GIMA

Geographical Information Management and Applications

Warmth use and thermal efficiency of remote dwellings: a Scotland case study.

Using smart meters to assess implications for carbon emissions, household expenditure and fuel poverty across geographies.

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2015

Universiteit Utrecht

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Warmth use and thermal efficiency of remote dwellings: a Scotland case study.

Using smart meters to assess implications for carbon emissions and household expenditure

Msc thesis for GIMA (Geographical Information Management and Applications), May 2015

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Preface

As far back as I can remember I have always regarded geographical information as a source of great utility. For long I have understood geographical information as merely maps that had some explanatory power. As much as the statement that 'a picture can say more than a thousand words' may be a cliché, it is not less true for that. However, as I learned more about geographical information, first during my BSc and later during my MSc at GIMA, I increasingly found appreciation for the value of numbers, and how much a good quantitative geographical analysis can tell. Geographical information, I believe, holds many treasures of valuable quantitative data than can profoundly improve our lives, in particular when large datasets are provided on large topics. This triggered me very much into further investigating what I regard as one of the biggest issues of the past, present and future; energy.

An earlier research during my MSc education lead me to appreciate the importance of geographical information on the supply side, researching the potential for an SDI for an energy company. A dataset made available through the ITC faculty of Geo-Information Science and Earth Observation via one of its researchers (my supervisor Alexey Voinov), gave me the opportunity to now research the demand side of it.

Excited though I was from the beginning to the end of this research (and honestly, really, also halfway), I have encountered many challenges I found difficult to overcome. But when solved, challenges can eventually only benefit one, as they have for me, increasing my skills, in particular in programming, my perseverance, and my focus.

For the programming part I have nobody to thank but myself. For the perseverance and focus, I have to acknowledge my deepest indebtedness to my hard-working and incredibly supporting mother; not only for the kind and supporting words but also because of her being an example on how to achieve the goals one has set for oneself.

I wish to thank my supervisor Dr. Alexey Voinov for his support and patience during my thesis. Also I want to thank him for his straightforward and clear critique during the process and for the recommendations that were given to me. In addition I want to than Dr. Voinov for giving me the opportunity of doing this research.
This research could not have been done without the help from the James Hutton institute that provided me the dataset, in particular Gary Polhill and Tony Craig, who provided the temperature feeds and the locations. In addition to that I wish to acknowledge the value of the critique and suggestions that Tony, Gary and Alexey have given me, although I wish I could have incorporated more of them into the research.

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Abstract

Many of the world's governments and citizens are concerned about the use of CO2 emitting fossil fuels and high expenditure on energy. Transportation and housing are among the primary sources of CO2 emissions and energy expenditure. In Scotland, more than two thirds of domestic energy use is used for heating purposes. The relevance of this issue is increased by the fact that large parts of the Scottish population are unable to heat their homes to adequate levels without spending at least 10% of their income on warmth use (so called 'fuel poverty'). In the year studied in this research (2011), fuel poverty in Scotland was between 25 and 30 percent. Unemployment, old age and retirement can make fuel poor persons extra vulnerable to being unable to heat their homes to adequate levels. Rural households use significantly more energy than urban households, both for transportation and warmth use. The differences in transportation can be explained by the necessity for private transport where presence of public transport is low and distance to services and is high. The differences in warmth use can partially be explained by higher heat loss (i.e. low thermal efficiency) in rural dwellings. However, previous research has shown that warmth demand in the UK has not gone down while thermal efficiency has gone up. Causes for this increased warmth demand are disputed. Among other things, this research attempted to shed light on this issue. Additionally, researched was what implications remote areas may have on CO2 emissions and household expenditure through transportation and warmth use.

The stated goal was *to develop a method to measure domestic warmth use from inside temperature data and to find how various degrees of remoteness influence energy use for households and to analyze the implications on CO2 emissions, fuel poverty and vulnerability of households.*

This research uses inside temperature data reports derived from smart meters in order to identify areas of high warmth use and low thermal efficiency. Identifying these areas by means of improved monitoring may help tackle fuel poverty and decrease warmth demand. Smart meters reporting inside temperature data are uncommon types although the additional information on inside temperatures can add value for monitoring purposes, as this research proves. Monitors reporting the inside dwelling temperature at 5 minute intervals were used to estimate and analyze the warmth use factors heater activity, thermal efficiency, warmth use and comfort temperature in 369 dwellings in Eastern Scotland. Data from 2011 in the month of January, April, June, September and November and in 2012 during June and September were analyzed from the smart meter reports.

Using kriging to interpolate outside temperature data, thermal efficiency was measured comparing the average hourly inside temperature with the average hourly outside temperature when the heater was expected to be off. Warmth use was measured as the average monthly amount of time the heater was on multiplied with the average temperature increase over the same period. Thermal comfort was measured as the stable temperature after a period of temperature increase. Network analysis was conducted to create remoteness indices to population centers. Drive time and vehicle use per area were used to estimate additional figures regarding CO2 emissions and £ spent on transport.

Total domestic warmth use in kWh in the UK was used as an indicator for the amount of warmth used in kWh in the area. Total domestic energy use in kWh per Scottish data zone was used in order to evaluate whether known energy use tended to correlate with thermal efficiency and warmth use. Thermal efficiency showed a weak correlation with average domestic energy use per data zone. Warmth use did not show a significant correlation, indicating that reliability of its figures were lower than those for thermal efficiency.

No relations for warmth use, thermal efficiency or comfort temperature could be found with income deprived households. Thermal comfort levels adapted to outside temperature throughout the year but varied heavily per household from month to month and did not differ by remoteness. Remote areas had significantly lower thermal efficiency and higher warmth use, which is an important conclusion in this research. Among the various remoteness indices used, drive distances to public services overall showed the strongest correlations with thermal efficiency and warmth use.

For further research the following is proposed; first, if SAP and NHER energy band data per individual dwelling can be obtained in combination with similar data as used in this research, it is proposed to find what can explain the differences in energy use outcomes between NHER and SAP.
Second, to conduct a weighted overlay, taking into account the strength of geographical factors that correlate with warmth use, in order to predict thermal efficiency and warmth use in other areas.
Third, conducting spatial autocorrelation to identify areas of low thermal efficiency, high proximity to other dwellings, high fuel poverty and high vulnerability, so that areas for prioritized insulation may be identified. Further development of that model may also try to identify thermally inefficient dwellings that are, although remote, within reasonable distance from each other in order to keep costs down. Achieving this would achieve more thermal efficiency where needed without disregarding the remote areas as previous insulation projects have turned out to do in the UK.

1. Introduction

In the beginning of the year 2013, the European Commission announced a new policy framework for climate and energy. Given today's economic hardships, depletion of fossil fuels and the goal to cut energy consumption by 20% of currently projected levels, by 2020 the following was stated: *"It will be important, therefore, to ensure the support of Member States, MEPs and public opinion, and to maximise synergies and deal with trade-offs between the objectives of competitiveness, security of energy supply and sustainability."*(EC 2013, p. 2).

The above statement stresses the relevance of saving both energy and money. Given almost two thirds of domestic energy is used to heat homes in the UK (Department of energy and Climate Change 2013a, table 1.04), an increase in energy efficiency of domestic dwellings can be an effective means for savings in terms of money as well as energy. The effect may be even stronger on the longer term, as prices may increase as the availability of resources declines (see for instance Hotelling 1931).

Taking action on this part in an effective manner requires data on household energy consumption and methods to find where to prioritize; that is, where most can be saved in terms of money and energy at the lowest possible costs. The introduction of new technologies such as smart meters allows for better monitoring of energy use than previously. By using smart meter data, this research attempts to provide a method to find areas of relatively high fuel and heat consumption. Scotland is used as a case study and particular emphasis is on remote areas, where energy consumption per household tends to be higher than in urban areas. Additionally, rural areas have suffered from a neglect of attention regarding measures to increase dwellings' thermal efficiency.

2. Theoretical Framework

"In a carbon-management environment, we believe people will focus on energy efficiency - the cheapest form of new energy we have." David O'Reily, CEO of Chevron (CNN Fortune, November 28th 2007)

2.1 Energy use on three levels: Europe, the United Kingdom and Scotland

The European Commission has set the goal to cut energy consumption within the EU by 20% of projected levels by 2020 (EC Eurostat 2012). However, between 2000 and 2010 there was an increase of 0.2% per annum in the EU as a whole. Luxemburg had the largest increase of energy consumption (2.5% per annum) and the United Kingdom (UK) had the largest decrease in the EU (0.9% decrease per annum) (EC Eurostat 2012). Today, the UK ranks 14 in amount of energy used per capita of all EU countries (U.S. EIA 2011). More than two thirds of domestic energy use is estimated to be for space heating purposes in Scotland (Energy Efficiency action plan 2009, p.56).

Within the UK, the region of Scotland has the highest domestic gas consumption per household. Overall, energy consumption per consumer in Scotland has decreased vastly, from 20.042 kWh in 2005 to 15.919 kWh in 2010 (Scottish Government 2012, p. 34-35). Home heating however, has slightly increased nation-wide and in particular as a share of household expenditure to energy (Department of Energy and Climate Change 2011a). Therefore it remains a topic of interest to decrease energy use for domestic dwellings particularly.

Energy consumption is still a concern for the UK government and many citizens. The Energy Efficiency Action Plan for Scotland (2009) summarizes the issues of highest concern. The issues of concern are most importantly:

- Climate change. Increased carbon emissions can lead to changes in climate. This is also why the EU has set goals to have carbon emissions by 2020 and 2050 that are below the currently projected growth;
- Fluctuating prices. Increase worldwide of energy demand results in more fluctuating prices, making that supply to Scottish consumers is unstable;
- Diminished future supply of fossil fuels and concerns about peak oil.
- Costly investments for increasing the nation's energy supply.
- Dependency for energy on politically instable countries.

Aside from decreasing the negative effects of the abovementioned issues, taking action should lead to benefits in several ways (Energy Efficiency Action Plan Scotland 2009):

- Being among the first to invest in energy-saving technologies boosts expertise in the field, which will turn beneficial when international demand for these technologies rises.
- Increase of energy efficiency should lead to more savings, which can result in lower fuel poverty, allowing households to spend or invest in other ways.
- It is stated that the measures to tackle the abovementioned should coincide with economic growth. Energy efficiency should lead to attractive prices for consumers, businesses and the public sector and increased savings.
- Decreased energy demand would lead to lower energy bills, which particularly benefits low income households, so that they can spend or invest money otherwise, which is particularly helpful in times of economic hardship such as these.

Traditionally the UK government has been able to influence the energy market through pricing policies. However, the abilities of the UK to influence the energy market and energy prices

diminishes with EU regulations, which aim for more privatization and liberalization, hence market prices will be more influential where previously they were more influenced by government policies (Fouquet 2008).
Since increasing the supply of energy is stated to be costly, the most logical step is to decrease demand, which is prioritized above increased or cheaper supply. Only where demand remains, the supply should increase through increase of renewable energy (Energy Efficiency Acton Plan 2009, p. 6). Domestic energy consumption can be decreased through improvement of the dwelling's thermal efficiency; i.e. the efficiency with which energy is conserved and transported. 53% of the future energy savings are estimated to come from the domestic sector (Energy Efficiency Acton Plan 2009, p. 37).

Taking action to increase the thermal efficiency of houses, whether privately or publicly, is not a new phenomenon in the UK and the thermal efficiency of houses has increased throughout the years. It has been stated that the reason why the increase of warmth demand still rises is due to the demand for warmer homes in the UK. Recent evidence however, shows that houses have not been any warmer between 1984 and 2007 (Shipworth 2011). The research was not able to conclude why warmth use has gone up. This suggests that better methods of monitoring may explain why energy consumption for warmth use does not appear to go down. Some explanations may be (Shipworth 2011):

- Houses have increased in size, requiring more energy to warm the entire house
- Windows and doors are opened more often, in turn decreasing the warmth inside the house
- Thermal efficiency of houses have been overestimated, leading to mistaken assumptions about the amount of energy saved in a household.
- Demand for warmer homes has increased in rented homes up to the point that they equal owner-occupied homes
- Demand for warmth over a longer time has increased
- Dwelling envelope thermal efficiency improvements will have increased average internal temperatures over time, resulting in a more even distribution throughout the house, followed by an increase in the dwelling's 24 h temperature when thermostat levels remain the same as before the improvement in thermal efficiency.
- Increased penetration of central heating would have increased average internal temperatures over time;

The disputed causes for higher warmth use can be monitored increasingly through smart meters. Some smart meters have a thermometer reporting the inside temperature, which can provide increased clarity on warmth use and demand for warm houses. Of the above possible explanations laid out by Shipworth (2011), inside temperature data can provide insight into:

- Thermal efficiency of the dwelling and deviations from the expected thermal efficiency, where sudden heat loss may be attributed to opening of doors and windows.
- The period of time with which warmth is demanded, indicating the total warmth demand.

This research investigates warmth demand by use of smart meters reporting inside temperatures (more on this is found in chapter 2.3).

