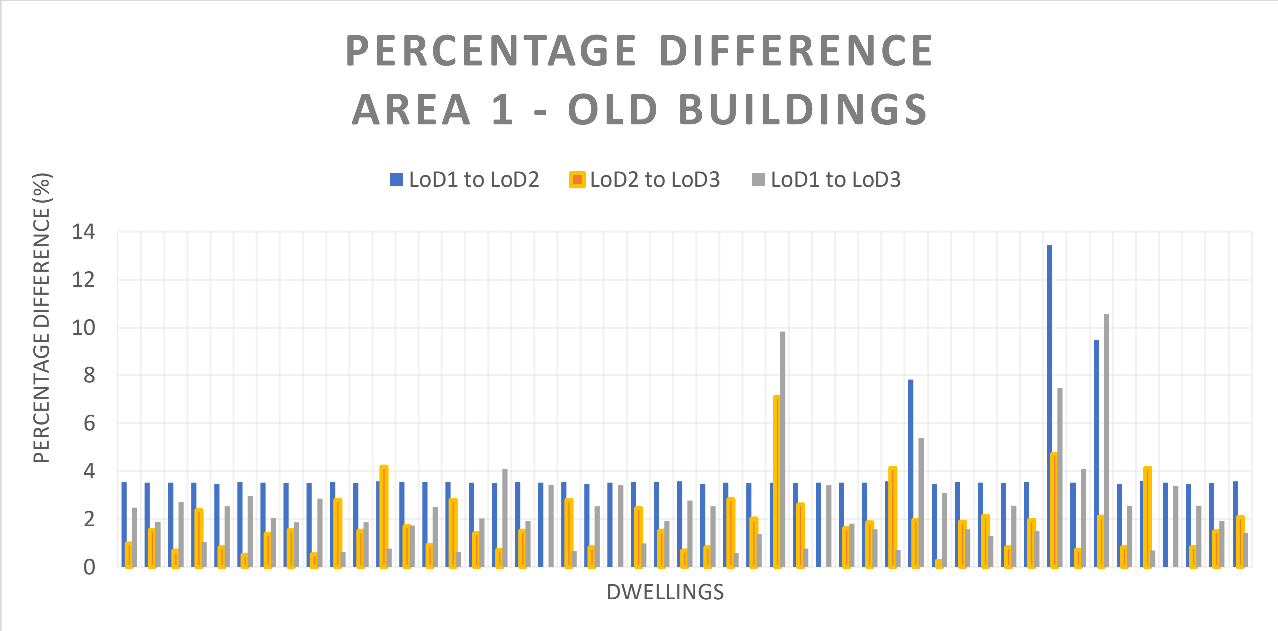



**Diagram 4-3 Percentage difference of the results for Annual Residential Heat Demand from a lower LoD to a higher LoD (Area 1- Old buildings)**

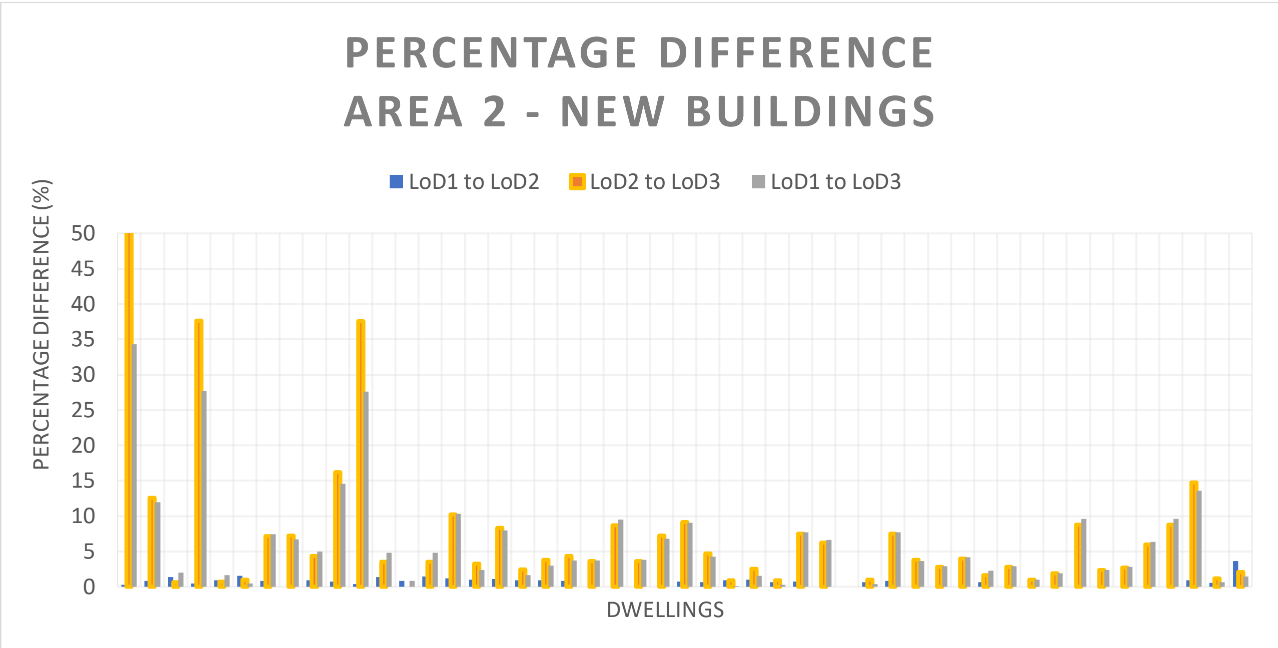



**Diagram 4-4 Percentage difference of the results for Annual Residential Heat Demand from a lower LoD to a higher LoD (Area 2- New buildings)**

As it can be seen at Diagram 4-3, there are, also, four buildings at area 1 with high percentage difference. More specifically, the highest percentage occurs for LoD1 to LoD2 upgrade, and it is around 13%. The next higher percentage is 10%, approximately, and occurs for the upgrade from LoD1 to LoD3. However, these are exceptions over many buildings and could happen, as LoD1 data are, mainly, assumptions and average values from literature review and typologies. Furthermore, the average percentage difference of the annual residential heat demand for the old buildings has been calculated equal to 3.94% for the upgrade from LoD1 to LoD2, 1.74% for LoD2 to LoD3 and 2.55% for LoD1 to LoD3. This means that, especially, for old dwellings the LoD1 is enough for the estimation of the heating demand at district scale.

Nevertheless, one could say that the percentage difference from LoD1 and LoD2 to LoD3 for the new buildings is higher, as there is a big difference at the three aforementioned buildings, which reaches even about the 50%. However, as it has been stated above these three buildings are an exception to the whole area, and this is possible to occur in new buildings in London as some of them are constructed with glazing facades. In spite of that, the average percentage difference from LoD1 to LoD2, from LoD2 to LoD3 and from LoD1 to LoD3 is 0.61%, 7.04% and 6.23%, respectively. These differences are, also, minor for the estimation of the thermal performance of buildings at district scale.

At the next maps the percentage difference of the Annual Residential Heat Demand is presented in a more convenient and obvious way, for both areas.

### 4.2.1 Percentage difference in Annual Residential Heat Demand at area 1 - old buildings

From the below maps, regarding area 1, that consists of old buildings, the findings that have been discussed at the previous section are visible with ease. At Figure 4-7, it can be seen that the majority of buildings has a small percentage difference from LoD1 to LoD2, with the highest to be for one building, that is represented with dark red colour and its percentage difference is between 10.72% and 13.4%.


**Figure 4-7 Percentage difference in Annual Residential Heat Demand from LoD1 to LoD2**

At Figure 4-8, for the upgrade from LoD2 to LoD3, there is a different appearance of the map from this area. As it can be seen, the percentage difference is lower than at Figure 4-7, which means that for old buildings at least, there is no need for the estimation of the WWR, as the percentage difference could be characterized as acceptable.