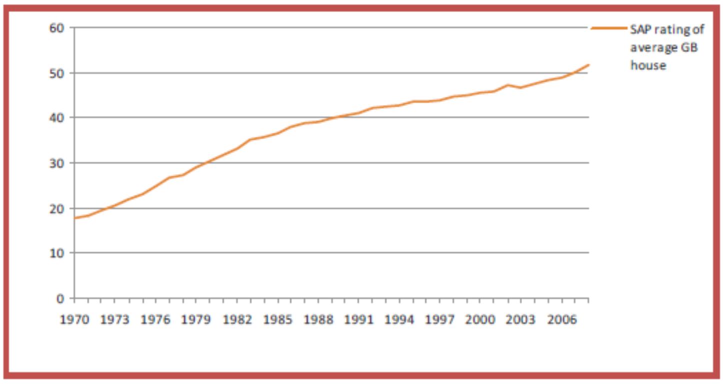
2.2 SAP and NHER

The British government assesses household energy use through the Standard Assessment Procedure (SAP). SAP ratings provide information that is used for policy making (SAP 2013). Energy use is estimated by evaluating properties of the houses such as materials used for construction, insulation, efficiency and control of the heating system and the fuel used. From that, a score between 0 and 100 is given with a higher number indicating a lower CO_2 output. The goal is to achieve a SAP rating of 80 for the average UK household by 2050 (ECI 2005, p. 96) and SAP scores are increasing (figure 2.1). Rural dwellings in Scotland today have an average score of 53.5 while for urban dwellings this is

64.3 (SHCS 2012, p. 20), which is probably explained simply by the fact that compact living in cities is more energy efficient than sprawled single-family houses in the suburbia. New homes have typically a rating of 80 (Department of Energy and Climate Change 2011b, p. 31).

The SAP method assumes standard use by occupants (Roberts 2008, p. 4483) and the SAP score given to the household is independent of household size, composition, ownership and efficiency of particular devices used to heat the homes (BRE 2011, p. 4-5). The method is disputed, in particular for very low- and low-energy homes and it may be claimed that more knowledge is needed on the influence of certain factors on the eventual SAP score. One of those factors is location (AECB 2008), which has an important place in the research conducted here. Location is not monitored through SAP (BRE 2011).

Figure 2.1: SAP ratings in Great Britain in the average house



Source: Department of Energy and Climate Change 2011b, p. 31

An alternative for measuring SAP scores is National Home Energy Rating (NHER) bands. It came into existence before SAP and measures all energy in the home including cooking and electrical appliances. Unlike SAP it also takes into account location and its climate conditions and the number of occupants of a dwelling. NHER uses a score of 0 to 20 where 20 is the highest possible score where no CO2 is emitted and no running costs exist. Like SAP, human behavior is not taken into account (SHCS 2012, p. 6 & Nesltd 2010).

A difficulty in assessing the suitability of an assessment procedure is to unite applicability and accuracy. Both the degree to which the assessment method is universally applicable as well and the accuracy should be as high as possible. However the more accurate, the more complicated the assessment becomes and that again results in disinterest among home-owners or consumers to adopt or understand the standards (Visscher and Mlecnik, 2009). It could be argued that both SAP and NHER may both be poor providers of information for individual consumers. Stein & Meier (2000) found that home energy ratings are often a poor indicator for individual actual energy bills. Even though on average the energy ratings tend to coincide with eventual use, the results widely vary for individual households. This was true especially for old buildings.

2.3 Measuring energy use by smart meters

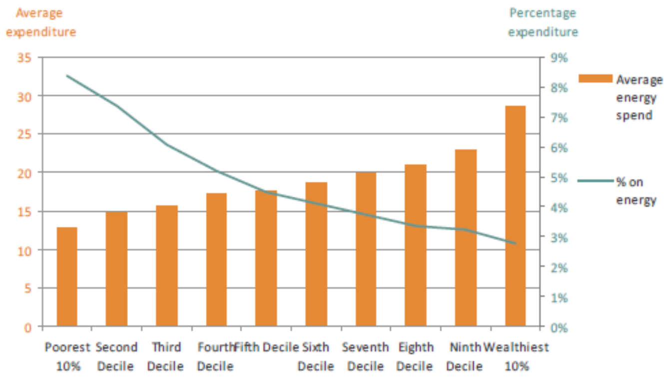
The measuring of energy use has been facilitated in recent years due to technological advancements. An important change has occurred due to the introduction of smart meters. Smart meters send data on the use of electricity from a household to the electricity company. Those data may be sent on a regular basis, so that energy use can be monitored throughout the day. Smart meters may include the total use of electricity, the amount of energy used for warmth, additional features such as humidity and temperature.

The new improvements in monitoring energy use can improve the monitoring of different factors that relate to domestic energy use. Monitoring climate change and energy use, as well as the effectiveness of policies and energy efficiency measures, has, at least until very recently, proven to be difficult due to lack of reliable data (Energy Efficiency Action Plan for Scotland 2009, p. 29-35). Smart meters allow checking on energy consumption at the individual household level, as opposed to current monitoring techniques that often register sector-wide consumption (Energy Efficiency Acton Plan 2009, p. 39-40). The monitoring counts not only for the energy providers but also for the consumers, so that introduction of a smart meter may by itself encourage consumers to consume less energy at certain points in time (Rijksoverheid 2012, Roberts 2008, p. 4486). Smart meters and other energy monitors generally do not have a thermometer even though those meters do exist. Their usefulness however, is largely still unknown. The James Hutton Institute in Scotland has provided temperature data from smart meters for the research conducted here and is interested in the question of how the data can be used. This research can be viewed as an addition to the North East Scotland Energy Monitoring Project (NESEMP) research conducted by Craig et al. (2014), a longitudinal study of household energy consumption patterns. The NESEMP study uses the same smart meter dataset but not the thermometer reports that were provided by it, while this research does.

2.4 Income and warmth use

On average, house size increases with income. Also, higher income implies the ability to spend more on energy. This explains partially why higher income households spend more money on fuel, light and power. Nonetheless the richest 10% of British citizens spend less money on these things as a percentage of their income than the poorest 10%. Poorer people tend to live in less insulated houses and simultaneously have less means to improve the condition of their homes. Conversely, richer households have fewer incentives to be energy-efficient since the energy bill is already a smaller proportion of their income. The explanations to why there exists a large difference in consumption of fuel and electricity however, are crude and knowledge on the subject is limited (Department of Energy and Climate Change 2011b, p. 23). Unsurprisingly, although paradoxical when considering the aim to reduce fuel poverty through cheaper energy provision, energy use has historically tended to increase when prices went down and particularly when income levels went up (Fouquet 2008, p. 276-277).

Figure 2.2: average UK weekly expenditure on fuel, light and power according to household income



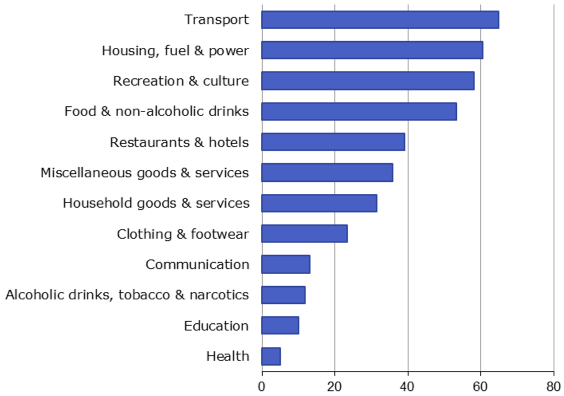
Source: Department of Energy and Climate Change 2011b, p. 23

Average household costs of energy use can give a distorted image of the actual situation. While most consumers consume below average energy use, a small number use very large amounts of energy. Hence benefits of thermal efficiency increases cannot be found by comparing with the average amount of energy use (Harvey 2006, p. 29). The above figure suggests the discrepancies between different groups. However it still does not show how the energy use is distributed among the income brackets themselves, and among the richest groups there may be households very far above the numbers we see in the graph. Similarly, among the poorest households in the UK there may be a number of households that use far more energy than what the above graph indicates.

2.5 Transportation

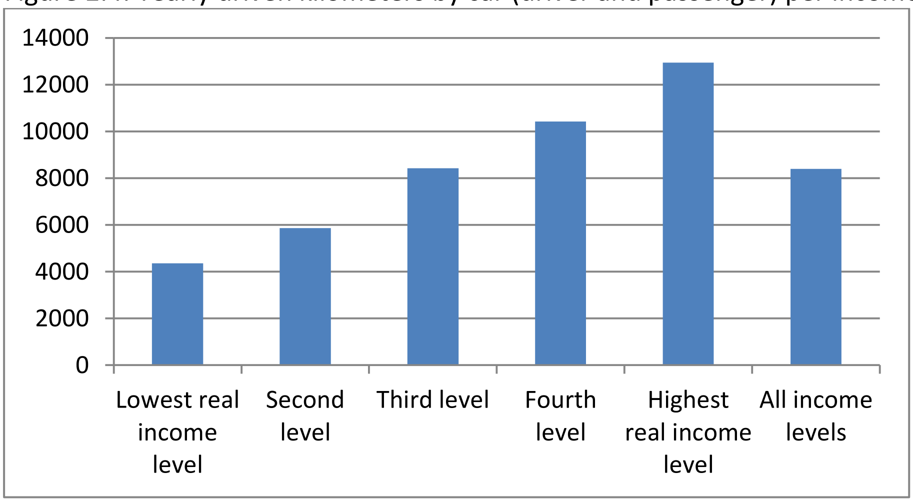
Transport, households and industry are the categories where most energy is consumed (31.7%, 26.7% and 25.3% respectively) within the EU as a whole (EC Eurostat 2012). In addition to energy being one of the primary causes of pollution, energy use is also one of the primary expenses for the household. In the UK, transportation and housing, fuel and power are the categories where expenses are highest. Transportation is commonly not taken into account when measuring fuel poverty. It nevertheless is the most important expenditure of average UK households (figure 2.3). Although transportation is a relevant topic for poor households, it should be noted that high-income households spend more time traveling than low-income households (figure 2.4)

Figure 2.3: Average weekly household expenditure on main commodities and services, 2010, UK.
Note: 2/3rds of the costs of transportation are spent on running costs.



Source: Office of National Statistics 2011, p. 1

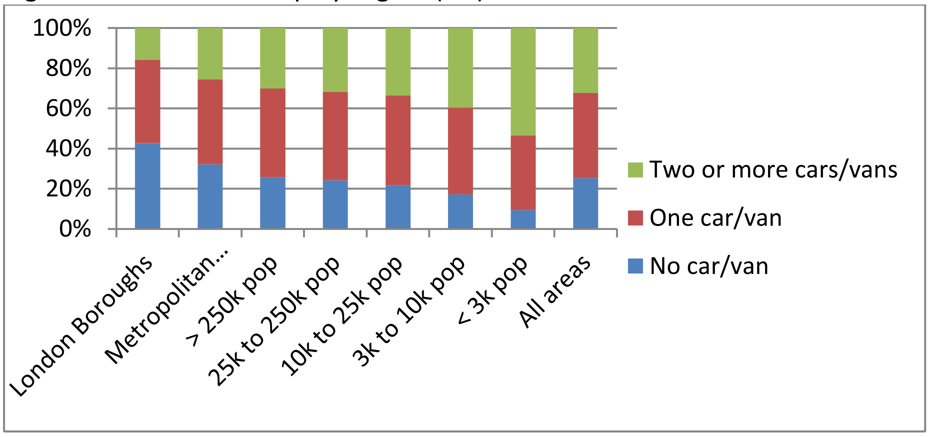
Figure 2.4: Yearly driven kilometers by car (driver and passenger) per income level in 2012



Source: Department for transport 2013, table NTS 0705

Transportation issues of rural environments in the UK have attracted attention from geographers due to low levels of public transportation, and the danger of hardship and isolation when private transport is lacking, with the effect that people can become more vulnerable to isolation and deprivation. Car ownership in rural areas in the UK is not necessarily a result of wealth as it is a necessary condition for living. Poverty, old age and disability are assumed to be the only reasons in rural areas not to have a car. Significant transportation problems can still occur when single car ownership occurs (Nutley 1996, p. 93-94). This in turn may explain why car ownership tends to increase as remoteness increases (figure 2.5)

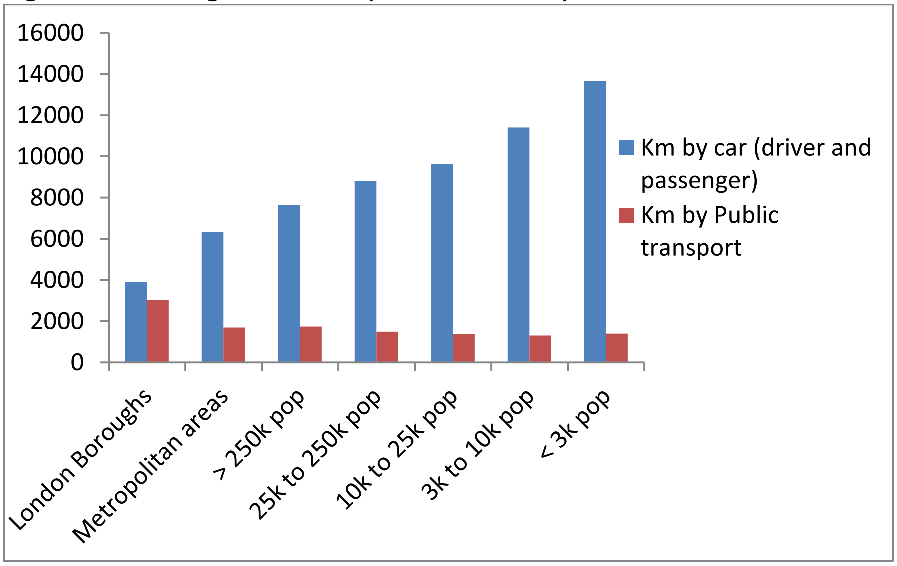
Figure 2.5: Car ownership by region (UK) 2010.



Source: Department for Transport 2012

Households in rural areas travel longer distances than households in urban areas. The average distance travelled in rural areas is 15,714 kilometers compared to 7,543 kilometers in London and 8491 kilometers in metropolitan areas (Department for Transport 2013, table NTS 9904) when walking and cycling are included. When only counting travel by car, the differences become even vaster, while public transport use is higher in large cities than in other areas (figure 2.6).

Figure 2.6: Average distance a person travels by mode and area in the UK, 2012



Source: Department for transport 2013

2.6 Remoteness and warmth use

In Scotland, the largest group of households uses the main gas network to heat their homes. Of all homes detached from the gas network, the largest group (about 353,000) uses electric heating. Some 33,000 use wood or coal, 135,000 households use heating oil, 18,000 use LPG to heat the house. The latter two sources are generally more costly for households and prices are particularly

volatile for these sources of energy (Consumer Focus Scotland 2012, p. 4). Households with those energy sources are more often found in rural areas than in urban areas. Older houses, which are plentiful in many rural areas, are often poorly insulated due to the building materials used. Lack of knowledge among landlords on how to improve the insulation can also be a reason (Consumer Focus Scotland 2012) while insulation is generally the most effective way to tackle energy inefficiency (EST 2013).
Unsurprisingly there is a significant difference in the energy efficiency of rural and urban households (table 2.1). Scottish urban dwellings also tend to be more environment-friendly; they emit on average 5.0 tonnes CO2 whereas rural dwellings emit 8.4 tonnes (SHCS 2011a, p. 24).

Table 2.1: Energy efficiency in rural and urban dwellings in Scotland (2009)

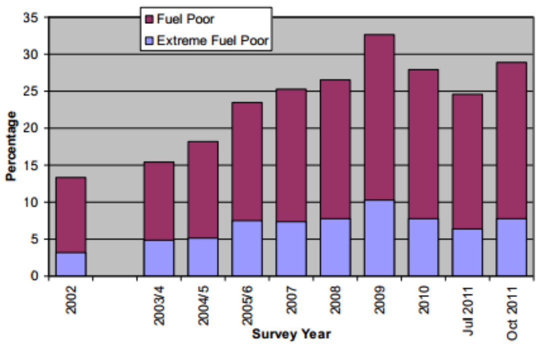
Energy efficiency (%)	**Urban**	**Rural**
Poor	1%	13%
Moderate	37%	61%
Good	61%	27%

Source: SHCS 2009

2.7 Fuel poverty and vulnerability

Fuel poverty is the situation where the household is unable to heat the home at reasonable costs, with the usual criterion that 10% of household income is spent on heating the home (Department of Energy and Climate Change 2012a, p. 3, Energy Efficiency Action plan for Scotland 2009, p. 31). However, different definitions of fuel poverty exist (Department of energy and climate change 2012a, p. 3). Fuel poverty has not gone down during the Scottish House Condition Survey from 2002 to 2011 (figure 2.7).
Fuel poverty is significantly higher in rural areas as opposed to urban areas (Consumer Focus Scotland 2012) and fuel poverty is significantly lower among households in the three largest cities in Scotland than the rest of the country (SHCS 2011b, table 8.10). Affordable solutions and energy efficiency programs have until now mainly been focused on urban areas (Consumer Focus Scotland 2012, p. 4).

Figure 2.7: energy poverty in Scotland, 2002 to 2011



Source: SHCS 2011a, p. 26

The fluctuations in fuel poverty can partially be attributed to energy prices. Other reasons include fluctuations in household incomes and fuel efficiency (SHCS 2011a, p. 26-27). With regards to fuel efficiency, the decrease in fuel poverty since 2009 may partially be attributed to the Community Energy Savings Programme (CESP), which ran from 2009 to 2012.
Through CESP, the UK government “[…] required certain gas and electricity suppliers and certain electricity generators to deliver energy saving measures to domestic energy users in specified low income areas of Great Britain” (Ofgem 2013, p. 1). One of the reasons for that is that social housing

was targeted in particular, which tends to be more located in urban areas than rural areas (Department of Energy and Climate Change 2011a, p. 20). Electricity companies have so far shown no interest in tackling specific geographical areas (Department of Energy and Climate Change 2011a, p. 7), but cost-effective solutions may be more easily found in urban areas, where economies of scale are more easily achieved (Consumer Focus Scotland 2012, p. 4). This gives an incentive for companies to prioritize insulation measures in urban areas above rural areas. Houses that were targeted in the CESP program fell inside geographically specified areas. These areas were chosen based on income levels, and not on fuel poor households in particular. Although exact figures are lacking, this may be one of the reasons why the number of rural homes included in this program can be said to have been notoriously low, since fuel poor households are predominantly located in rural areas. It has also been noted that the measured income level, which is based on the (Scottish) multiple deprivation index ((S)MDI), is a poor way of measuring the real degree of poverty in rural areas since the index is based on poverty in clustered areas (De Lima 2008). Currently CESP has been replaced by the Home Energy Efficiency Programme for Scotland (HEEPS), in which geographical targeting is achieved through area-based schemes (ABS). Funds are allocated by the following criteria (HEEPS:ABS 2013):

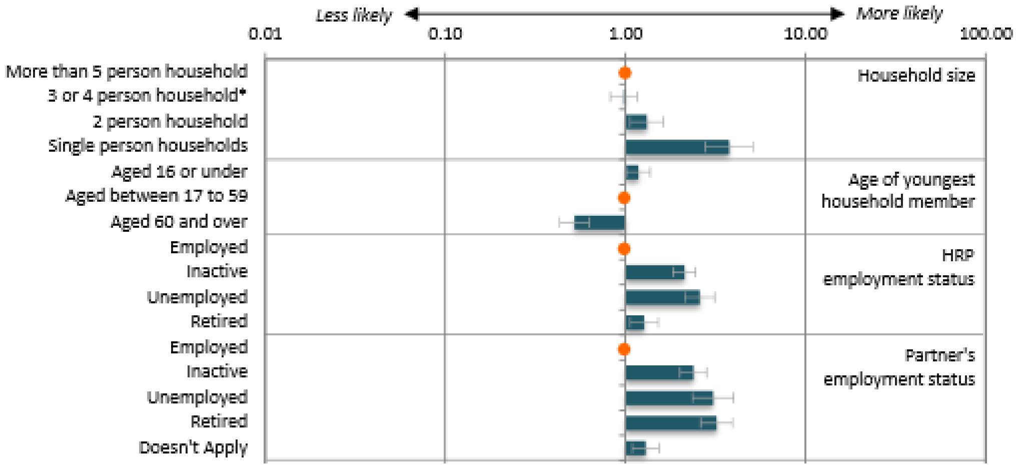
- 20% for national fuel poor households within a local authority area;
- 30% for total local authority area population which is fuel poor;
- 30% for national share of dwellings which have solid walls; and
- 20% for national share of dwellings with hard-to-treat cavity walls.

While the Area-based Schemes may be more effective than the CEPS programme to tackle fuel poverty in rural areas, it should also be noted that merely improving energy efficiency may change behavioural patterns in energy use while not alleviating energy expenditure as a percentage of income. Increased energy efficiency is known to cause so-called ‘rebound effects’, so that it increases the incentive to utilize the saved energy, which in turn does not result in lower energy expenditure. Fouquet (2008, p. 365-366) argues that when consumer prices go down, consumers react and spend more fuel, while when the prices rise, politicians are expected to take action.

While some households may be fuel poor particularly because their houses are insulated badly, others may be fuel poor rather because their income is low. Thus for monitoring fuel poverty and CO_2 emissions on the one hand, and on the other hand for energy efficiency measures to be effective, this means that specifically the individual houses where energy efficiency is low should be targeted rather than merely the criterion that a household is fuel poor.

Energy use varies by gender, age and culture (Lück 2012, p. 6). Employment status and household size and composition may also matter (figure 2.8). Rural dwelling’s energy sources differ significantly from dwellings in urban areas (Craig et al. 2014), but due to fluctuating energy prices it is not possible to state that this difference inherently results in a difference in expenditure on warmth.

Figure 2.8: Effect on the odds of being fuel poor in England (note: not UK as a whole, so Scotland is not included).



Source: Department of Energy and Climate Change (2013b, p. 18)

Unemployment, retirement and old age are factors that diminish the possibilities for residents to increase their income in order to become less (fuel) poor. Given that fuel poverty is higher in remote areas while thermal efficiency is lower, resident's risks of being fuel poor in these areas increases even further. With the exception of moving (if at all possible and effective), vulnerability to remain in fuel poor conditions can be extremely difficult if not impossible. Vulnerability is researched by measuring the factors that contribute to these conditions; these factors include income deprivation, retirement and old age and unemployment.

2.8 Measuring remoteness

The Oxford English Dictionary describes the phrase 'remote' as follows: "1. (of a place) situated far from the main centers of population; distant" (Oxford Dictionary 2014). From the earlier chapters it can be concluded remote areas have often higher heating costs and that simultaneously, tackling fuel poverty through energy efficiency appears to be most difficult in remote areas. However, it is difficult to say to what degree the two variables coincide. The distinction between rural and urban is not always clear and a variety of ways exists to measure the remoteness of an area.

Services and goods can be said to be accessible to the degree to which one has access to the service according to income and in the degree that the service or good is accessible through transport. Therefore it may be argued that before accessibility to a service or good (for instance, health care or insulation) is raised financially, access for groups of people may more effectively be raised by increasing geographical access. Dunne et al. (2001, p. 7) argue that "*[…] interventions to deal with remoteness should first identify geographically remote areas, then target interventions to the most appropriate and disadvantaged groups within those areas (i.e. adopt a two-stage approach)*". Although this is not the way that additional (public) services are commonly established, it does give a foundation for bringing in the geography of availability before the identification of the group that needs the service.

In Australia, a classification scheme has been used for evaluating access to services where data collection districts (e.g. census districts) are grouped into zones of access to service centers. Access is measured in terms of travel distance by road, and the presence of a service is estimated at the hand of population clusters. An index is made at the hand of the access to a service center of a particular size and the estimated distance to that service center (Dunne et al. 2001). Since remoteness can be

regarded as the opposite of access, methods of accessibility measures may as well be used for remoteness measures.
The Scottish government uses four kinds of ways to measure remoteness, a 2-fold, 3-fold, 6- fold and 8-fold classification scheme (table 2.2).

Table 2.2: Scottish classification of rural and urban settlements (Higher numbers indicate higher remoteness).

Population	**Drive time to settlement of 10.000 inhabitants or more**	**Category**	**Classification (lowest number is most accessible)**			
			8-fold scheme	**6-fold scheme**	**3-fold scheme**	**2-fold scheme**
> 125.000		Large urban area	1	1		
> 10.000 < 125.000		Other urban area	2	2		
> 3.000 < 10.000	< 30 minutes	Accessible small town	3	3		
> 3.000 < 10.000	> 30 minutes	Remote small town	4	4		
> 3.000 < 10.000	> 60 minutes	Very remote small town	5			
< 3.000	< 30 minutes	Accessible rural	6	5	2	
< 3.000	> 30 minutes	Remote rural	7	6	3	
< 3.000	> 60 minutes	Very remote rural	8			
> 3.000		Urban			1	1
< 3.000		Rural				2

Source: Scottish Government (2013)

A crucial difference between the Australian and the Scottish measurement scheme is that in the former, more categories of remoteness exist, and the distance to population centers is taken into account. In the Scottish scheme, the remoteness is related to the distance to one other area. For the Australian scheme however, the distance to all population centers matters. So both the distance to a nearby small town and the distance to a larger town or city may matter.

The different schemes, it can be argued, all have their advantages and disadvantages. Drive times over the road network as a proxy for accessibility to population centers is advantageous because it offers a more realistic view of accessibility than the distance in a horizontal line. The disadvantage is that none of the existing schemes use accessibility of transport (private or public) and gasoline prices are not taken into account. However, accessibility to a service changes when transport costs change, due to fluctuating gas prices for instance, or tickets for public transport. Also, it cannot be assumed that everybody owns a car so accessibility may change dramatically when car ownership is taken into account.
Taking away proximity to population centers as a whole however, creates new problems. It may be argued that the advantage of solely looking at the population size of an area is that it is transparent and easy to use since the size of the population is most accurately measured within the census district. However, the large disadvantage is that it does not take into account the proximity to other larger districts and services. So a sparsely populated district near a metropolitan area may be regarded as ‘remote’ as a district with the same sparsely distributed population near even more sparsely populated areas, which gives a distorted view of the true accessibility.

In conclusion, various means of measuring remoteness can be identified;

- As the population density of the area
- As the distance to defined population clusters
- As the distance to a service

2.9 Climate, housing and their impacts on warmth use

It has been mentioned previously that energy use varies widely across consumers. One of the reasons for this is the energy efficiency of the house. The thermal efficiency, which overall has the most influence on the energy efficiency, depends on the degree to which heat is influenced by the weather outside. Heat loss depends on the temperature difference between the inside and outside temperature (a linear relationship exists, where the larger the difference, the quicker the rate of exchange; i.e. the more heat has to be added or decreased to maintain the same temperature) as well as the rate of air exchange, which is influenced by the dwelling properties (Harvey 2006, p. 38). Additionally, humidity appears to impact energy use, even though the effects on warmth demand are often unclear. Humidity affects the temperature due to conductivity of air. Higher humidity results in higher conductivity, resulting in higher drop of inside temperature when outside temperature is lower than inside (Lück 2012). While indoor temperature appears to have a strong effect on heat consumption, it is dubious that changes in humidity alone would lead to significant changes in heat consumption (Lück 2012, p. 5), rather the increase can be attributed to larger conductivity of cold air when the air is humid. It is also known historically that wetter periods drove up the demand for heating resources. There is reason to believe that wind also has a real effect on the demand for energy but the historical effect this has had, remains unclear (Fouquet, 2008, p. 69-70).