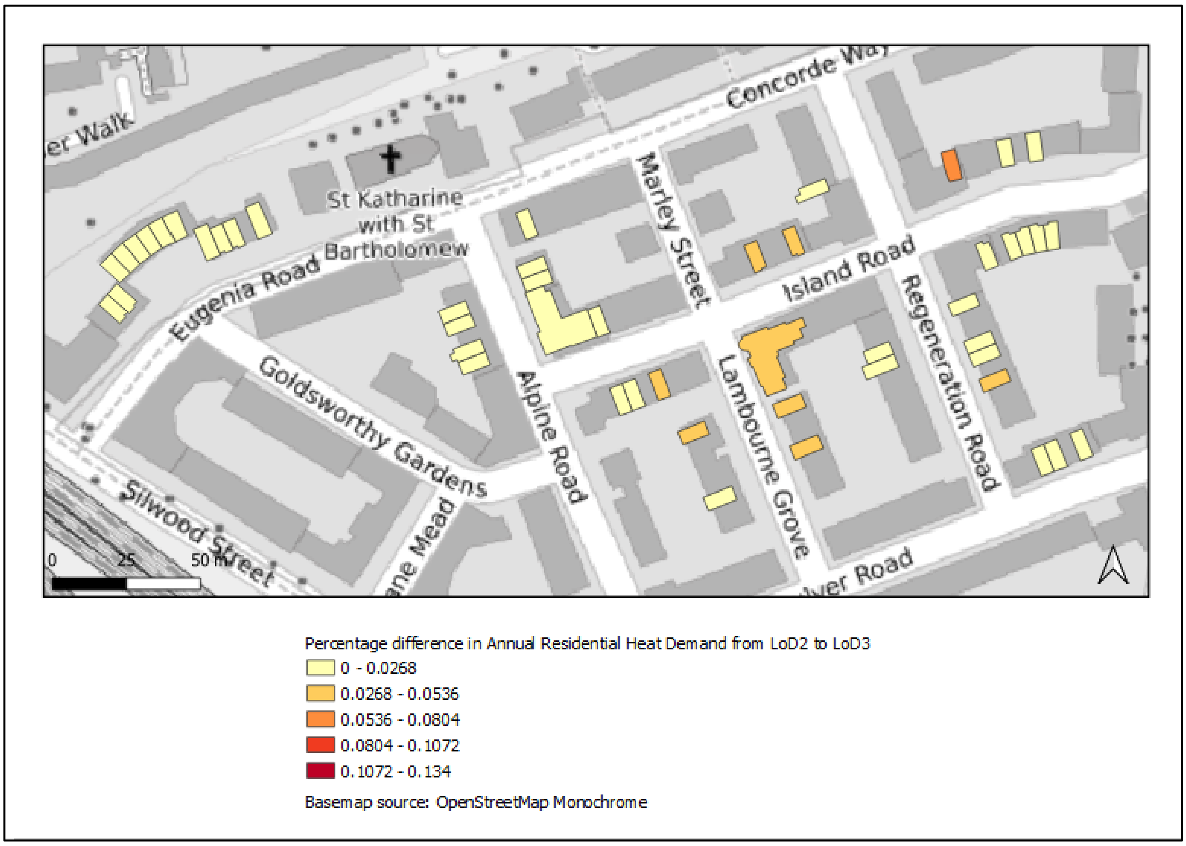



**Figure 4-8 Percentage difference in Annual Residential Heat Demand from LoD2 to LoD3**

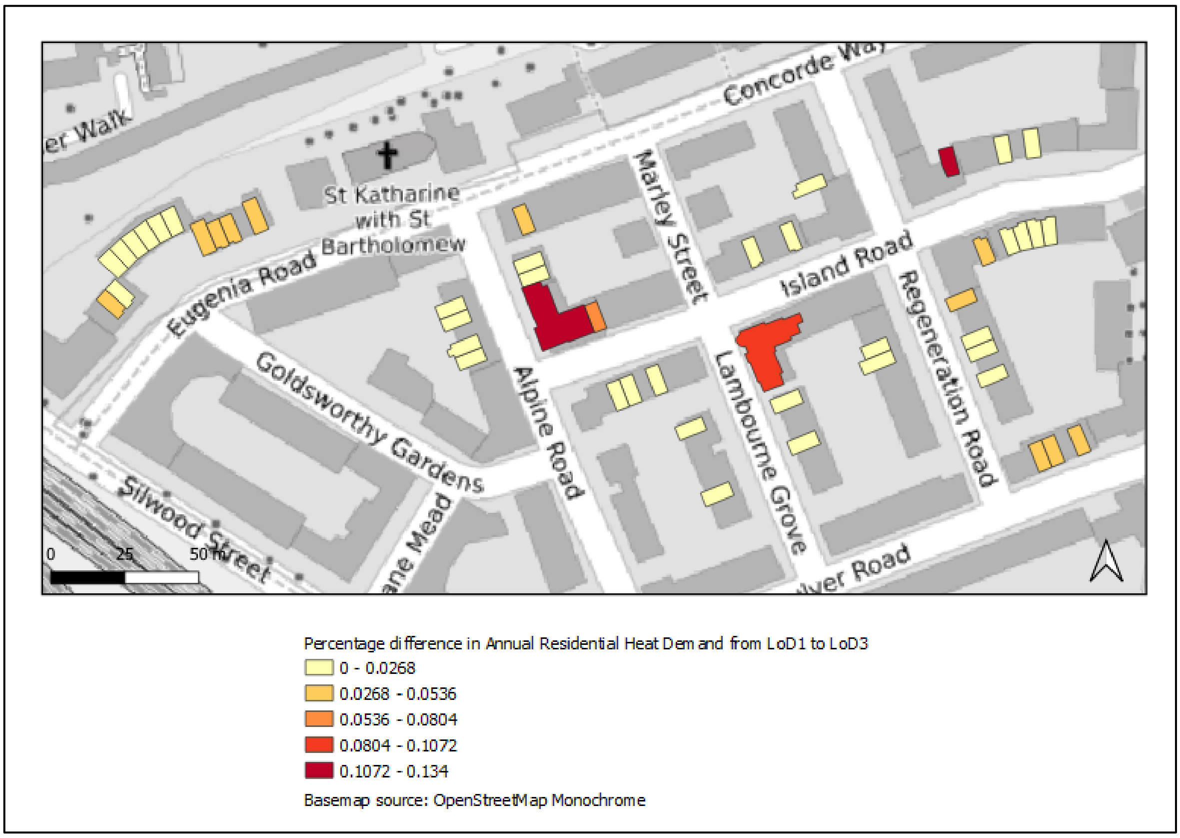



**Figure 4-9 Percentage difference in Annual Residential Heat Demand from LoD1 to LoD3**

Finally, at Figure 4-9, which represents the percentage difference from LoD1 to LoD3, with a quick glance, it is obvious that the appearance of the map changes slightly, and most buildings are represented with light yellow and light orange colours, which indicate low percentage difference. However, overall, it could be seen that the higher proportion in differences is observed at buildings with larger footprint and, mainly, at detached building forms.

### 4.2.2 Percentage difference in Annual Residential Heat Demand at area 2 - new buildings

At this subsection, the percentage difference of the annual heat demand for the upgrade of a lower LoD to a higher is presented. As dwellings that have been left at this area and have analysed are more spread to the map, areas of the main map have been zoomed in, in order to some dwellings to be more visible.

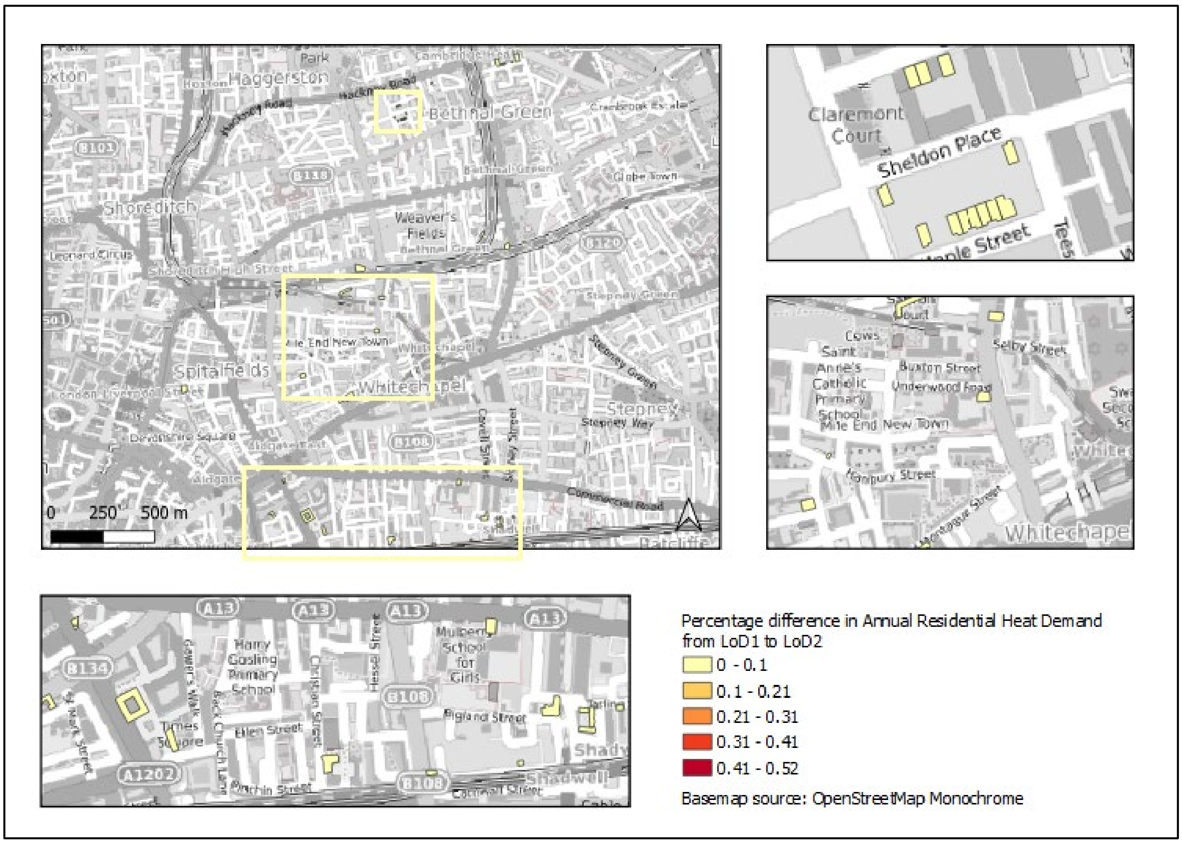



**Figure 4-10 Percentage difference in Annual Residential Heat Demand from LoD1 to LoD2**

As it can be seen at Figure 4-10, there is not a variety of percentage differences from LoD1 to LoD2, because not all shades of colours are visible. Hence, buildings with dark red colour or orange are not visible, that represent a percentage difference up to 52 % and are the minority. In contrast, the buildings at the map are represented only with light yellow, which represents a percentage difference range from 0 to 10%. Hence, even the highest percentage difference is low from the upgrade of LoD1 to LoD2 and acceptable.

At Figure 4-11 and Figure 4-12, an homogeneity can be observed in the results, again, as the majority of buildings is represented with light yellow color, which means that there is a low percentage difference in the annual residential heat demand. However, this percentage is up to 10%. The rest colors of the legend are the minority of buildings, and more specifically, are the three exceptions, that have been stated at the above subsections.