Costs and savings involved when improving the thermal efficiency of the dwelling is highly dependent on the house type (Bell & Lowe 2000, p. 276). Among the most important factors influencing thermal efficiency of the building are the following (Harvey 2006, p. 36):

- Insulation levels in the walls, ceiling and basement,
- Resistance to moisture migration,
- Thermal and optical properties of windows and doors,
- Rate of exchange of inside air with outside air through infiltration and exfiltration
- Presence of shared walls with other buildings.

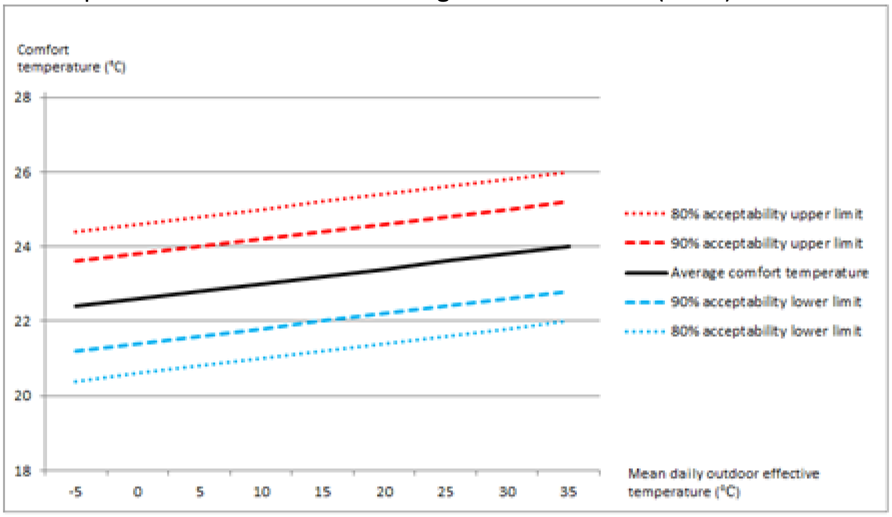
Heat loss can be reduced by added materials that are used upon the loft or walls (insulation). Simultaneously, air is a poor conductor of heat. This is why double glazing increases thermal efficiency and why most post-war buildings have a cavity between the bricks of the inner and outer wall (so-called cavity walls). Energy efficiency of houses is often achieved through retrofitting, adding insulation such as double-glazing, cavity wall insulation (CWI) and loft insulation. However, there are limits to the possibility to increase efficiency. CWI is not effective in very wet climates (Harvey 2006). Also, even if possible, insulation is not always economically feasible. Certain homes can be particularly hard to treat. The lack of gas supply or loft space and high-rise blocks may often be classified as being hard-to-treat, making insulation not an economically feasible option. The same counts for Non-cavity wall buildings (Roberts 2008, p. 4483). When these factors are found in particular geographies, this will have an impact on expenses and CO2 emissions on warmth. A previous study within the same study area (Craig et al. 2014) found that the heating type used for urban dwellings emits significantly less CO2 than heating types for rural dwellings.

2.10 Behavioral aspects to warmth use

The effect of weather conditions and thermal efficiency on warmth use has been treated in the previous chapter. These aspects only tell half the story about warmth use. Sonderegger (1978, p. 323) found that 46% of differences in house warmth consumption could be attributed to behavior. The research concluded that models for predicting the heat demand should not be pushed too much in a deterministic fashion and the effect of retrofitting should be tested on many dwellings and people. As has become clear from previous chapters, thermal efficiency has increased over the years.

As the influence of the dwelling properties on warmth use diminishes through increased thermal efficiency, the influence of the behavioral patterns rises if those patterns remain unchanged. On behalf of behavioral patterns influencing warmth use, they do so through both cognition (attitude, expectations, preferences) and through habits or culture (de Dear 1997, p. 4). A research conducted by de Dear et al. (1997) showed that the optimal perceived temperature inside depended on the weather outside. As a result of adaptability, the average temperature inside the home tends to be colder in winter than in summer, but the degree to which it changes is a slower change than the changes in outdoor temperature. Comfort temperature depends aside from outside temperature on clothing and seating and air speed. When these cannot be observed, de Dear et al. (1997, p. 161) estimated that generally 22.6 degrees inside is desired by an outside temperature of 0 to most people. 90% of the people still feel comfortable when the inside temperature at that point is 1.2 degrees warmer or colder while 80% still feel comfortable at 2 degrees warmer or colder (figure 2.9).

Figure 2.9: adaptive comfort model according to de Dear et al. (1997)



Source (data): de Dear et al. 2007, p. 162-164.

Adaptive Comfort Theory tells us that people adapt (physiological, psychological or behavioral adjustment) due to outside weather conditions that modify their perception of thermal comfort. The hypothesis from de Dear is that "The adaptive hypothesis indicates that one's satisfaction with an indoor climate is achieved by a correct matching between the actual thermal environmental conditions prevailing at that point in time and space, and one's thermal expectations of what the indoor climate *should* be like." (de Dear 1997, p. 6-7).

De Dear's model of thermal comfort was originally intended to be applied to office buildings' HVAC (heat, ventilation and air-conditioning) systems. Research has shown that the model can also be applied to buildings of all types across all populations (Lück 2012, p. 3). Yet it has also been

suggested that the model varies per place and culture. Singh (2011) and Toe & Kubota (2013) for instance found that people respond differently due to different climates. Their differences in clothing and expected warmth made them respond differently to what they perceived to be the most desirable temperature inside the home. One research found that the average monthly expected comfort of free-running buildings can be predicted by taking the average outside temperature to predict average inside temperature.
DeDear notes that adaptive ability in the office can have many constrains due to the following issues (deDear 1997, p.9):

- Climate; which has implications for the buildings built hence implications for ability to adjust (e.g. ventilation)
- Economic; not able to afford a warmer home
- Customs and regulation (energy policy, clothing in office)
- Task or occupation (influencing the clothes worn)
- Design of the HVAC system; ability to adjust awnings, windows, etc.

Office and residential buildings can differ strongly. This has implications for the clothes worn and the ability to control the heat in the home (e.g. centralized or decentralized; thermostat or not; automated or not automated). The factors task and occupation may therefore not be relevant for house warmth use. However it should be stressed that customs are; we see that habits and cultures influence clothing and thereby warmth use.

The differences in preference are even further backed by the fact that perceptions seem to have changed vastly throughout the years. In early 19thcentury Britain it had been stated that 15 °C was the most desirable temperature, while it has also been stated at the half of the century that it would be 18 degrees. By the end of the 20thcentury, British buildings tended to be heated to 23 °C (Fouquet 2008, p. 81).

2.11 Conceptual Model

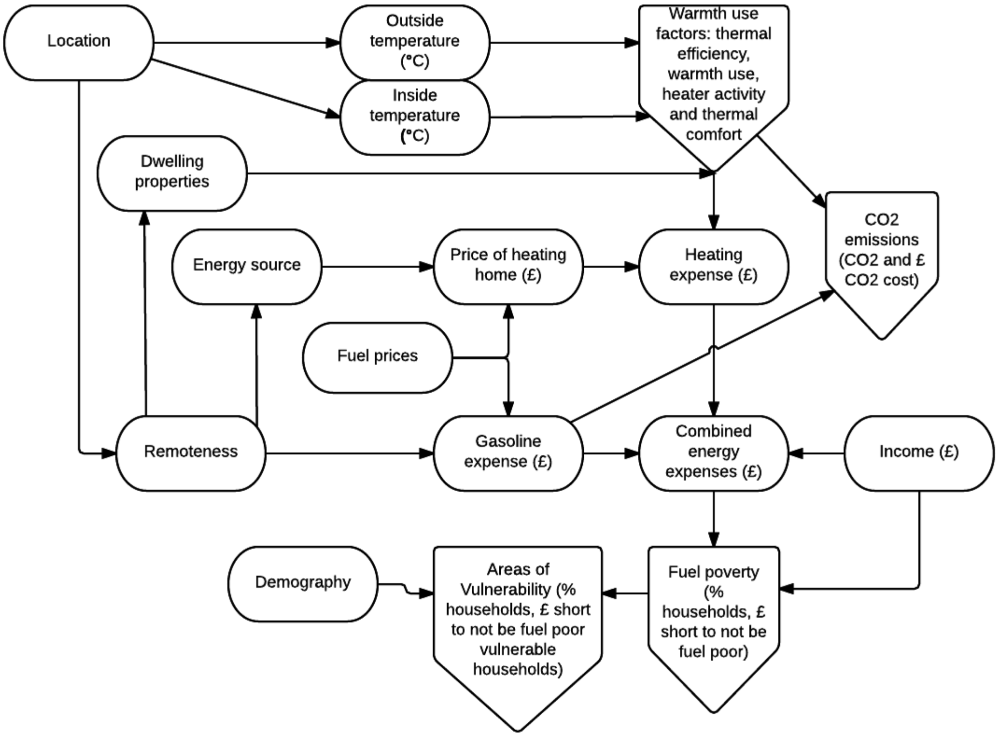
The conceptual model shows how location data can explain (to an extent) the warmth use factors of the area and its implications on CO_2 emissions, expenditure, vulnerability and fuel poverty (figure 2.9). Among other things, warmth use and energy use are influenced by location; due to climate and due to geographical characteristics in the area.
Climate factors are location dependent and interfere. This has to be taken into account for understanding the relationship between inside and outside temperatures at a specific location at a point in time. Although wind and humidity are important factors in analyzing inside temperatures, these are not taken into account since it would highly increase the scope of this research which was deemed too large for an MSc thesis.
Warmth use is also influenced by the geographical characteristics of the area. Regarding warmth use, an important geographical characteristic is the remoteness of the area as it is a known factor to influence warmth use and costs. The amount of warmth required tends to be higher in remote areas, typically due to its dwelling properties. The costs differ due to different availability of energy for warmth use. In addition, overall energy demand per capita tends to be higher in remote areas due to higher demand in fuel. Outside and inside temperatures are used to estimate the amount of warmth that was used. Their warmth use may additionally be explained by their dwelling properties (figure 2.9).

The extent to which these influences are visible however, will depend on the measures of remoteness used. Remoteness is measured in terms of population density and estimated accessibility to services. In another sense, more remote areas can be said to be less accessible. Consequently they make areas where vulnerable people live, more vulnerable due to the lack of accessible essential services. Drive times can be expected to shrink with more accessibility to services.

The total of transport expenses and energy required for heating add up to the final CO2 emissions and expenditure on fuel in general.
Energy for house warmth varies per location. The total fuel expenses together with income levels add up to a degree of fuel poverty. Fuel poverty is an estimate of the area here since income data are known by location but not by individual household.
Fuel poverty influences areas of vulnerability. In areas where fuel poverty is estimated to be high, people are more likely to cut their energy consumption, decreasing their abilities for transportation and heating the home. Elderly and disabled people are particularly vulnerable in these situations. The danger of isolation or lack of required help decreases with the amount of services that are available. Available services are estimated at the hand of zones of relative access, as was done in the research conducted by Dunne et al. (2001) in Australia. More remote areas tend to have fewer services available. In turn, areas are often perceived as being more remote precisely due to their limited amount of services.

The conceptual model shows no direct relation between remoteness and required energy for heating; only an assumed relation between remoteness to dwelling properties to required energy for heating. The relation between dwelling properties and energy use cannot be tested due to the lack of data on the dwelling properties of the houses that were measured. However the warmth use and thermal efficiency are tested and compared per remoteness of the area.
The relation between various measures of remoteness and energy required for heating are measured directly; i.e. without taking into account the dwelling properties in advance. In reality however the relation is assumed to exist due to differences in dwelling properties, which differ per degree of remoteness. Differences in behaviour and demand for thermal comfort may also exist per degree of remoteness but no evidence exists to suggest this. The relation between remoteness and thermal comfort is tested but its relation cannot be assumed and was therefore not included in the conceptual model.

Figure 2.9: Conceptual model



Pentagons indicate the final results of the research. Oval figures indicate the factors analyzed to get to final results.

3. Goals and objectives

3.1 Research goals

There are concerns about high energy consumption for heating purposes, thereby increasing costs and CO_2 emissions. Measures are taken to deal with these developments, but those measures are location-dependent. Rural areas in Scotland have suffered relative neglect of attention in spite of the significance of the problems that occur in those areas. The main research goal is stated as follows: *To develop a method to measure domestic warmth use from inside temperature data and to find how various degrees of remoteness influence energy use for households and to analyze the implications on CO_2 emissions, fuel poverty and vulnerability of households.*

The relevance of increased understanding of what smart meters can provide as useful information, has been addressed in the topic 'measuring energy use by smart meters'. The first objective is related to that topic:

1. To find what useful information can be derived from temperature data provided by smart energy monitors.

Useful information refers to information that would remain unknown without the information provided by the temperature monitor. Tested are the factors that relate to the eventual warmth use of the dwelling. These "warmth use factors" include:

- Activity of the heater
- Thermal efficiency of the dwelling
- Total warmth use

Thermal comfort levels may also be regarded as a warmth use factor, but in this research warmth use factors refer to the above three factors unless mentioned otherwise.

Analyzing locational attributes and their spatial relations can be done using Geographic Information Systems (GIS). GIS has been used in previous researches for monitoring energy use, but the influence of remoteness on domestic heat loss is largely unknown. A method needs to be developed to find how locational attributes are related to remoteness and to domestic heat loss. The second objectives are:

2a. To develop a GIS-based methodology for finding correlations of remoteness on domestic heat loss and fuel consumption.

2b. To find how different measures of remoteness (distance to services, classification schemes, population per km^2) influence the relation between remoteness and domestic heat loss and fuel consumption.

Completing objective 1 and 2 will allow mapping the locations of dwellings where high levels of heat loss occur and where drive times are long. This information can be combined with information known about the areas, such as insulation levels, weather conditions and drive times. In addition, those location-specific attributes relate to a large extent to remoteness. Finding out the relations between remoteness, location-specific characteristics and energy consumption, allows for fulfilling the third objective:

3. To find what location-specific characteristics of an area have a visible impact on warmth use factors.

In addition to the information acquired by fulfilling the third objective, demographic information about the areas can reveal how energy consumption impacts particular demographic groups such as elderly and low-income households. Demographics vary per location. A relation exists between location, energy use and its influence on demographics. Mapping the remoteness, location-specific characteristics, energy use and demographics allows for achieving the fourth objective:

4. To show whether areas with high fuel poverty and existence of vulnerable households tend to coincide with high energy use.

As a consequence of the above stated research goals, the information can be brought together, showing where energy use on the one hand and fuel poverty, vulnerability and CO_2 emissions on the other hand are relatively high. When these factors are tied to different degrees of remoteness, the maps may explain why heat consumption is high or low in that area, and what its consequences may be. The results may help anticipate where a certain degree of warmth is demanded, based on geographical data on dwelling types and demography combined with thermometer data connected to a smart meter. These insights can make smart grids work more effectively and efficiently in supplying the amount of energy desired. They also can give an indication where more energy can possibly be saved through insulation levels by showing where excessive heat loss is signaled.

3.2 Hypotheses

H 1: Warmth use factors increase as remoteness increases.

The warmth use factors include thermal efficiency, heater activity and total warmth use

H 2: More remote areas tend to have higher warmth use, even when using various measures of remoteness.

H 3: A higher degree of remoteness results in a higher degree of;
CO_2 emissions due to:

- Required energy for heating
- Higher fuel consumption for transportation
- Energy sources

H 4: A higher degree of remoteness results in a higher degree of;
Expenditure in terms of money due to:

- Required energy for heating
- Higher fuel consumption for transportation
- Energy sources

H 5: A higher degree of remoteness results in a higher degree of;
Fuel poverty due to:

- Household income levels
- Higher heating costs
- Higher fuel costs

H 6: A higher degree of remoteness results in a higher degree of;
Vulnerability due to:

- Higher fuel poverty
- Demography in rural areas (age, disability)

4. Method

4.1 Data preparation

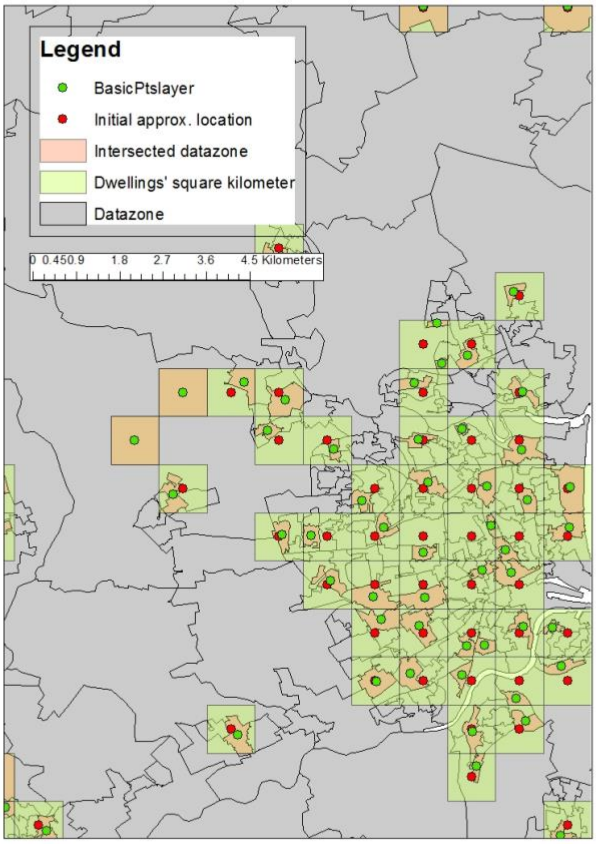
Dwelling location estimation

A total of 369 dwellings are measured. Geographical data other than locations of dwellings are given on Middle Super Output Area (MSOA), data zone 2001 and data zone 2011 levels. The location of the dwellings is known at approximate levels. Each given location is somewhere in an area of 1 km^2 of the given location (figure 4.1), so a squared area is made of 500 meters left, right, up and down around the given point. Since weather conditions do not differ very significantly over a square kilometer, the influence of any inaccuracies in the provided dwelling locations should be negligible. However, the approximation has significant influence over the demographic and energy use statistics assigned to them since those figures are registered by geographic areas, and 1 km^2 may fall within several geographic areas.

It is known that rural dwellings tend to consume more heat warmth urban dwellings do, among other factors due to dwelling conditions. To what extent these conditions vary in the study area can be determined with the information available on dwellings' location and the attribute data of the geographical areas these belong to. For increased reliability of the attribute data assigned to the dwellings, estimated dwelling locations are relocated in order to retrieve the data from the district the dwellings are most likely to be located in. The dwellings are not relocated for transportation data; here a network analysis is conducted where the points are snapped to the most approximate road in the road network from their original locations. Since the true location of the dwelling remains unknown and the influence of 1 km is very little when travelling by road, any distortions should be low to negligible. For weather data it is of insignificant importance whether the estimated location of the dwelling is off by one kilometer.

Demographic and energy consumption characteristics for individual dwellings are unknown. Demographic characteristics are known on 2001 data zone levels (census districts) and energy consumption levels on 2011 data zone levels. The procedure of estimating the characteristics of the dwellings is done as follows. First, the characteristics of demographics on the basis on location are determined (at the 2001 data zone level).
Dwellings are assigned the characteristics of the data zone they are most likely to be contained in. In case the square within which the dwelling is contained is located entirely within one datazone, that dwelling is assigned the same attribute data that this data zone has. In case the square overlaps with more than one data zone, it is estimated that the dwelling is located in the datazone with the highest estimated population in the overlapping area. This is done as follows:
First, the average population per hectare is calculated for each data zone.
Second, an intersect operation is done on all data zones that overlap with the square kilometers belonging to the dwellings.
Third, the size of each of these intersected areas is calculated and multiplied with the average population.
Since it is most likely that the dwelling is located in the area where most people live, the dwelling is assigned the attribute data belonging to that area. The dwelling's original point on the map is also relocated to the middle of the intersected part of that data zone (Figure 4.1).

Figure 4.1: Map of original dwelling locations provided and their relocation based on estimated population within its 1km² vicinity. Area of Aberdeen.



The grey areas are datazones, containing attributes that are assigned to the dwellings, such as type of housing and demographics. The attributes of the data zone that the dwelling is most likely to be located in, are assigned to that dwelling.

The most likely location of a dwelling is within the dark brown areas or 'intersected data zones'; these parts have the highest estimated population contained within the dwellings' square kilometer (light brown).

The dwelling locations are relocated from their initial approximate position (red) towards the middle of the intersected data zones (green) as an estimate for their most likely position.

As approximate locations have been estimated, the dwellings are assigned attribute data according to attributes in that data zone. These include among other things drive distances to services, dwelling properties, energy use and demographic factors.
In addition to assigning attribute data, relocated dwellings are used to estimate the dwelling's distances to settlements over 125.000 inhabitants (cities), more than 10.000 inhabitants (towns), and more than 3000 inhabitants (villages) over the road network. The results of three network analyses (location-allocation towards villages, towns and cities) are merged together so that one dataset shows for each dwelling the nearest village, town and city over the road network (source data: remoteness).
A second dataset for transportation is created by analyzing the closest route from a dwelling to any settlement. The settlements closest to each dwelling are regarded as the settlement the dwellings belong to. Then, dwellings are divided into categories larger than 25.000 (large urban), larger than 10.000 (medium urban), larger than 3.000 (small urban) and less than 3.000 (rural) (source data: transportation).

Remoteness indices

Remoteness is not easily defined and levels of remoteness may strongly depend on their criteria. The Scottish government uses a variety of levels of remoteness, based on distance to population centers of 3000 inhabitants 10.000 and 125.000 inhabitants. Four types of remoteness indices are used:

- The existing 2-fold, 3-fold, 6-fold and 8-fold classification schemes (Scottish Government 2012b) (ordinal variables).

A vector layer is provided containing the classifications. With a spatial join with the estimated dwelling point locations as target features and the vector map as join feature, the classifications are added to the dwellings' attribute table. As a result, each dwelling has the remoteness index in accordance with the existing classification schemes (Appendix I figure 1-3).

- Distance to services (interval variable).

A variety of average driving distances to services per municipality are provided by Scottish Neighbourhood Statistics (SNS 2013). The drive times to services are joined together and divided by the number of distance to service indicators. Then the distances are added to the attribute table of the dwellings, in accordance with the datazone that they are expected to belong to (Appendix I figure 4).

- Drive times towards population centers based on a standardized score (interval variable).

A standardized score is given to each dwelling according to its estimated location. Through a standardized score, the distance to a city, town or village of one location is given in its relation to all other location distances involved in this research. A network analysis can give for all locations combined the average distance (μ) to a city, town and village and the standard deviation σ from these population centers. The dwelling's distance value x is then used to find the Z value by the equation $Z = (x- \mu)/\sigma$ (Appendix I figure 5). The road network data were taken from Ordnance Survey (2013).

- Population density (interval variable).

The population density of the data zone is provided by the Scottish Neighbouthood Statistics (2013).

As the dwellings are assigned the different indices of remoteness, the indices are subsequently compared in order to establish the reciprocity between them. Remoteness indices that have relatively high reciprocity with other indices may be regarded as more steadily indicating the remoteness. If stronger correlations occur for remoteness indices with more steady remoteness indicators, this would show that for measuring warmth use indicators, the ambiguous term 'remoteness' can be measured in a way that is most coherent with existing remoteness indices as well as being a useful index in evaluating and possibly predicting warmth use indicators in different geographical areas.
Spearman's correlation is conducted on the reciprocity between the ordinal classifications schemes as assigned by the Scottish Government (2012b). Pearson's correlation is conducted on all other indices, which are interval variables.

4.2 Calculation of outside temperature

The weather data are spatially interpolated. For wind data in England, cokriging by using elevation data as a multivariate have been proven to increase data accuracy when elevation and wind are correlated. Without the correlation, cokriging and kriging accuracy gives about similarly accurate results (Luo et al. p. 955, 2008). Hartkamp et al. (1999) conclude that splining and co-kriging for temperature data are preferable to inverse distance weighting (IDW) while Collins & Bolstad (1996) conclude that co-kriging and kriging give better results than IDW, and IDW to splining.

The semivariogram (figure 4.3) comparing weather station data with elevation (figure 4.4) shows that no correlations were found for elevation with outside temperatures in the area. Ordinary kriging therefore was used interpolating weather data.

Figure 4.2: semivariogram of deviations of temperatures as influenced by height.

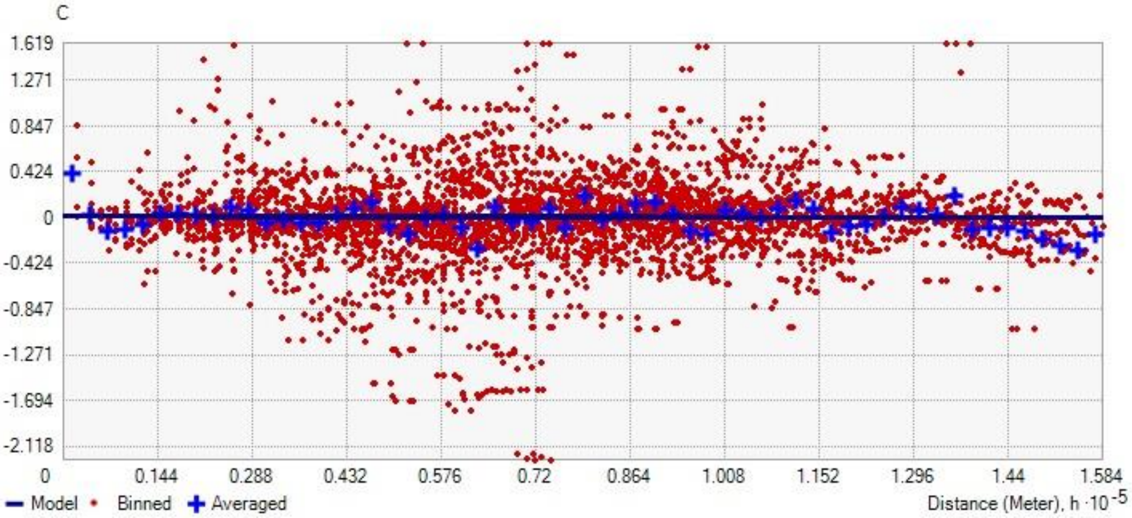
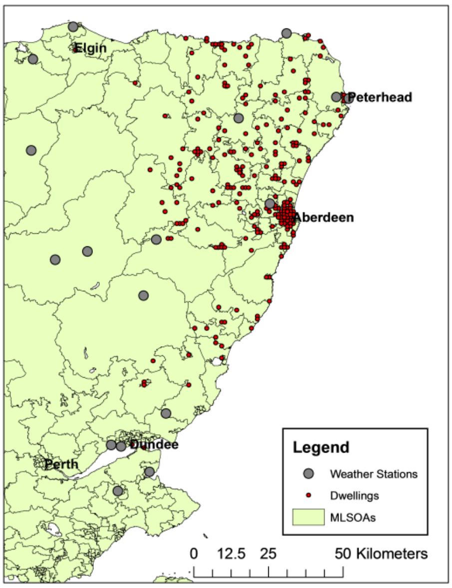
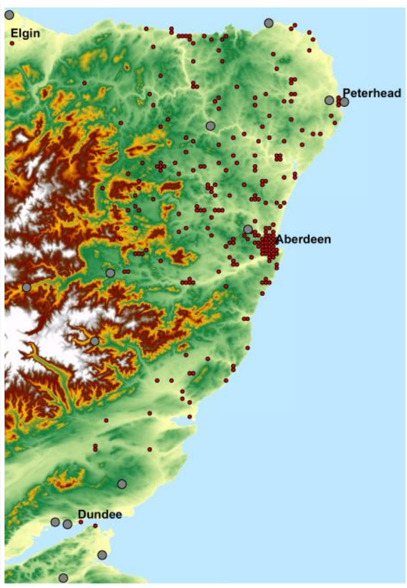


Figure 4.3: Weather stations used for kriging

Vector map



Elevation map



Outside weather conditions are retrieved from the UK meteorological office (2013). The given time interval is 1 hour, and monthly temperature data of weather stations were used from January 2010 to April 2013. An OutsideTimeID per month is added as a new field to the attribute table. The OutsideTimeID changes from t1 to t+1 for every hour.