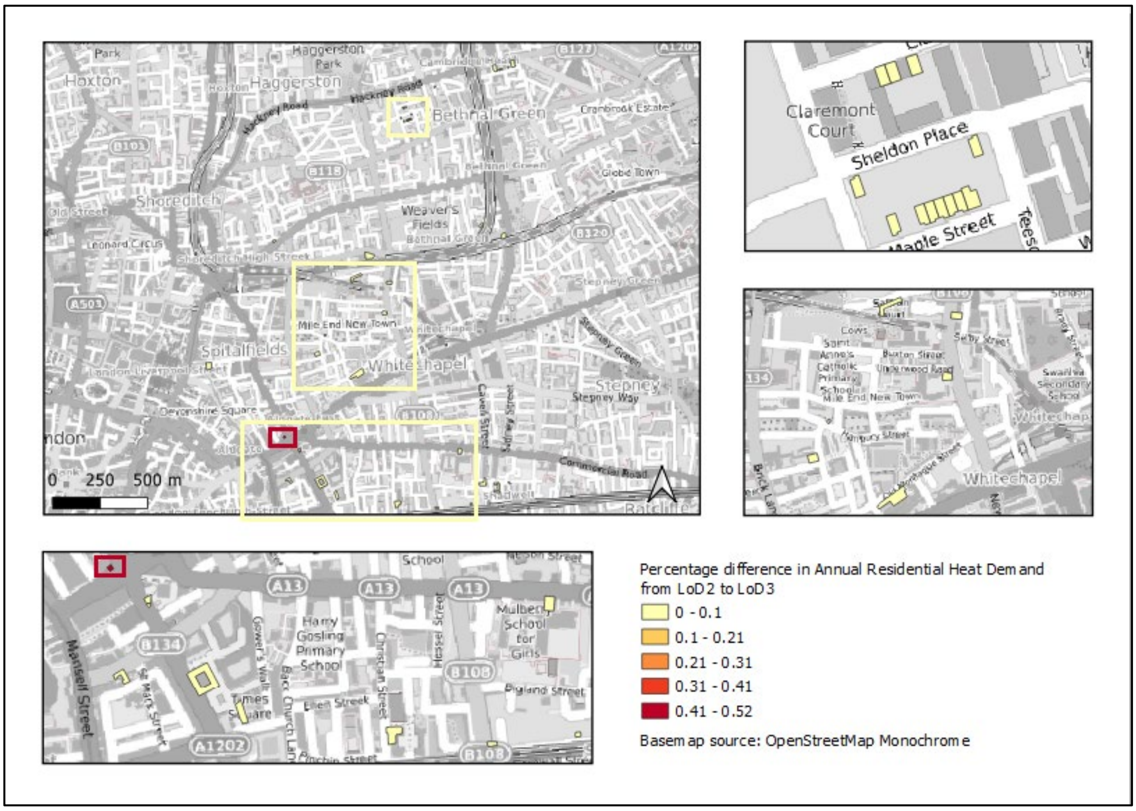



**Figure 4-11 Percentage difference in Annual Residential Heat Demand from LoD2 to LoD3**

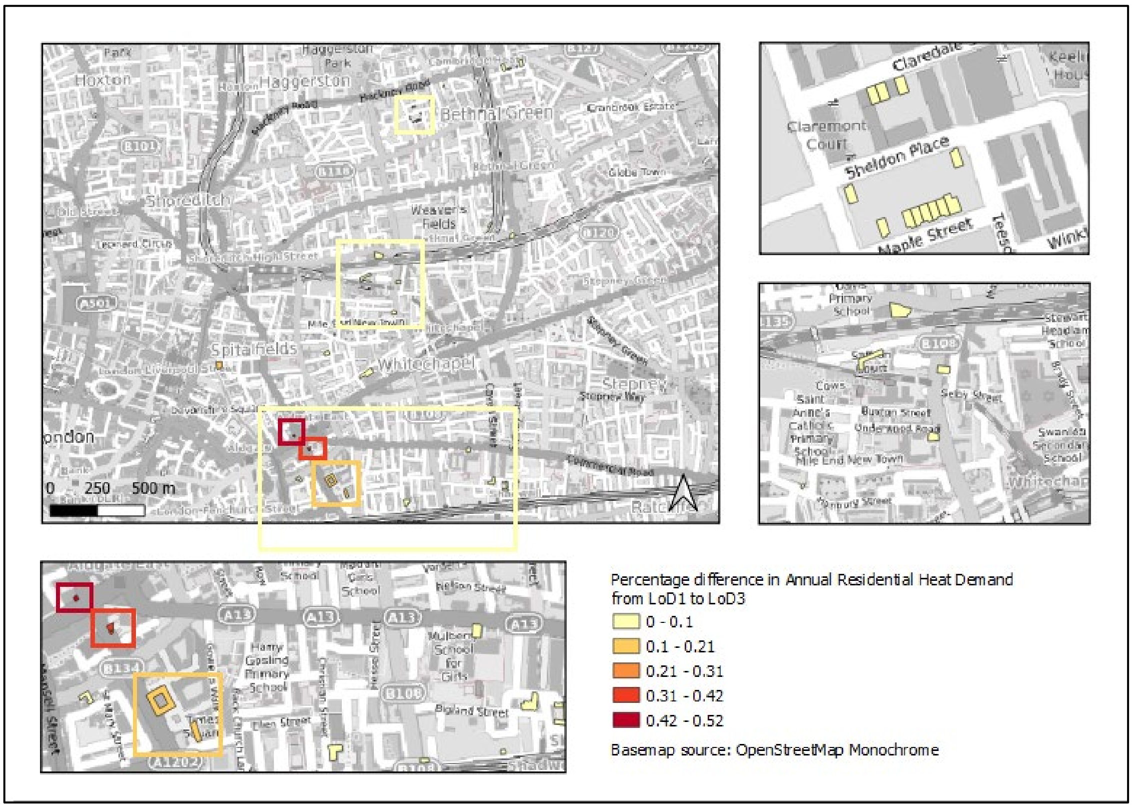



**Figure 4-12 Percentage difference in Annual Residential Heat Demand from LoD1 to LoD3**

More particularly, one building of them is shown at Figure 4-11, inside the dark red box with dark red color which represents the highest percentage difference and another one is shown at Figure 4-12 with dark orange color, which represents the second highest difference, as it has been aforementioned. Finally, at Appendix 3, Table 0-7 and Table 0-8, the exact results from both areas are presented.

## 4.3 Extending the area 1 (old buildings)

Due to the homogeneity of the area with the old buildings, as it has been stated at Methodology chapter, some missing dwellings have been inserted, in order to create some maps with more dwellings. Hence, at the next figures, maps of the annual residential heat demand and the percentage difference from the upgrade of LoD1 to LoD2 or LoD3, are illustrated for the extended area 1 of old dwellings.