The kriging interpolation (*spatial interpolation*) results in a raster surface. The values of the raster surface are subsequently extracted to the points representing the approximate dwelling locations (figure 1 appendix II). The process is iterated according to the amount of hours per month, resulting in a maximum number of 720 OutsideTimeIDs; this is the number of hours for months with 30 days. The last 24 hours for months with 31 days were not measured; this is not regarded as an issue. Measuring 24 hours more or not should not result in significantly different outcomes with the amount of data that was used (source data: InsTemp and OutsTemp according to TimeID).

Since time intervals for inside temperature are provided at the 5 minute level, the OutsideTimeIDs and their temperature values are interpolated again to a 5 minute interval (this time *temporal interpolation*). Next, new TimeIDs are assigned through temporal interpolation, where TimeID is 1 at 00:00 day 1 of the month and the TimeID 2 is assigned at 00:05 of the first day of the month. With the temporal resolution of a 5 minute interval it is possible at all times to measure whether the heater on or off. Lower temporal resolution may have resulted in underestimating the heater activity of some of the dwellings, especially when dwellings are relatively small, well-insulated or when the heater functions intensely. With the data provided it was not possible to know any of these factors so heater measuring heater activity was key and 5 minute intervals are considered to be no exaggeration.

Temporal interpolation of TimeIDs at 5 minute level goes as follows: a date and time are provided at which a temperature is first measured (for instance: t1 = 1/1/11 0:00). This number can be converted into a floating point number (here: 40544.00000000). The next time interval t2 = 1/1/11 00:05 is converted into floating point number 40544.00347222. The formula 1 + (t2+((t2-t1)*287)-t1) results in an increment of t1+1 per 5 minutes. 287 is the number of times 5 minutes pass in a day – 1. Outside temperatures are assigned linearly to the interpolated TimeIDs. For inside temperatures, TimeIDs are already given on the 5 minute interval. As a result inside and outside TimeIDs tables can be joined and their temperature data compared (Appendix II, table 1).

4.3 Transportation

The available data on drive distances to services are not used in order to estimate transportation costs. This is because when being remote to access to a service, one may decide to visit the service less often than when close to it. An example is that one may do more groceries at one time when living at a long distance from a supermarket, and fewer groceries more frequently when living further away. The available data on access to services shows the drive distances but not the frequency with which these services are visited. Transportation figures are known at Local Administrative Unit–1 (LAU-1) levels (Department of Energy and Climate Change, 2014) in total amounts of fuel used per LAU-1 unit. The per capita fuel consumption in CO_2 and £ are calculated combining the following datasets;

- Population data (Scotland’s census 2011b, p.7).
- Data on the amount of CO_2 emitted per fuel amount and £ according to vehicle type (Schlömer et al. 2014, p. 1337).
- Data on the amount of £ spent per vehicle type in the last quarter of 2012 (Department of Energy and Climate Change, 2012b, p. 57-58). No earlier data on fuel prices in the UK were found, otherwise the year 2011 would have been more applicable since analysis on warmth use factors starts in that year.
- LAU-1 energy use (Department of Energy and Climate Change, 2014).

The dwellings are regarded as using the amount of transportation according to the area type they are closest to. Factors of driven amounts are assigned to each dwelling according to their area type.

The factor is calculated by dividing the amount of kilometers driven per area type with the average amount of driven kilometers (table 4.1).

Table 4.1: Amount driven yearly per area type in absolute and proportional numbers, UK as a whole.

Area type of residence:	Car / van driver (km)	Factor
London Boroughs	915.43	0.420221
Metropolitan built-up areas	1543.06	0.70833
Large urban (over 250k population)	1879.25	0.862655
Medium urban (25k to 250k population)	2121.79	0.973991
Small / medium urban (10k to 25k population)	2405.28	1.104125
Small urban (3k to 10k population)	2822.51	1.295651
Rural areas	3561.82	1.635026
Average	2178.45	

Source: Department for Transport (2013), table NTS 9904

After dwellings have been assigned a factor of driven amount of kilometers, they are assigned the average amount of fuel used in the LAU-1 area. Fuel use is divided into different types; buses, diesel, petrol and motorcycles are distinguished. Figures on freight transport were not taken into account; only figures on private transport were used.

The amount of energy for transport is combined with figures indicating the amount of CO2 emitted and the average amount of costs made per kilometer according to Schlömer et al. (2014). It is assumed that buses are diesel (not hybrid diesel), both diesel and petrol cars are mid-size light duty vehicles and motorbikes fall within the same category. This is because no other data was provided in the study of Schlömer et al. (2014) in CO2 emissions of motorbikes except for up to 200cm3 cylinder types.

4.4 Heater activity

Thermal efficiency of a dwelling is measured by the speed with which the inside temperature decreases relative to the outside temperature. Inside temperatures are provided at a 5 minute intervals while outside temperatures have been estimated at a 5 minute intervals based on interpolated data from a variety of weather stations as explained in chapter 4.2. Thermal efficiency can be measured only when there is no interference of an active heater; hence the precondition is that the heater should be off. This can be established on the basis of the relation between inside and outside temperature. Based on heater activity and increase of the inside temperature relative to the outside temperature, warmth use can be measured. Warmth is used only when the heater is on. Higher temperature increases when the heater is on, indicate more intense heater activity and hence more warmth used. The warmth use factors are thus summarized as heater activity, thermal efficiency and warmth use. Measurement of both thermal efficiency and warmth use depend on the activity of the heater. Conditions for functioning of the heater are given in table 4.2.

Table 4.2

Colder inside than outside	Outside		
Inside	Increase	Remains equal	Decrease
Increase	ON	ON	ON
Remains equal	OFF	OFF	OFF
Decrease	OFF	OFF	OFF
Inside and outside equal	Outside		
Inside	Increase	Remains equal	Decrease
Increase	ON*	ON	ON
Remains equal	OFF	OFF	ON
Decrease	OFF	OFF	OFF
Warmer inside than outside	Outside		
Inside	Increase	Remains equal	Decrease
Increase	ON	ON	ON
Remains equal	ON	ON	ON
Decrease	OFF	OFF	ON**

* If increase inside > increase outside
** Condition: If decrease inside < decrease outside

Data are missing for inside temperatures below 10 degrees. When data were not recorded or temperatures were below 10 degrees is not clear. Therefore missing data are not taken into account in the analysis. A drawback is that this may give distorted images of warmth use since certain dwellings may long have their temperature off while this is not taken into account. However it may be argued that its occupants are unlikely to be at home at these inside temperatures. This means that warmth use factors of the dwelling were measured unless data was lacking or if it can be realistically assumed that occupants are not at home.

No dwelling recording has its inside temperature measured for each 5 minutes each month. The amount of times the temperature was on is therefore recorded as a proportional measure; for instance where the heater was recorded to be off 20% of the time while recordings took place (i.e. while data is available) it is assumed this applies to the whole month.

4.5 Thermal efficiency

Thermal efficiency is defined as the degree to which warmth is conserved in the home. This is measured by the velocity of inside temperature change relative to outside temperature change when the heater is off. Thermal efficiency cannot be measured when the heater is on, since the velocity of inside temperature change will be distorted by the intensity of the heater, while the intensity of the heater is unknown. The relation between outside and inside temperature on thermal efficiency is measured as a linear equation; hence a decrease of one degree in dwelling A means two times more energy efficiency than a decrease of two degrees in dwelling B in case the outside temperature is equal both at dwelling A and B. Some time delay is to be expected for inside temperature to decrease to the outside temperature, so inside temperature at time t2 should be compared to outside temperature before that time (t1).

In an environment with no insulation and perfect conductivity, the inside temperature at time t should be equal to outside temperature at time t. The less conductivity, the more time t is required before inside temperature reaches the equivalent of outside temperature. The temperature difference between the inside temperature at t1 vs. the outside temperature at t2 shows the inside temperature decrease that is to be expected at t2 if perfect conductivity and no insulation would apply. Any degree to which this temperature decrease differs from the actual temperature decrease indicates the thermal efficiency (table 4.3). The intensity of the heater is unknown from the raw data, and therefore this method works only when the heater can be assumed to be off, so the intensity of the heater does not interfere with the inside temperature decline. The result for thermal efficiency of all dwellings is found in source data: InitialThermalEfficiency (raw data) and InitialThermalEfficiency\Output (summarized statistics per dwelling per month).

Table 4.3: Example of how to measure the decay of inside temperature

Inside	**Outside**	**Time**	**Temp. dif.**	**Change ins.**	**Thermal efficiency**
Loc. A					
20°C	n.a.	t1 12:00	n.a.	n.a.	n.a.
19°C	15°C	t2 12:05	5	1	1/5=0.20
18°C	13°C	t3 12:10	6	1	1/6=0.17
Loc. B					
23°C	n.a.	t1 12:00	n.a.	n.a.	n.a.
19°C	18°C	t2 12:05	5	4	5/4= 1.25
19°C	19°C	t3 12:10	0	0	n.a.
Loc. C					
20°C	n.a.	t1 12:00	n.a.	n.a.	n.a.
16°C	15°C	t2 12:05	5	1	1/5=0.20
12°C	13°C	t3 12:10	3	3	3/3=1

It is possible for temperature to be higher outside than inside in summer, and thereby measuring thermal efficiency as well. However in that case there is still no guarantee that the heater is off; it may be turned on during the time that the outside temperature is higher than the inside temperature.
Although it is possible that this scenario sometimes occurs, this is not very likely to often be the case. Considering the fact that there are usually > 1000 N TimeID instances per dwelling per month when the heater is off (the defined precondition for measuring thermal efficiency), there should be enough occurrences to adequately measure thermal efficiency only when outside temperature is below inside temperature. Taking into account the influence of high outside temperatures on relatively low inside temperatures would not add sufficiently to the data quality and these instances are therefore disregarded.

4.6 Warmth use

Determination of a warmth use indicator

The monthly amount of warmth use is measured as the average amount of inside temperature increase when the heater is on. For example, a total of 400 degrees increase in 6000 time intervals amounts to 400 / 6000 = 0.15 degrees increase per time interval measured. The temperature increase during that hour is divided by the difference between the average inside temperature and average outside temperature during that hour. Measurement of whether the heater was on or off is measured according to the alternative method for measuring heater activity type II (see further in this chapter, chapter 4.7), and not according to the method of measuring heater activity as has been discussed earlier in chapter 4.4.

Inside temperature is regularly not recorded, so to measure the total amount of temperature increase during that month, this figure has to be estimated for those times data were missing. The average amount of time the heater is on is measured by dividing the total amount of time the heater was on with the total amount of records recorded, resulting in a number between 1 (heater is always on) and 0 (heater is always off). That number is multiplied by the total amount of possible time intervals when all records were recorded, which results in the total amount of temperature increase that is estimated to have taken place during that month. 8640 possible time intervals of 5 minutes exist for the months of April, June, September and November. 8928 time intervals exist for the months of January and December.

The method does not take into account the influence of outside temperatures on inside temperature increases. There is inevitable influence of outside temperature on inside temperature increase and thus on warmth use. The degree to which this is the case for each dwelling however, is unknown. The intervening factor of dwelling's thermal efficiency influence on the warmth use further complicates the measurement of inside temperature increases when the heater is on. This comes down to the decision to take into account the intensity with which the heater operates solely on the basis of the amount of temperature increase over time but not controlling for simultaneous outside temperatures, whose influence on inside warmth increase is in its turn influenced by the dwelling's thermal efficiency. The resulting amount of warmth use is found in source data: warmth use (raw data) and WarmthUse\WarmthUseOutput (summarized statistics per dwelling per month).

Estimating the amount of CO2 emissions and expenditure in £
The amount of estimated warmth use results in an estimated amount of kWh. Resulting CO2 emissions and expenditure depend on their energy use types. Energy use types are given at the data zone level (Scotland's census 2011c). The dwellings measured are regarded as representing the estimated warmth use of that data zone, resulting in an estimated amount of CO2 emitted and £ expenditure per household per data zone. Although it cannot be assumed that single dwellings in the area represent the area's warmth use, by using 359 dwellings it may be possible to find correlations of warmth use with properties known at the data zone level such as remoteness, fuel poverty, vulnerability or general dwelling properties. A chart of the method estimating CO2 emissions and £ expenditure is found at the end of this chapter (figure 4.4)

Typical British households used 16,500 kWh of gas in 2011 (ofgem 2011). The average increased inside temperature per dwelling per month was 1258.2 °C (the months of January 2011 and December 2010 are not taken into account due to the relatively low amount of dwellings monitored in these months). Based on these numbers the estimated amount of kWh per degree increase (16,500 / 12) / 1258.2 = 1.0928 kWh per degree increase.
The researcher is aware that this method leads inevitably to at least three errors;
Firstly, that gas use is not equal to warmth use; households may use gas for various reasons while other households may warm their houses with electricity. That means it needs to be assumed that households using electricity for heating use the same amount of warmth to heat their homes and moreover that where gas is used for heating, this provides a sufficient indicator of warmth use and total gas use for other purposes than heating has a limited effect on total gas consumption in the UK.
Secondly, gas use, or warmth use in general, is not geographically equally distributed within the UK. As a result gas use or warmth use in general may be significantly higher or lower in the study area than the figure of 16,500 kWh used in this study due to a relatively large or small amount of presence of dwellings connected to the gas grid.
Thirdly, regarding the aggregate number of degrees warmth added to the dwelling by the heater, this number is likely to be imprecise since not all numbers of the month were taken into account, thereby leading to a distortion. Nonetheless the months that are taken into account are from each season, thus limiting the distortion compared to using for example only winter months or summer

months where for the former, more and for the latter less warmth use is to be expected than when accounting for all seasons, or all months.

As explained, the amount of kWh of total temperature increase per month has been estimated per dwelling. The amount of CO2 and £ spent on warmth use depends on their energy sources.
For warmth use, monthly energy prices in £ worldwide are used from a meta-study (Schlömer et al. 2014, p. 1332-1333). This meta-study provides minimum, maximum and median CO2 and $ expenditures; here the median CO2 emissions are assigned to warmth use data. No data were found on domestic energy prices according to their types for the UK individually. CO2 emissions per energy source are provided by the same study.
For solid fuels the statistics are used for CO2 and £ expenditure on dedicated biomass. Electricity could come from different types of energy sources and it is assumed that for electricity production the division of energy sources within the study area is equal to that as for Scotland as a whole. Data on the origins of energy production are derived from the Department of Energy and Climate Change (2012c, p.43). The division of electricity use is shown in table 4.4. The category of “other fuels” was not taken into account as the type of fuels this category is composed of, is unknown. Oil (making up 0.74% of supply for electricity) is not taken into account because the study from Schlömer et al. (2014) does not provide data on $ expenditure and CO2 emissions on oil for domestic use. Wind energy is assumed to be offshore wind.

Table 4.4: proportions of fuel used in electricity generation in the UK 2011, expressed in TWh

Electricity supplied	**TWh**	**Percentage**	**gCO2eq / kWh**	**£ per kWh**
Coal	102.94	31.22%	255.98	0.015630414
Gas	142.68	43.27%	212.01	0.021942288
Nuclear	62.7	19.01%	2.28	0.012083548
Hydro	5.66	1.72%	0.412	0.000385635
Wind	15.78	4.79%	0.57	0.00522213
Total	344.61	100.00%	471.26	0.055264015

Source: TWh per energy source are from Department of Energy and Climate Change 2012c, p.43. Other figures are the researcher’s own calulations. gCO2eq/kWh and £ per kWh are taken from Schlömer et al (2014).

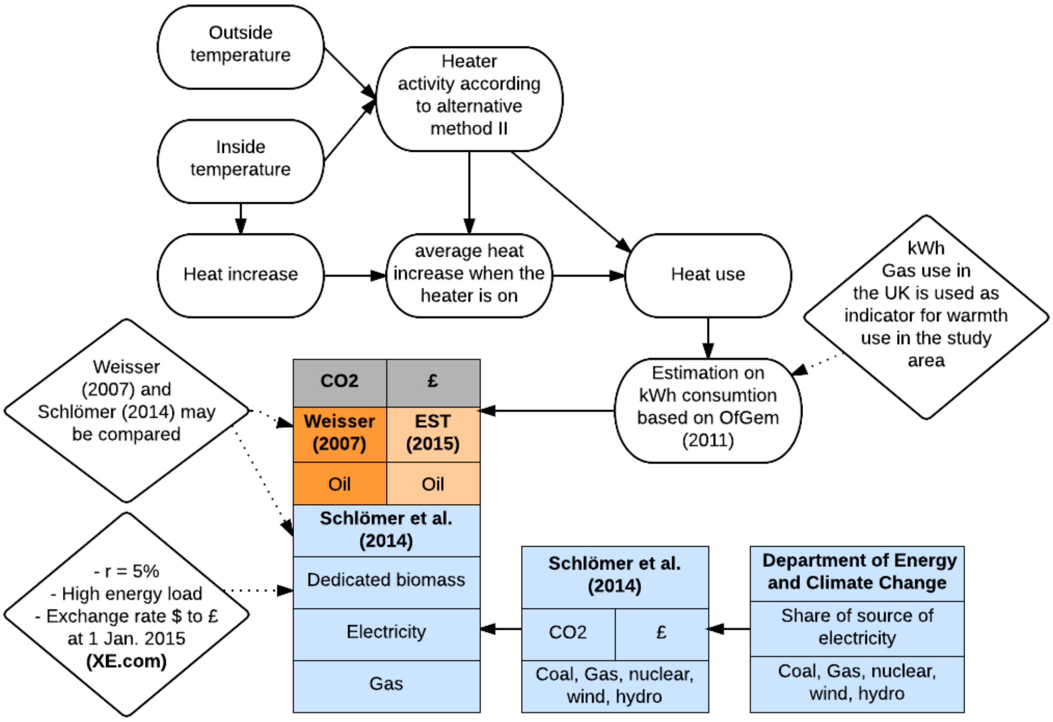
Since oil is not given in the study of Schlömer et al. (2014), data are taken from Weisser (2007), which indicate a CO2 output of 700-800 gCO2eq / kWh for oil. The median of 750 gCO2eq / kWh is used as eventual indicator.
Gas in Scotland, England and Wales in February 2015 cost 4.29 pence while heating oil cost 5.36 pence, which is about 25% more expensive than gas (EST 2015). It is assumed that the costs for heating oil relative to gas are the same for 2011. This assumption was made because more precise and reliable data on the cost of heating oil per kWh in 2011 were not found. The price ratio between natural gas and heating oil on global markets was more or less similar on January 2011 as it was in January 2015 (Nasdaq 2015).

Prices are given in dollars and converted to £ at the exchange rate at the beginning January 1st 2015; at this point the exchange rate of 0.641933 $ per £ (XE.com, 2015).

CO2 emissions can be measured in costs of CO2 emissions per MWh according to the levelized costs of electricity (LCOE). LCOE is a measurement used to express the costs of CO2 emitted by the power source, accounting for all costs involved in the process of expropriation of the power source to the eventual emission. LCOE is expressed as the following formula; $\mathrm{LCOE} = \frac{\alpha \,.\, \mathrm{I} + \mathrm{OM} + \mathrm{F}}{E}$ where α is the capital recovery factor, I is the investment costs including finance costs for construction, OM are the net annual operation and maintenance costs and F are the annual fuel costs. E is energy expressed in MWh, and E is the only given figure derived from warmth use data as explained above. E depends on the full load hours. The capital recovery factor α consists of formula $\alpha = \frac{r}{1-(1+r)^{-L}1}$ where r is the weighted average cost of capital. It is assumed here that r = 5%. Similarly to costs expressed in £, minimum, maximum and median figures are provided, and median values were chosen in this case to express the costs in LCOE. Schlömer et al. (2014) distinguish high and low full load hours, resulting in different LCOE. High full load hours are assumed.

The resulting table per dwelling can be found in source data: HeatUseCosts. A summary of measuring warmth use through which CO2 and £ expenditure is measured is displayed in figure 4.4.

figure 4.4: method of estimating warmth use and the CO2 emissions and £ expenditure that follows.



Oval shapes indicate the information that is needed to estimate the kWh consumed per dwelling for warmth use. Diamond shapes indicate assumptions. Square shapes indicate the source that provides LCOE of kWh.

4.7 Alternative methods of measuring warmth use factors

No more than one decimal was recorded when inside temperatures were measured. Consequently, whether the temperature inside the home was rising or not during these five minutes, cannot be measured when recorded temperatures don't change by at least 0.1 degree every five minutes. Alternative methods are used to measure thermal efficiency and whether the heater was on or off, using temperature changes over a period of one hour.

Two types of measurement for heater activity are used, method I for establishing whether the heater was off during the whole hour and method II for establishing whether the heater was on during any time interval within the hour;

I: Here the following assumptions are made on the functioning of the heater;

1. When any of the five minute intervals measure a temperature decrease inside the dwelling, the heater is off;
2. When the temperature over one hour time has not increased, it cannot be established that the heater was on or off, since the inside temperature remaining equal may be attributed either to a well-insulated dwelling or a minimal difference with the outside temperature, so no heater activity is measured in these cases;
3. Accurate and comparative measurement can only take place when all measurements take place over the same amount of time; in this case one hour;

Thermal efficiency was measured according to this method. Measurement of thermal efficiency was discussed previously. Due to the lack of accuracy of data caused by the measurement of only up to 1 decimal, thermal efficiency was re-calculated on the basis of the alternative method for functioning of the heater. The principles of measurement of thermal efficiency remain, but are now calculated based on hourly averages. Again, thermal efficiency was only measured when the heater was assumed to be off. The inside temperature decrease is divided by the difference of average outside temperatures over 1 hour with the average inside temperature during that hour.

II: Here the following assumptions are made on the functioning of the heater;

1. Measurement of heater activity is conducted per hour increase, so the temperature must have increased and the temperature inside must be higher than the outside temperature from the first time of measurement to one hour later.
2. That accurate and comparative measurement can only take place when all measurements take place over the same amount of time; in this case one hour;

Re-calculated warmth use was measured based on this method: the amount of temperature increase was measured when these conditions were satisfied. The amount of temperature increase multiplied with the amount of time the heater was on constituted the average amount of temperature increase while warmth use measurement was conducted.

Alternative method I was used for thermal efficiency because the heater may have been on for a short period of time if inside temperature increased during the hour of measuring thermal efficiency. In that case the functioning of the heater, even when only during a short period of time, would distort outcome in thermal efficiency.
Alternative method II was used for warmth use because the heater must have been on if outside temperature increases while it was colder outside than inside.

4.8 Occuring errors in measurements of warmth use factors

Thermal efficiency results in figures varying between 0 and 1. Thermal efficiency of 0, below 0 or above 1 is not considered to be realistic. Yet these figures may occasionally occur. This can have the following reasons:
Thermal efficiency is 0: this means that thermal efficiency is 100%, yet these types of dwellings do not exist since some heat is always lost over a period of time. This figure may occur when no temperature was recorded at a certain time interval.
It may also happen when inside temperatures remain equal or rise, but these figures have been filtered out previously in the data preparation. Figures were not filtered out in the data preparation when no inside temperature was recorded, hence these are filtered out at a later stage.

Thermal efficiency is below 0: this would mean that thermal efficiency is higher than 100%. This occurs when average inside temperature is lower than average outside temperature, while inside temperature decreases within the hour. This can occur due to three factors;

1. Inherent inaccuracy of the method and data. Temperatures over 1 hour are taken into account. While it is possible that the average inside temperature is lower than average outside temperature, the inside temperature should equal outside temperature over a period of time. Especially for well-insulated dwellings it may take time for the home (possibly more than one hour) to get to outside temperature levels.
Under these conditions, when outside temperature remains more or less equal, the average outside temperature remains to be higher than the inside temperature. On the other hand when outside temperature drops significantly, the average temperature decreases, making it more likely that the average inside temperature during this period of time ends up being higher. When the average outside temperature increases significantly on the other hand, it is impossible for inside temperature to decrease when its temperature already was lower than the outside temperature.

2. Incomplete figures regarding inside temperature, measured at one decimal.
Actual inside temperature may have been slightly higher than outside temperature, but not been recorded due to the amount of decimal figures recorded for inside temperature; an inside temperature of 14.44 and 12.44 results in an average temperature of 13.44 while the recorded temperature would be 14.4 and 12.4, resulting in 13.4 as average temperature. An outside temperature of 13.41 would imply a higher outside temperature while actual inside temperature should be higher.

3. Errors due to spatial and / or temporal interpolation.
Interpolation may result in outside temperature that is not in accordance with the actual temperatures that occurred. This issue is elaborated further in this chapter, paragraph *errors due to interpolation*.

Thermal efficiency is above 1: this would mean that thermal efficiency is lower than 0%, meaning that the dwelling loses heat more quickly than the outside environment. The figure occurs when the difference between average outside temperature and average inside temperature is less than the decline in inside temperature. The figures turn up when average outside temperatures are close to equal to average inside temperature. A slight decrease in inside temperature may then result in a high number, indicating low thermal efficiency. Similar to the errors described above, these figures may occur due to incomplete decimal numbers and interpolation errors.
In opposition to numbers occurring with thermal efficiency figures below 0, it may not occur due to inherent inaccuracies in the method measuring thermal efficiency over the hour. With thermal efficiencies above 1, it is always warmer inside than outside and it can never happen that the average inside temperature within the hour is then lower (thus decreased more altogether) than the average outside temperature within that hour.