### 4.3.1 Annual Residential Heat Demand

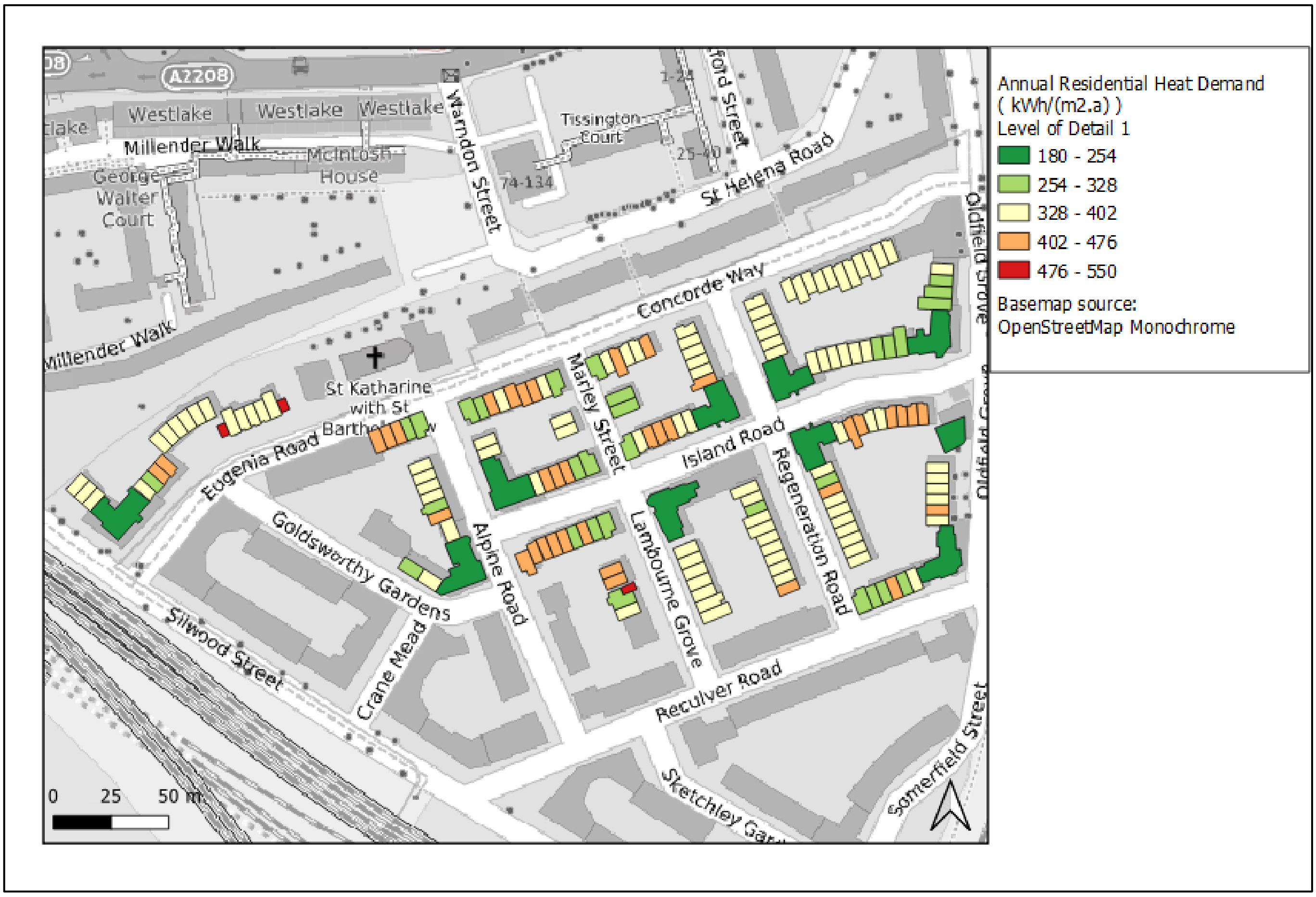



**Figure 4-13 Annual Residential Heat Demand for Level of Detail 1**

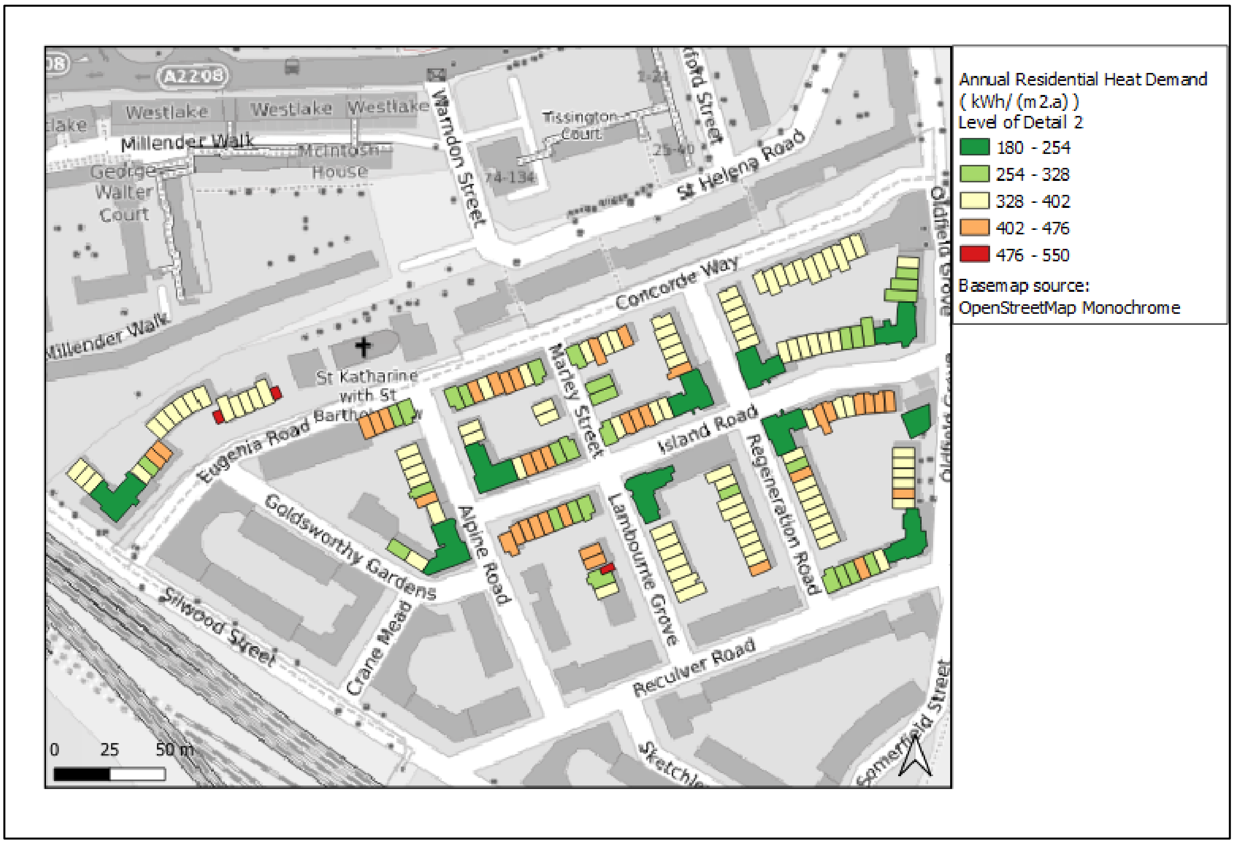



Figure 4-14 Annual Residential Heat Demand for Level of Detail 2

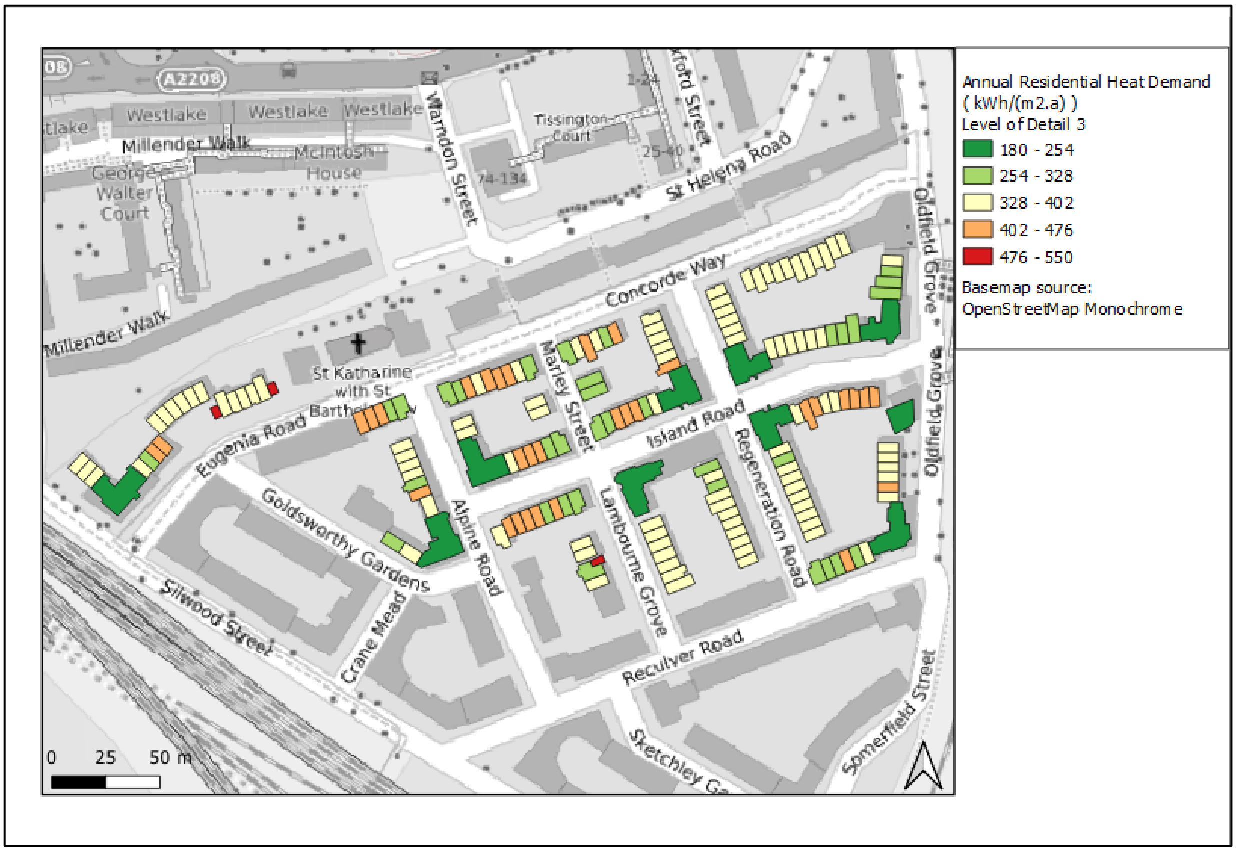



Figure 4-15 Annual Residential Heat Demand for Level of Detail 3

As it is obvious from the above figures, the new maps for the extended area 1 are fuller with a range of colours in residential buildings. Obviously, by taking a quick glance at the maps, as it has been seen above, there is no big difference from LoD1 to LoD2 and LoD3.

### 4.3.2 Percentage difference in Annual Residential Heat Demand from lower to higher LoDs

At this subsection, the percentage difference of the extended area 1 is shown for the upgrade from lower to higher LoDs. There is no doubt that the image that the below map give is the same as the image at Figure 4-7, 4-8 and 4-9. In more details, a small percentage difference is shown from LoD1 to LoD2, where the majority of the dwellings are represented with light yellow color, and the highest percentage difference occurs for one building, which is from 8% to 10%. This means that the percentage difference is at an acceptable level, as it has been seen at the subsection 4-2-2.

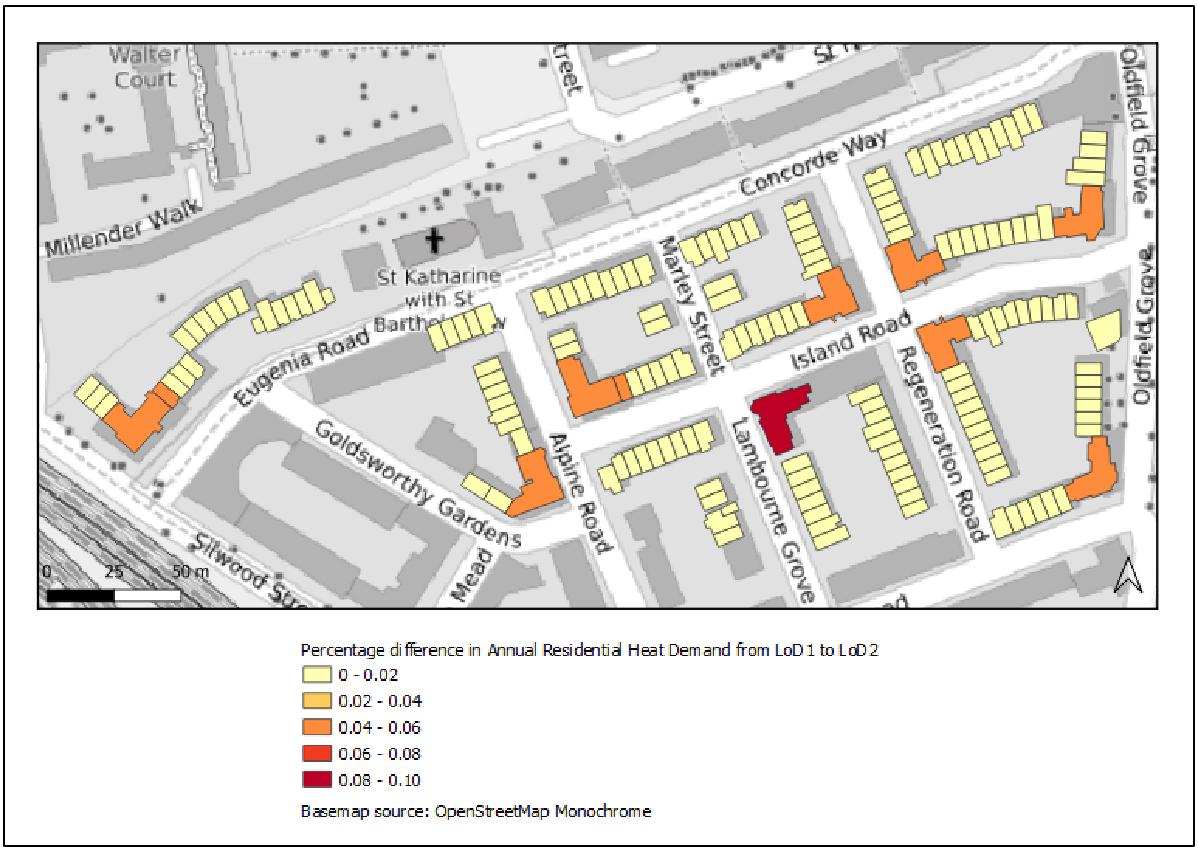



**Figure 4-16 Percentage difference in Annual Residential Heat Demand from LoD1 to LoD2 (extended area 1 – old buildings)**

As regards the upgrade from LoD2 to LoD3, the map shows the same results as above, with the difference that is fuller, due to the addition of the dwellings. Finally, at Figure 4-18, where the percentage difference from LoD1 to LoD3 is illustrated, a variety in the percentage difference can be seen, as at Figure 4-9. However, the majority of the residential buildings is characterized from low percentage difference, which is up to 2%. Also, as above, the buildings with the higher percentage difference seem to be those with the larger floor area and this could be explained from the fact that these buildings are built in corners, which means that they have more external walls and complexity at their architectural form. Hence, the assignment of a uniform values for all buildings is a more general approach for the specific buildings. This means that for another time, it is concluded that there is no need for the estimation of the WWR.

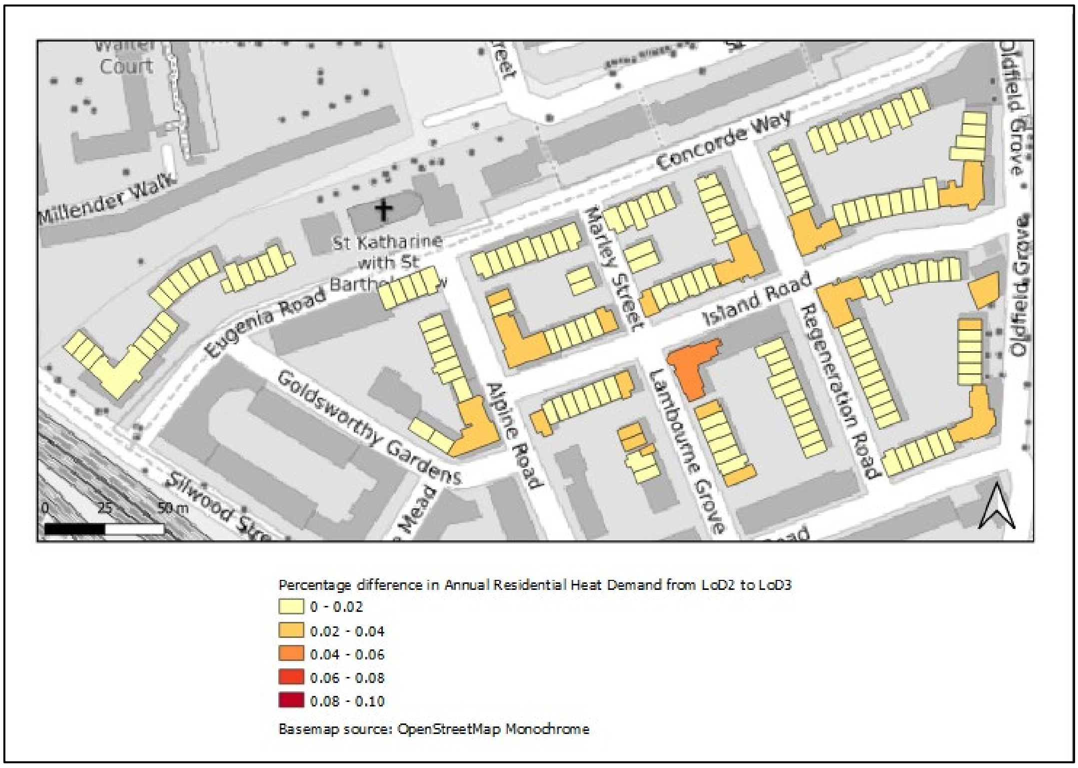



**Figure 4-17 Percentage difference in Annual Residential Heat Demand from LoD2 to LoD3 (extended area 1 – old buildings)**

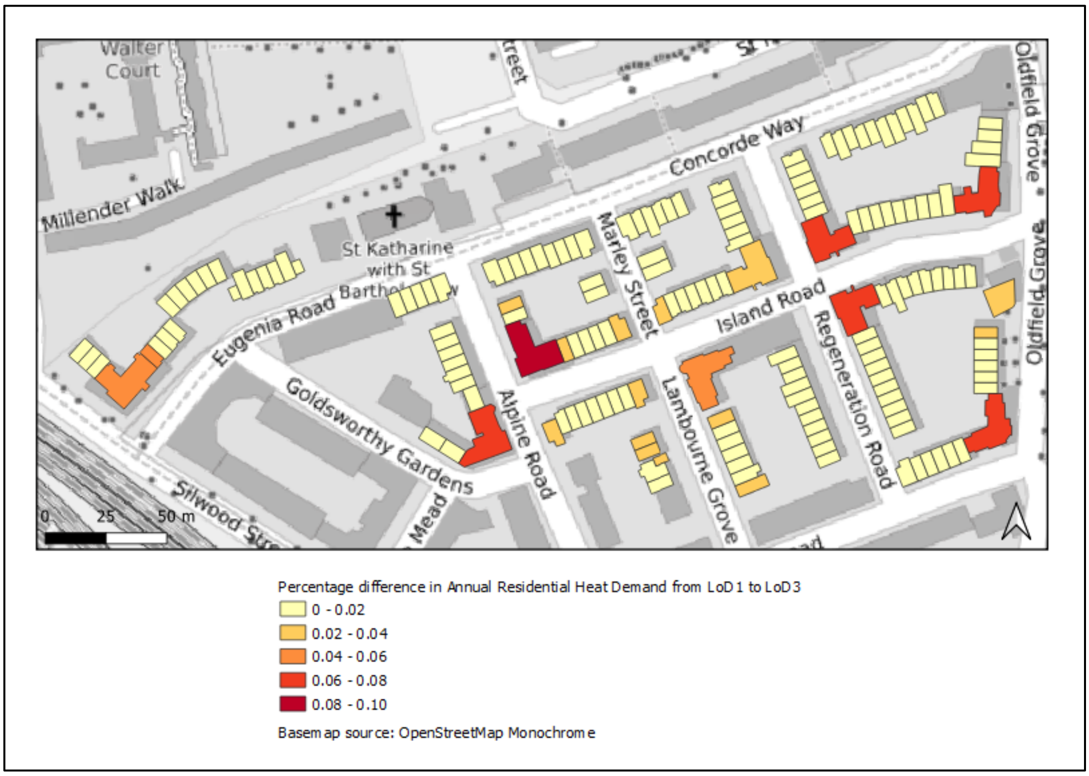



**Figure 4-18 Percentage difference in Annual Residential Heat Demand from LoD1 to LoD3 (extended area 1 – old buildings)**

## 4.4 Statistical Analysis

### 4.4.1 Dependent T-Test for significance level of the difference on Annual Residential Heat Demand

The results from the Data Analysis Tool of Excel software are presented below. The table below shows the output regarding the update from LoD1 to LoD2, namely adding the actual roof type rather than assuming it.

**Table 4-2 't-Test: Paired Two Sample for Means' from Excel for the difference of the output from LoD1 to LoD2**

| | *Heat Demand-LoD2* | *Heat Demand-LoD1* |
|---|---|---|
| *Mean* | 315.52 | 314.77 |
| *Variance* | 11291.10 | 11424.46 |
| *Observations* | 222 | 222 |
| *Pearson Correlation* | 0.99 | |
| *Hypothesized Mean Difference* | 0 | |
| *df* | 221 | |
| *t Stat* | 3.92 | |
| *P(T<=t) one-tail* | 5.86E-05 | |
| *t Critical one-tail* | 1.65 | |
| *P(T<=t) two-tail* | 1.17E-04 | |
| *t Critical two-tail* | 1.97 | |

As it can be seen, from the p-value, which is much lower than the significance level (0.05), there is a low possibility that a difference between the output with the assumed roof type and the actual roof type will be high. Hence, there is no significant improvement to the output from LoD1 to LoD2.

Therefore, the next step has been to check the progress to the output from LoD2 to LoD3. The results from Excel software are illustrated at Table 4-3.

**Table 4-3 't-Test: Paired Two Sample for Means' from Excel for the difference of the output from LoD2 to LoD3**

| | *Heat Demand-LoD3* | *Heat Demand-LoD2* |
|---|---|---|
| *Mean* | 313.91 | 315.52 |
| *Variance* | 10751.46 | 11291.10 |
| *Observations* | 222 | 222 |
| *Pearson Correlation* | 0.99 | |
| *Hypothesized Mean Difference* | 0 | |
| *df* | 221 | |
| *t Stat* | -3.67 | |
| *P(T<=t) one-tail* | 1.5E-04 | |
| *t Critical one-tail* | 1.65 | |
| *P(T<=t) two-tail* | 3E-04 | |
| *t Critical two-tail* | 1.97 | |

The results from the statistical test, and more specifically, the low value of p-value has shown that even by adding the WWR parameter from the approximate calculation from Google Street View, there is no big difference at the output regarding the annual residential heat demand.

Nonetheless, the upgrade at the output from LoD1 to LoD3 has been examined, too. The results are illustrated at the following table.

**Table 4-4 't-Test: Paired Two Sample for Means' from Excel for the difference of the output from LoD1 to LoD3**

| | *Heat Demand-LoD3* | *Heat Demand-LoD1* |
|---|---|---|
| *Mean* | 313.91 | 314.77 |
| *Variance* | 10751.46 | 11424.46 |
| *Observations* | 222 | 222 |
| *Pearson Correlation* | 0.99 | |
| *Hypothesized Mean Difference* | 0 | |
| *df* | 221 | |
| *t Stat* | -1.76 | |
| *P(T<=t) one-tail* | 0.04 | |
| *t Critical one-tail* | 1.65 | |
| *P(T<=t) two-tail* | 0.08 | |
| *t Critical two-tail* | 1.97 | |

As it can be seen there is a difference to the results compared to the previous outputs. More specifically, the p-value for the one-tail is lower than 0.05, which means that the significance level of the difference is minor. However, for the two-tail is higher than 0.05 and equal to 0.079, that means there is 7.9% probability for difference. This could point that by upgrading both the roof type and WWR, and giving actual measurements of both variables, there could be a higher probability to obtain different results, but not that high to deserve the time and money.

Overall, from the results above, there is no significant upgrade to the approximation of the heating demand for dwellings, which means that building typologies and archetypes could be a solution to avoid the time and money consuming process of measurement on site.

### 4.4.2 Pearson correlation / t-statistic test (percentage difference – building age and building form)

The slightly different results between the old and the new buildings, lead to the need for the estimation of the relativity that building age can have with the percentage difference of the annual heat demand, but also, the association of the building form with this percentage difference. The statistical analysis has been done by merging the extended area 1 with the old buildings and the area 2 with the new buildings, in order to include different building ages and forms, but also the sample to consist of more buildings.

The results from the Pearson correlation and the t-statistic test are presented below.

#### 4.4.2.1 Building age – Percentage difference in Annual Residential Heat Demand

At the following table, the statistical analysis for the relationship between the building age and the percentage difference from lower to higher LoD is shown.

**Table 4-5 Pearson correlation and t-statistic test for building age and percentage difference**

| *Statistical Analysis (building age – percentage difference)* | | | |
|---|---|---|---|
| | LoD1-LoD2 | LoD2-LoD3 | LoD1-LoD3 |
| *Coefficient (r):* | 0.07 | 0.56 | 0.52 |
| *N:* | 225 | 225 | 225 |
| *T statistic:* | 1.10 | 9.97 | 9.09 |
| *DF:* | 223 | 223 | 223 |
| *p value:* | 0.86 | 1.00 | 1.00 |

As it can be seen from the table, the p-value for the percentage difference in heat demand from LoD1 to LoD2 is smaller than for LoD2 to LoD3 and for LoD1 to LoD3. However, it still be higher than 0.05. This means that the null hypothesis, namely that there is a strong dependence between the percentage difference from the upgrade of LoD1 to LoD2 and the building age, is true. For the upgrade from LoD2 to LoD3 and from LoD1 to LoD3, the p-value is even higher, which means that there is a stronger dependence.

Therefore, the building age has an impact regarding the roof type, but also, it influences the percentage difference of the annual heat demand, when concerning the WWR more.

#### 4.4.2.2 Building form – Percentage difference in Annual Residential Heat Demand

At Table 4-2, the relationship between the building form and the percentage difference in the annual residential heat demand from the upgrade from a lower to a higher LoD is presented.

**Table 4-6 Pearson correlation and t-statistic test for building form and percentage difference**

| *Statistical Analysis (building form – percentage difference)* | | | |
|---|---|---|---|
| | LoD1-LoD2 | LoD2-LoD3 | LoD1-LoD3 |
| *Coefficient (r):* | 0.49 | 0.33 | 0.41 |
| *N:* | 225 | 225 | 225 |
| *T statistic:* | 8.46 | 5.27 | 6.74 |
| *DF:* | 223 | 223 | 223 |
| *p value:* | 1.00 | 1.00 | 1.00 |

As it is obvious, for all kind of updates (LoD1 - LoD2, LoD2 - LoD3, LoD1 - LoD3), there is a strong dependence between the percentage difference in annual residential heat demand and the building form, as the p-values are higher than 0.05, which means that the null hypothesis (strong relationship between the percentage difference and the building form) is true.

### 4.4.3 Statistical test for Root Mean Squared Error (percentage difference – building age and building form)

As a last step, the RMSE has been calculated for the difference to the annual heat demand between the LoD1 to LoD2, the LoD2 to LoD3 and the LoD1 to LoD3. The results have shown that the RMSE is equal to 2.89, 11.26 and 7.99, respectively. Therefore, taking into account that the RMSE has the same units as the values that are being compared, the RMSE has shown that there is not much difference from the upgrade of lower to a higher LoD. This means that the improvement to the accuracy of the results is minor, so there is no reason for moving to higher LoDs, which is a time and money consuming process.

# Chapter 5

# Conclusion

# 5 Conclusion

*This chapter presents a summary of the entire study, as regards the parametric study of different Levels of Detail in dwellings for the estimation of the heat demand. Furthermore, some conclusions that have been obtained from the study are mentioned. Finally, at this chapter some suggestions for future studies are mentioned.*

## 5.1 Summary

The aim of this research project has been to investigate the most appropriate Level of Detail that is necessary, for the determination of the heat demand in buildings in urban scale, and more specifically, the annual heat demand of dwellings in London. Due to lack of data, two different areas in London have been examined. The first consists of old dwellings and every building form, and the second consists of new residential buildings and every building form, in order to examine every archetype of dwellings. The annual heat demand has been calculated with the Python console of QGIS, where the model of Dochev's research has been used, modified with climate data for the city of London and with input parameters associated with UK dwellings [14]. Hence, maps of the annual residential heat demand and the percentage difference from lower to higher LoDs have been constructed, in order to compare the results of the different LoDs with convenience. Furthermore, due to the homogeneity of area 1, some dwellings that have been deleted from the principal dataset due to the lack of building age and form, have been added, and new maps of an extended area 1 have been presented. Finally, a statistical analysis has been done, to examine the dependence of the percentage difference of the heat demand from the upgrade of lower to higher LoDs and the building age, and form.

## 5.2 Conclusions & Recommendations

After creating the maps for the percentage difference of the annual heat demand from lower to higher Level of Details and the statistics the following conclusions emerge.

From the environmental and energy aspect, one could argue that data on building renovation dates is important for a more accurate estimation of heat demand. This means that there is a high simplification at this project, as the results have been obtained by assuming that none of the dwellings has been renovated through its lifespan. However, this has not been an obstacle for this research study, as the aim of the project has been to compare the annual residential heat demand, when adding the detail of the roof type (LoD2) and of the window to wall ratio (LoD3). Moreover, from the energy point of view, concerning the uncertainty that exists to data, such as the occupancy, the inside temperature, and the appliance use, which affects the internal gains, there is a gap that should be fulfilled. As it is mentioned to the research paper of Molina et al., in order to mitigate data uncertainty in the upcoming years, the surveying house organizations should collaborate to make linking their results simpler [85]. Furthermore, it should be clear that physical phenomena play a significant role to energy simulations, and it should be understood when simplifications and statistics are used [86]. Despite these simplifications, it has been seen that the annual heat demand in older buildings is dramatically higher than in the new constructions, which has been expected as their insulation level is worse than the new. Also, it has been seen that the size of the footprint of the building could have an effect on its heating demand, as from the maps there was a clear difference between small and large buildings. In addition, as regards to the WWR, as at previous studies, it has been shown that the rise of the proportion of the windows to walls can lead to the increase of the heat demand [64].

Nevertheless, the purpose of the research project is related to the data requirements for the determination of the energy performance of dwellings at district scale. First of all, it has been seen that the OS MasterMap Topography layer, as well as the Building Height attribute have been essential for the project. The first reason is that the location (longitude and latitude) of the buildings and the geometry were needed, in order to determine the perimeter and the area of each building and create the maps, as the dataset from ‘Colouring London’ project has not included geospatial information. Apart from this, the height has been extracted from the Building Height attribute of Ordnance Survey, as the ‘Colouring London’ data is VGI (Volunteered Geographic Information), which means that there is a high possibility much information to be missed. However, as other attributes from ‘Colouring London’ dataset have been necessary, it is concluded that it would be good for analyzers and modelers of energy performance applications, to exist a collaboration between surveying companies, in order to connect all the useful information. For instance, the statistical analysis has shown that there is a strong dependence between the results of the annual heat demand and the building age and type. However, it has been turned out that geometrical detail is not necessary for the energy demand calculation at urban scale, as it has been stated to Strzalka’s research before [73].

Moreover, from the analysis, the findings have shown, as the initial hypothesis has stated, that the upgrade of the LoD1 to LoD2 and LoD3 is not a necessity. Hence, the roof type and the windows to wall ratio could be assumed from archetypes and building age, for the estimation of heat demand at district scale. Therefore, surveying companies, such as Ordnance Survey, could provide energy performance analysers with the minimum LoD1, and the findings could be similar to LoD2 and LoD3 results, as the statistical analysis has demonstrated, too. Consequently, the money wasting and time-consuming process, by obtaining data from in situ measurements, could be avoided that way. Nonetheless, even for LoD1, much geospatial information is needed. Hence, data from Ordnance Survey and ‘Colouring London’ project have been necessary, in order to achieve these findings.

## 5.3 Suggestions for Future Studies

This research study has revealed that the use of Level of Detail 1, which assumes the roof type and the WWR by building typologies, is an effective way to evaluate annual residential heat demand at the city scale. Nonetheless, there are a number of immediate methodological and data improvements, as well as some new research options to investigate, that should be explored. Regarding some suggestions for future studies, from the energy performance rating aspect, it would be useful to analyze bigger areas with mixed-age dwellings, for the comparison of the results regarding the building age, and the generalization of the initial hypothesis, as the current dataset has included old dwellings in area 1 and new buildings in area 2. Moreover, an interesting parametric study could be the increasement and decreasing of the indoor temperature, as it is a physical parameter that most of the times is assumed. In addition, as it has been aforementioned the refurbishment rate is a gap to this research, that it could be taken into consideration for future studies, in order to lead at more representative results for every dwelling. Regarding the energy models, the one that has been used for this study could be modified easily, as it has been written in Python language and for someone that has the knowledge, it could be easy to change details, regarding the location that is under study. However, it would be simpler, if there has been a model that somebody without programming knowledge could modify to the needs of his case study. Therefore, a future research could be about the construction of an open energy model that the input parameters could be comfortably change. Finally, there is no doubt that future studies, regarding the simplest way to link the required data for the energy modelling from different surveying companies into a single dataset, that could be easily used from analysers, could be done, as by this way policy makers could be helped more, regarding the reduction of the residential energy demand and carbon dioxide emissions.

# Appendixes

## Appendix 1 – Tabula typologies

**Table 0-1 Thermal transmittance (U-value) for roofs from Tabula typology [81]**

| Building Form | Building Age | U-value - Roofs |
|---|---|---|
| Semi-Detached/ Detached | =<1964 | 2.3 |
| | 1965-1980 | 1.5 |
| | 1981-2003 | 0.4 |
| | 2004-2009 | 0.25 |
| | >=2010 | 0.18 |
| Mid-Terraced/ End-Terraced | =<1964 | 2.3 |
| | 1965-1980 | 1.5 |
| | 1981-2003 | 0.4 |
| | 2004-2009 | 0.25 |
| | >=2010 | 0.18 |

**Table 0-2 Thermal transmittance (U-value) for walls from Tabula typology [81]**

| Building Form | Building Age | U-value - Walls |
|---|---|---|
| Semi-Detached/ Detached | =<1944 | 2.1 |
| | 1945-2003 | 1.6 |
| | 2004-2009 | 0.35 |
| | >=2010 | 0.28 |
| Mid-Terraced/ End-Terraced | =<1944 | 2.1 |
| | 1945-2003 | 1.6 |
| | 2004-2009 | 0.35 |
| | >=2010 | 0.28 |

**Table 0-3 Thermal transmittance (U-value) for floors from Tabula typology [81]**

| Building Form | Building Age | U-value - Floors |
|---|---|---|
| Semi-Detached/ Detached | =<1990 | 0.72 |
| | 1991-2003 | 0.5 |
| | 2004-2009 | 0.25 |
| | >=2010 | 0.22 |
| Mid-Terraced/ End-Terraced | =<1990 | 0.59 |
| | 1991-2003 | 0.5 |
| | 2004-2009 | 0.25 |
| | >=2010 | 0.22 |

**Table 0-4 Thermal transmittance (U-value) for Windows from Tabula typology [81]**

| Building Form | Building Age | U-value - Windows |
|---|---|---|
| Semi-Detached/ Detached | =<1980 | 4.8 |
| | 1981-2003 | 3.1 |

| | | |
|---|---|---|
| | >=2004 | 1.85 |
| **Mid-Terraced/ End-Terraced** | =<1964 | 4.8 |
| | 1965-2003 | 3.1 |
| | >=2004 | 1.85 |

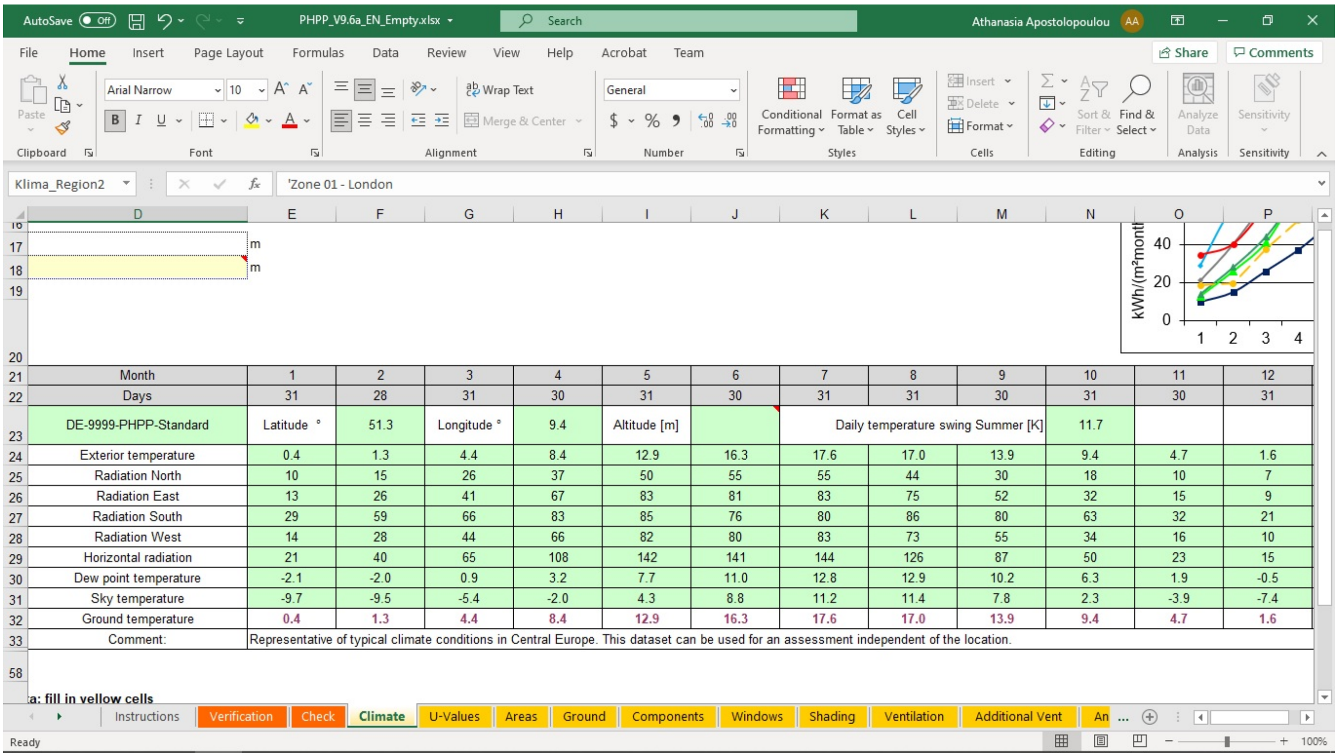
**Table 0-5 Thermal transmittance (U-value) for Renovated Walls from Tabula typology [81]**

| Building Form | Building Age | U-value – Renovated Walls |
|---|---|---|
| **Semi-Detached/ Detached** | =<1944 | 0.3 |
| | 1945-2003 | 0.6 |
| | >=2004 | no refurbishment |
| **Mid-Terraced/ End-Terraced** | =<1944 | 0.3 |
| | 1945-2003 | 0.6 |
| | >=2004 | no refurbishment |

**Table 0-6 Thermal transmittance (U-value) for Renovated Windows from Tabula typology [81]**

| Building Form | Building Age | U-value – Renovated Windows |
|---|---|---|
| **Semi-Detached/ Detached** | =<1964 | 2.2 |
| | >=1965 | no refurbishment |
| **Mid-Terraced/ End-Terraced** | =<1964 | 2.2 |
| | >=1965 | no refurbishment |

## Appendix 2 – Climate data



| Month | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Days | 31 | 28 | 31 | 30 | 31 | 30 | 31 | 31 | 30 | 31 | 30 | 31 |
| DE-9999-PHPP-Standard | Latitude ° | 51.3 | Longitude ° | 9.4 | Altitude [m] | | Daily temperature swing Summer [K] | | | 11.7 | | |
| Exterior temperature | 0.4 | 1.3 | 4.4 | 8.4 | 12.9 | 16.3 | 17.6 | 17.0 | 13.9 | 9.4 | 4.7 | 1.6 |
| Radiation North | 10 | 15 | 26 | 37 | 50 | 55 | 55 | 44 | 30 | 18 | 10 | 7 |
| Radiation East | 13 | 26 | 41 | 67 | 83 | 81 | 83 | 75 | 52 | 32 | 15 | 9 |
| Radiation South | 29 | 59 | 66 | 83 | 85 | 76 | 80 | 86 | 80 | 63 | 32 | 21 |
| Radiation West | 14 | 28 | 44 | 66 | 82 | 80 | 83 | 73 | 55 | 34 | 16 | 10 |
| Horizontal radiation | 21 | 40 | 65 | 108 | 142 | 141 | 144 | 126 | 87 | 50 | 23 | 15 |
| Dew point temperature | -2.1 | -2.0 | 0.9 | 3.2 | 7.7 | 11.0 | 12.8 | 12.9 | 10.2 | 6.3 | 1.9 | -0.5 |
| Sky temperature | -9.7 | -9.5 | -5.4 | -2.0 | 4.3 | 8.8 | 11.2 | 11.4 | 7.8 | 2.3 | -3.9 | -7.4 |
| Ground temperature | 0.4 | 1.3 | 4.4 | 8.4 | 12.9 | 16.3 | 17.6 | 17.0 | 13.9 | 9.4 | 4.7 | 1.6 |
| Comment: | Representative of typical climate conditions in Central Europe. This dataset can be used for an assessment independent of the location. | | | | | | | | | | | |

**Figure 0-1 Screenshot from 'Climate' spreadsheet at PHPP for London city**

## Appendix 3 – Annual Residential Heat Demand

**Table 0-7 Annual Residential Heat Demand in area 1 - old buildings**

| *Dwellings* | *LoD1-HD (kWh/(m2.a))* | *LoD2-HD (kWh/(m2.a))* | *LoD3-HD (kWh/(m2.a))* | *Difference from LoD1 to LoD2 (%)* | *Difference from LoD2 to LoD3 (%)* | *Difference from LoD1 to LoD3 (%)* |
|---|---|---|---|---|---|---|
| *1* | 385.22 | 398.89 | 394.97 | 3.55 | 0.98 | 2.47 |
| *2* | 410.57 | 425.07 | 418.55 | 3.53 | 1.54 | 1.91 |
| *3* | 495.85 | 513.32 | 509.71 | 3.52 | 0.70 | 2.72 |
| *4* | 443.66 | 459.30 | 448.36 | 3.52 | 2.38 | 1.05 |
| *5* | 458.77 | 474.68 | 470.73 | 3.47 | 0.83 | 2.54 |
| *6* | 403.24 | 417.59 | 415.53 | 3.56 | 0.49 | 2.96 |
| *7* | 483.87 | 500.94 | 493.95 | 3.53 | 1.39 | 2.04 |
| *8* | 465.34 | 481.59 | 474.14 | 3.49 | 1.55 | 1.86 |
| *9* | 481.83 | 498.62 | 496.02 | 3.48 | 0.52 | 2.86 |
| *10* | 465.52 | 482.00 | 468.50 | 3.54 | 2.80 | 0.63 |
| *11* | 463.98 | 480.21 | 472.86 | 3.50 | 1.53 | 1.88 |
| *12* | 421.93 | 436.98 | 418.71 | 3.57 | 4.18 | 0.77 |
| *13* | 385.45 | 399.10 | 392.27 | 3.54 | 1.71 | 1.74 |
| *14* | 393.42 | 407.42 | 403.59 | 3.56 | 0.94 | 2.52 |
| *15* | 468.68 | 485.25 | 471.69 | 3.54 | 2.80 | 0.64 |
| *16* | 491.35 | 508.66 | 501.53 | 3.52 | 1.40 | 2.03 |
| *17* | 510.96 | 528.89 | 532.65 | 3.51 | 0.71 | 4.07 |
| *18* | 420.31 | 435.19 | 428.53 | 3.54 | 1.53 | 1.92 |
| *19* | 428.09 | 443.23 | 443.23 | 3.54 | 0.00 | 3.42 |
| *20* | 416.77 | 431.61 | 419.51 | 3.56 | 2.80 | 0.65 |
| *21* | 451.16 | 466.83 | 462.95 | 3.47 | 0.83 | 2.55 |
| *22* | 492.85 | 510.22 | 510.22 | 3.52 | 0.00 | 3.40 |
| *23* | 383.15 | 396.75 | 386.97 | 3.55 | 2.46 | 0.99 |
| *24* | 433.84 | 449.19 | 442.35 | 3.54 | 1.52 | 1.92 |
| *25* | 421.18 | 436.20 | 433.21 | 3.56 | 0.68 | 2.78 |
| *26* | 451.79 | 467.48 | 463.60 | 3.47 | 0.83 | 2.55 |
| *27* | 515.54 | 533.65 | 518.59 | 3.51 | 2.82 | 0.59 |
| *28* | 435.08 | 450.35 | 441.23 | 3.51 | 2.02 | 1.39 |
| *29* | 398.11 | 412.18 | 441.45 | 3.53 | 7.10 | 9.82 |
| *30* | 462.57 | 478.76 | 466.18 | 3.50 | 2.63 | 0.78 |
| *31* | 439.47 | 455.00 | 455.00 | 3.53 | 0.00 | 3.41 |
| *32* | 439.41 | 454.84 | 447.47 | 3.51 | 1.62 | 1.80 |
| *33* | 437.95 | 453.41 | 444.92 | 3.53 | 1.87 | 1.57 |
| *34* | 383.63 | 397.39 | 380.93 | 3.59 | 4.14 | 0.71 |
| *35* | 368.20 | 397.01 | 389.22 | 7.83 | 1.96 | 5.40 |
| *36* | 451.59 | 467.28 | 466.00 | 3.48 | 0.27 | 3.09 |
| *37* | 396.91 | 411.02 | 403.23 | 3.56 | 1.89 | 1.57 |
| *38* | 460.27 | 476.54 | 466.36 | 3.53 | 2.14 | 1.31 |

| | | | | | | |
|---|---|---|---|---|---|---|
| *39* | 581.68 | 601.96 | 596.95 | 3.49 | 0.83 | 2.56 |
| *40* | 394.01 | 407.96 | 399.94 | 3.54 | 1.97 | 1.48 |
| *41* | 329.03 | 373.26 | 355.64 | 13.44 | 4.72 | 7.48 |
| *42* | 497.23 | 514.74 | 518.37 | 3.52 | 0.71 | 4.08 |
| *43* | 183.51 | 200.92 | 205.14 | 9.49 | 2.10 | 10.54 |
| *44* | 449.67 | 465.29 | 461.45 | 3.47 | 0.83 | 2.55 |
| *45* | 379.89 | 393.53 | 377.24 | 3.59 | 4.14 | 0.70 |
| *46* | 424.52 | 439.45 | 439.45 | 3.52 | 0.00 | 3.40 |
| *47* | 580.70 | 600.92 | 596.04 | 3.48 | 0.81 | 2.57 |
| *48* | 478.45 | 495.18 | 487.75 | 3.50 | 1.50 | 1.91 |
| *49* | 383.00 | 396.74 | 388.51 | 3.59 | 2.07 | 1.42 |
| ***Average*** | 436.72 | 453.32 | 447.37 | 3.94 | 1.74 | 2.55 |

**Table 0-8 Annual Residential Heat Demand in area 2 - new buildings**

| *Dwellings* | *LoD1-HD (kWh/(m2.a))* | *LoD2-HD (kWh/(m2.a))* | *LoD3-HD (kWh/(m2.a))* | *Difference from LoD1 to LoD2 (%)* | *Difference from LoD2 to LoD3 (%)* | *Difference from LoD1 to LoD3 (%)* |
|---|---|---|---|---|---|---|
| *1* | 90.96 | 91.25 | 138.39 | 0.32 | 51.66 | 34.27 |
| *2* | 65.56 | 66.11 | 74.43 | 0.84 | 12.58 | 11.92 |
| *3* | 81.82 | 82.97 | 83.49 | 1.41 | 0.62 | 2.00 |
| *4* | 84.71 | 85.12 | 117.21 | 0.49 | 37.70 | 27.73 |
| *5* | 86.70 | 87.53 | 88.18 | 0.96 | 0.74 | 1.68 |
| *6* | 74.14 | 75.29 | 74.51 | 1.55 | 1.05 | 0.49 |
| *7* | 67.12 | 67.68 | 72.54 | 0.82 | 7.19 | 7.47 |
| *8* | 174.41 | 174.41 | 186.99 | 0.00 | 7.21 | 6.72 |
| *9* | 70.69 | 71.31 | 74.43 | 0.88 | 4.37 | 5.03 |
| *10* | 59.75 | 60.20 | 69.97 | 0.76 | 16.23 | 14.61 |
| *11* | 116.05 | 116.47 | 160.25 | 0.36 | 37.59 | 27.58 |
| *12* | 118.19 | 119.85 | 124.14 | 1.40 | 3.57 | 4.79 |
| *13* | 141.32 | 142.47 | 142.47 | 0.82 | 0.00 | 0.81 |
| *14* | 80.59 | 81.74 | 84.63 | 1.43 | 3.53 | 4.77 |
| *15* | 83.63 | 84.62 | 93.26 | 1.18 | 10.22 | 10.33 |
| *16* | 84.36 | 85.19 | 82.40 | 0.98 | 3.27 | 2.37 |
| *17* | 155.50 | 157.22 | 144.06 | 1.11 | 8.38 | 7.94 |
| *18* | 92.81 | 93.64 | 91.32 | 0.89 | 2.48 | 1.63 |
| *19* | 74.72 | 75.43 | 72.57 | 0.95 | 3.80 | 2.97 |
| *20* | 77.14 | 77.76 | 74.39 | 0.81 | 4.34 | 3.70 |
| *21* | 95.12 | 95.12 | 91.68 | 0.00 | 3.61 | 3.75 |
| *22* | 137.57 | 137.57 | 125.66 | 0.00 | 8.66 | 9.48 |
| *23* | 116.38 | 116.38 | 112.13 | 0.00 | 3.65 | 3.78 |
| *24* | 114.90 | 114.90 | 123.23 | 0.00 | 7.25 | 6.76 |
| *25* | 84.52 | 85.15 | 92.94 | 0.74 | 9.16 | 9.06 |

| | | | | | | |
|---|---|---|---|---|---|---|
| *26* | 90.56 | 91.19 | 86.89 | 0.69 | 4.71 | 4.23 |
| *27* | 123.69 | 124.84 | 123.68 | 0.93 | 0.93 | 0.00 |
| *28* | 121.76 | 123.01 | 119.88 | 1.02 | 2.54 | 1.57 |
| *29* | 259.09 | 260.75 | 258.40 | 0.64 | 0.90 | 0.27 |
| *30* | 81.09 | 81.71 | 87.84 | 0.77 | 7.51 | 7.69 |
| *31* | 138.69 | 138.69 | 130.04 | 0.00 | 6.24 | 6.65 |
| *32* | 244.44 | 244.44 | 244.44 | 0.00 | 0.00 | 0.00 |
| *33* | 265.23 | 266.89 | 264.25 | 0.63 | 0.99 | 0.37 |
| *34* | 79.21 | 79.83 | 85.81 | 0.79 | 7.49 | 7.69 |
| *35* | 242.49 | 242.49 | 251.66 | 0.00 | 3.78 | 3.64 |
| *36* | 195.78 | 195.78 | 190.18 | 0.00 | 2.86 | 2.94 |
| *37* | 200.60 | 200.60 | 192.56 | 0.00 | 4.01 | 4.17 |
| *38* | 254.14 | 255.80 | 260.04 | 0.65 | 1.66 | 2.27 |
| *39* | 201.02 | 201.02 | 195.41 | 0.00 | 2.79 | 2.87 |
| *40* | 192.74 | 192.74 | 190.86 | 0.00 | 0.97 | 0.98 |
| *41* | 259.79 | 259.79 | 264.75 | 0.00 | 1.91 | 1.87 |
| *42* | 232.67 | 232.67 | 212.22 | 0.00 | 8.79 | 9.64 |
| *43* | 273.54 | 273.54 | 280.11 | 0.00 | 2.40 | 2.35 |
| *44* | 198.47 | 198.47 | 193.02 | 0.00 | 2.75 | 2.83 |
| *45* | 211.23 | 211.23 | 198.59 | 0.00 | 5.99 | 6.37 |
| *46* | 237.75 | 237.75 | 216.92 | 0.00 | 8.76 | 9.60 |
| *47* | 263.32 | 265.62 | 304.72 | 0.88 | 14.72 | 13.59 |
| *48* | 207.73 | 208.98 | 206.47 | 0.60 | 1.20 | 0.61 |
| *49* | 383.00 | 396.74 | 388.51 | 3.59 | 2.07 | 1.42 |
| ***Average*** | 150.75 | 151.63 | 153.93 | 0.61 | 7.04 | 6.23 |

## Appendix 4 – Project Management Plan/ Gantt Chart

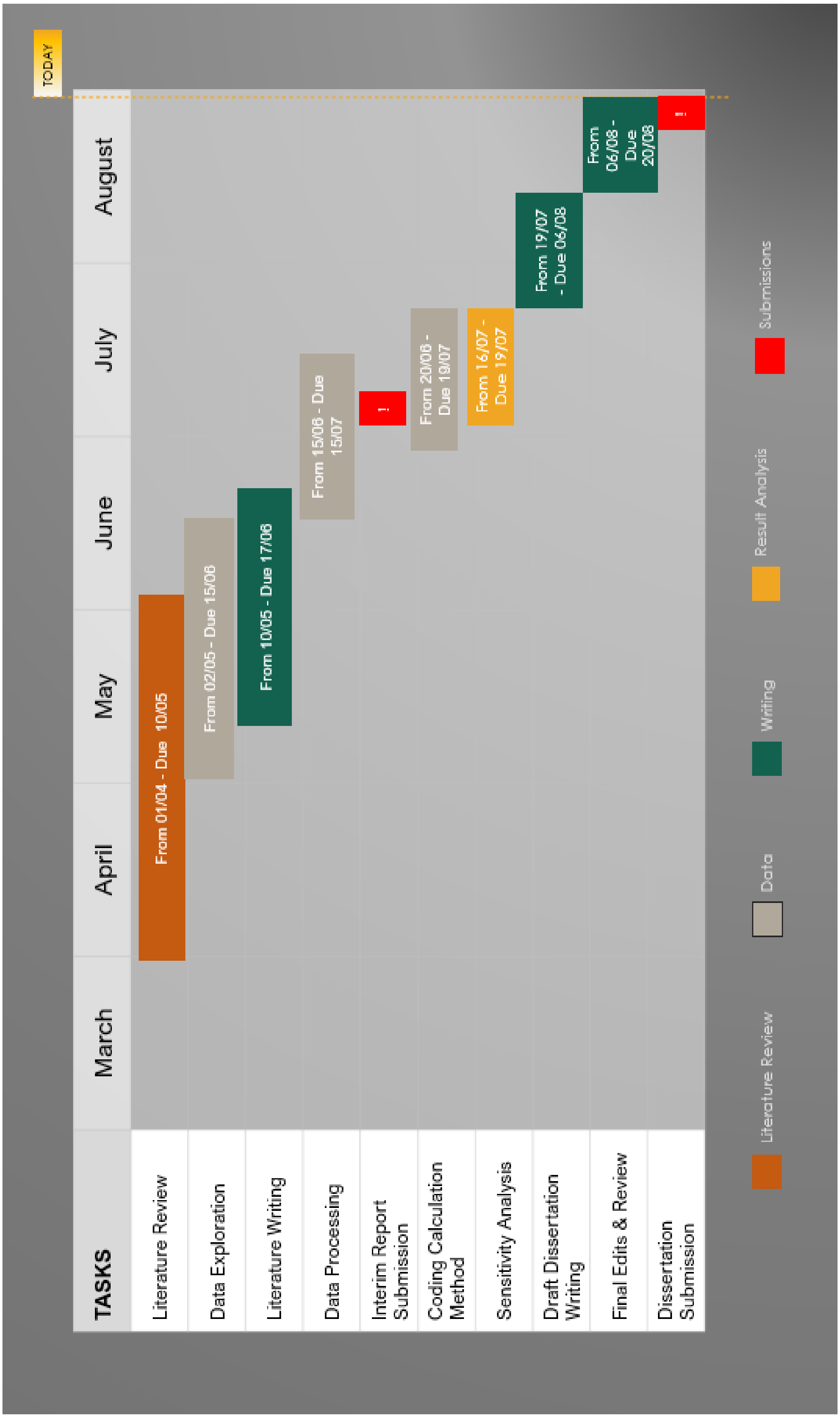



Figure 0-2 Project Management Plan/ Gantt Chart

## Appendix 5 – Structure of the report

**Table 0-9 Report Structure**

| SECTION | CONTEXT |
|---|---|
| **1. Introduction** | Introduces the background knowledge to this research study. Furthermore, it presents the aims and the objectives of the project, the methodology and the structure of the Master of Research thesis. |
| **2. Literature Review** | Presents the relevant theory regarding the subject of the project in detail. Also, at this stage of the report, studies and research projects that are related to the current dissertation are being reviewed, to give a guide to solving the research problem. |
| **3. Methodology** | The steps that have been followed for the investigation of the problem are presented with the methodological workflow diagram. |
| **4. Results & Discussion** | The results that have been obtained are presented. Simultaneously with the illustration of the results, a discussion about them is done. |
| **5. Conclusions** | Presents a summary of the entire study, as regards the parametric study of different Levels of Detail in dwellings for the estimation of the heat demand. Moreover, some conclusions that have been obtained from the study are mentioned. Finally, recommendations for future studies are made. |

## Appendix 6 – Data Management Plan

### 1) Provide the title and briefly describe the aim and objectives of the MRes project.

Title: Parametric Study of different Levels of Detail in buildings for the estimation of Annual Heating Demand: A case study in Nottingham, UK

Aim & Objectives: The aim of the research is the investigation of the most appropriate Level of Detail that is necessary, in order to determine the heating demand in buildings in urban scale.

The objectives of the research are:

1. Understanding the data requirements for energy modelling at city scale;
2. Exploring the significance of adding details in building characteristics for the estimation of the heating demand at urban scale;
3. Formulating recommendations in terms of datasets, for forecasting the heating demand of a city, by investigating the LoD that gives satisfactory results and requires as smaller as it is possible size of data.

**2) What data has been produced?**

All data used at this research is digital and existing data. So, for this study, secondary data has been used, which had been collected for other purposes, but are relevant to that topic.

More particularly, building information has been collected as the basic input data from ‘Colouring London’ project and building geospatial information has been collected from OS MasterMap Topography layer and Building Height attribute. Apart from that, weather data has been used for Nottingham, which is spatial and temporal data. Finally, information about thermal properties of the construction materials of the buildings have been used from statistical data, namely Tabula Episcope.

Hence, the types of data that has been used are observational data, such as the surveys for the building age and the thermal properties of construction materials, and simulation data, that will be the output of the research from the model of Ivan Dochev’s research that has been used as preliminary stage for the estimation of annual heat demand. The scale has been in district level regarding the GIS dataset and the weather data is monthly.

The format is vector data and the volume is approximately 8.6 GB. The methods of data collections are Open data archives e.g. ’Colouring London’ project and Proprietary data archives e.g. Digimap-Ordnance Survey.

**3) How will data be structured and stored?**

The data of the project has been structured under the appropriate file naming. The one file is the ‘Search_Data’, where all data that have been downloaded has been stored, and the other is the ‘Active_Data’, where data that has been used, has been stored. Also, the OneDrive under University of Nottingham IT services has been used, in parallel with an external hard disc for often back-ups. The back-up strategy is, at first, daily back-ups and at a second phase, weekly back-ups. Also, at the end of the project all back-ups have been deleted and only the final data Information System has been left and stored. Finally, the final data folder has been uploaded and kept at OneDrive.

**4) How will the data be shared during and after the project? (Access, data sharing and reuse)**

Data of the project will be shared through OneDrive of University of Nottingham between the principal researcher and the academic and industrial supervisors. After the project, data will be retained to OneDrive for the whole duration of the upcoming PhD, until October 2024.

**5) Who has responsibility for implementing the DMP and are resources required?**

For the particular research, there have been no tasks and roles to be allocated as this research study is an individual dissertation for MRes in Geospatial Data Science. Hence, the postgraduate researcher has been responsible for the DMP and its update during the process of the project.

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