Example: thermal efficiency is first unrealistically high (above 1) and then drops to unrealistically low levels (below 0) (table 4.5). Inside temperature is declining while outside temperature rises at some moments to above inside temperature levels.
No inside temperatures are recorded after TimeID 3902 since temperature rises again within one hour. In total 10019 of these cases were found and ignored from the analysis. A total amount of reports was not made, but considering that for the month of April of only dwelling 0 there were 3477 reports given on thermal efficiency, it is regarded that data were sufficient to conduct an analysis. However, all dwellings with an unrealistically high or low thermal efficiency number

reported were excluded from the analysis. The amount of excluded dwellings varies per month source data: ThermalEffAllReports).

Table 4.5: errors in measurement of thermal efficiency. Dwelling ID 11, month of April.

TimeID	Inside Temp	Inside temp. difference	Outside avg. temp.	Outside temp.	Avg. ins. Temp. – avg. outs. Temp	Thermal efficiency
3895	13.7	0.5	13.22409	12.5098	0.209242	2.389581
3896	13.7	0.6	13.31131	12.67522	0.072025	8.330441
3897	13.6	0.5	13.38549	12.84063	-0.05216	-9.5862
3898	13.5	0.4	13.44664	13.00605	-0.15497	-2.58106
3899	13.4	0.3	13.49476	13.17147	-0.23642	-1.2689
3900	13.4	0.3	13.52984	13.33688	-0.29651	-1.01178
3901	13.4	0.3	13.55189	13.5023	-0.34356	-0.87321
3902	13.4	0.3	13.56091	13.51132	-0.37758	-0.79454
3903	13.4			13.52033		
3904	13.3			13.52935		
3905	13.2			13.53837		
3906	13.2			13.54738		
3907	13.1			13.5564		

Errors due to interpolation

The errors that occur due to interpolation may either be the result of interpolating weather temperature data across space using kriging (spatial interpolation), or may be the result of interpolating weather temperature data across time (temporal interpolation). The hourly outside temperatures have been interpolated in order to measure them relative to inside temperatures which were recorded every 5 minutes.
Where thermal efficiency levels are unrealistic, these figures are filtered out of the analysis of measuring thermal efficiency. The amount of occurrences of thermal efficiency figures above 1 and below 0 are reported in order to control for data quality. High occurrences of these reports would indicate that this method is not a reliable one, at least not in those dwellings these figures frequently occur.

Frequent subsequent erroneous data may indicate a lack of accuracy in spatial interpolation; in these occurrences outside temperature data would be over- or underestimated for some areas. When erroneous data occurs due to a dwelling's distance from a weather station at a place in time and space, it is relatively likely that this error will occur again at the same place in the next time step.

Erroneous data that are not subsequent but occur more individually point to errors in temporal interpolation. This is because hourly inside and outside temperatures are compared. Fluctuations within the hour are not measured for outside temperatures. A quick drop in inside temperature over one hour time will occur due to a quick drop in outside temperature during that same hour. However, this quick drop in outside temperature may not have been recorded when between two times of measurement. These errors occur more individually because they are less likely to occur in the time following, as the time following approaches the actual time of measuring outside temperature, thus being influenced less, or not at all, by the temporal interpolation.

4.9 Thermal comfort

What is perceived as a comfortable indoor temperature (thermal comfort) varies among individuals and groups. Thermal comfort is also changeable. Adaptive comfort theory states that people prefer certain inside temperatures while also being dependent on the natural temperature outside. It has been established that the desired comfort at home is influenced by outside temperature and varies across geographies and cultures (as has been discussed in the chapter 4.10).

Thermal comfort is estimated on the basis of average inside monthly temperature. A precondition for measuring the desired inside temperature is that the heater should be on when the inside temperature reached a level beyond which no substantial increase is found as long as there is no temperature decrease measured. The average figure per month is regarded as the thermal comfort level of that month.

Dwellings within the same range of average outside temperatures may be expected to have somewhat similar thermal comfort levels according to adaptive comfort theory. The adaptive comfort is measured by

- Comparing average monthly inside temperature with average monthly outside temperature.
- Comparing percentages of dwellings that fall within the predicted acceptability levels. According to Lück (2012) adaptive comfort levels of free running buildings, a predicted comfort level is at inside temperature Tc = 13.5 + 0.54 TO where TO is outside temperature and Tc is comfort temperature.
  Toe & Kubota (2013, p.284) found Tneutop = 0.18Toutmm + 19.3 where Toutmm is the monthly outside temperature and Tneutop is the neutral operative temperature (in this research Tneutop is regarded as the thermal comfort temperature, since the study found that neutral operative temperature is almost exactly similar to the thermal comfort level (Toe & Kubota, 2013, p. 288)).
  Both the formulas of Lück (2013) and of Toe & Kubota (2013) are tested for the area. These figures provide an indication whether remote or non-remote areas are more or less prone to inside temperatures following acceptability levels. It is expected that 90% of occupants have acceptability levels within 1.2 degrees and 80% within 2.0 degrees higher and lower. The 80% and 90% levels are based on DeDear et al. (1997).

Heaters do not heat the dwelling to their thermal comfort levels instantly. Thermal comfort is applicable only when the heater has heated the dwelling to the occupant's comfort level. Inside temperature is measured as thermal comfort when:

- The heater is on.
- The inside temperature does not increase substantially. In order to deal with the ambiguity of the word "substantially", two different conditions may be used;
  - Inside temperature increases no more than 0.2 during the next hour;
  - Inside temperature increases no more than 0.5 during the next hour;
- Outside temperature is lower than inside temperature. When outside temperature is higher than inside temperature, the occupant's influence over the desired inside temperature is very limited so it should not be measured in this case.
- Temperature hasn't dropped in the past hour.

The differences in expected comfort temperatures according to theory and actually measured temperatures can be tested for their variance across degrees of remoteness.

4.10 Demographic and remaining geographical factors

Thermal efficiency, warmth use and heater activity are tested with variables that are known at 2001 data zone levels; these variables relate to dwelling type, number of rooms, income and demographic data.
The primary factors influencing thermal efficiency of the building according to Harvey (2006, p. 36) (see also chapter 2.9) have only been used to a limited extent, but it should be acknowledged that with the data accessible to the researcher the research could have taken into account almost all of these factors.

- Insulation levels in the walls, ceiling and basement: are not given.
- Resistance to moisture migration: Humidity data are available from the Meteorological Office (2013) database.
- Thermal and optical properties of windows and doors; these are not given but with the amount of data it may be possible to have sufficient data to measure warmth use and thermal efficiency only during night time intervals, when windows and doors are usually closed.
- Rate of exchange of inside air with outside air through infiltration and exfiltration: these may be influenced by wind speed, which is available through the Meteorological Office (2013) database.
- Presence of shared walls with other buildings; these data are not available per dwelling but are on the 2001 data zone level. Dwellings were subdivided in flats, semidetached, detached and terraced.

Where data were accessible but not used, the negligence of these factors were due to time constrains. The choice was eventually to limit the research to the influence of outside temperature on warmth use factors.

5. Results

5.1 Remoteness

To measure the implications of remoteness it should be established whether the different degrees by which remoteness may be analyzed, coincide with each other so that the definition of ‘remoteness’ is not used arbitrarily. This is part of the second research goal;

- To develop a GIS-based methodology for finding correlations of remoteness on domestic heat loss and fuel consumption.
- To find how different measures of remoteness (distance to services, classification schemes, population per km^2) influence the relation between remoteness and domestic heat loss and fuel consumption.

The choice to start analyzing the results of the second research goal was made because first identifying the significance of relations of remoteness allows to better analyze what remoteness means with regards to warmth use factors. Warmth use factors are part of the first research goal and are related to remoteness.

The correlation among remoteness indices is significant above the 99% confidence interval (table 5.1). The strongest relation exists with the classification scheme “aggregated distances to services”. For the 8-fold classification, no dwellings were located in the 5th and 8th classification type, resulting in 6 categories. This explains why the strength of the relationships for the 6-fold categories are equal to that of the 8-fold categories. The boxplots in figure 1 Appendix III and figure 2 Appendix III show that the spread is equal although the classifications are different.

Table 5.1: Reciprocity between remoteness as classified by the Scottish Government and other remoteness indices

			Distance to Cities	Distance to Tows	Distance to Villages	AvgAllDist	PopPerSqKM	Aggegated DistToServices
Spearman's rho	UR8FOLD	Correlation Coefficient	.737**	.683**	.515**	.794**	-.836**	.864**
		Sig. (1-tailed)	.000	.000	.000	.000	.000	.000
		N	369	369	369	369	369	369
	UR6FOLD	Correlation Coefficient	.737**	.683**	.515**	.794**	-.836**	.864**
		Sig. (1-tailed)	.000	.000	.000	.000	.000	.000
		N	369	369	369	369	369	369
	UR3FOLD	Correlation Coefficient	.601**	.560**	.605**	.702**	-.809**	.813**
		Sig. (1-tailed)	.000	.000	.000	.000	.000	.000
		N	369	369	369	369	369	369
	UR2FOLD	Correlation Coefficient	.564**	.509**	.660**	.685**	-.805**	.810**
		Sig. (1-tailed)	.000	.000	.000	.000	.000	.000
		N	369	369	369	369	369	369

The correlation between all ratio / interval variables is significant at more than 99% confidence interval (table 5.2). Distances to population areas show the highest reciprocity with the exception of distances to villages (3000 inhabitants or more). Outside of relations between distances to population centers, the aggregated distances to services and aggregated distances to population areas show the highest correlation coefficient. Proportional point maps were made of the dwelling locations according to all remoteness measures (figure 1 – 9 appendix III)

Table 5.2: reciprocity between all interval variables classified.

		Distance to Cities	Distance to Towns	Distance to Villages	AvgAllDist	PopPerSqKM	AggegatedDistToServices
Distance to Cities	Pearson Correlation	1	.821**	.380**	.891**	-.508**	.585**
	Sig. (2-tailed)		.000	.000	.000	.000	.000
	N	369	369	369	369	369	369
Distance to Towns	Pearson Correlation	.821**	1	.348**	.879**	-.424**	.550**
	Sig. (2-tailed)	.000		.000	.000	.000	.000
	N	369	369	369	369	369	369
Distance to Villages	Pearson Correlation	.380**	.348**	1	.700**	-.451**	.640**
	Sig. (2-tailed)	.000	.000		.000	.000	.000
	N	369	369	369	369	369	369
AvgAllDist	Pearson Correlation	.891**	.879**	.700**	1	-.560**	.718**
	Sig. (2-tailed)	.000	.000	.000		.000	.000
	N	369	369	369	369	369	369
PopPerSqKM	Pearson Correlation	-.508**	-.424**	-.451**	-.560**	1	-.704**
	Sig. (2-tailed)	.000	.000	.000	.000		.000
	N	369	369	369	369	369	369
AggegatedDistToServices	Pearson Correlation	.585**	.550**	.640**	.718**	-.704**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	
	N	369	369	369	369	369	369

Correlations between aggregated distances and population figures are negative because larger distances result in more remoteness, while less population per square kilometer indicates a higher degree of remoteness

The Aggregated Distances index shows the highest reciprocity with the other interval remoteness indices. For the categorical remoteness indices it may be established that the ordinal remoteness factors are sufficiently correlated with other remoteness indices in order to assume that where warmth use factors and CO_2 emissions and £ expenditure correspond with the interval remoteness index, this will do so as well with a categorical remoteness index.

Since the 8-fold classification is not as commonly used as the 6-fold classification but shows the same results due to two classifications missing, the 8 fold classification is not used any further in this research. Since the 3 fold classification is not commonly used and shows less significant correlations with the interval remoteness indices than the 6 fold classification, the 3 fold classification is not used any further in this research. The dichotomous classification however is very commonly used and will be used further in this research as well, in spite of relatively low correlation with the interval remoteness indices.

Regarding the relation between remoteness and the research questions, it may be concluded that a GIS network analysis has shown to be effective in analyzing remoteness degrees. Simultaneously, correlations show that the various remoteness types are sufficiently dissimilar so that the correlation between warmth use will and remoteness will strongly depend on the remoteness type that is used.

5.2 Transportation

Having established the relations among remoteness indices, a second part of the second research goal is to find how fuel consumption is related to remoteness. In this part the influence of remoteness on transportation expenditure and CO_2 emissions is analyzed. After that, the implications for CO_2 emissions and expenditure on warmth use can be established, providing a full indication of the amount of CO_2 emissions and household expenditure of both warmth use and transportation.

The effect of both the LAU-1 area indicating fuel type use as well as the proximity to population centers (note that these are not the same classifications as used for remoteness; see chapter 4.3) is visible (appendix I, figure 10).

Student's t-tests are conducted to find whether carbon emissions are higher for rural than for urban households for carbon emissions and £ spent on transport of all types. Both CO_2 emissions and £ spent on energy were higher for rural than for urban areas for all transport types used (table 5.3 and table 1 appendix III).

Table 5.3: t-test for CO_2 emitted and £ spent by rural / urban classification

	2 fold classification	N	Mean	Std. Deviation	Std. Error Mean
Estimated CO2 emitted by bus transport per capita	Urban	192	120.400997	31.9433873	2.3053154
	Rural	177	177.722057	21.6597368	1.6280455
Estimated CO2 emitted by diesel per capita	Urban	192	439.526039	142.7996012	10.3056735
	Rural	177	709.901635	92.5208894	6.9542959
Estimated CO2 emitted by petrol per capita	Urban	192	633.310428	196.9179555	14.2113293
	Rural	177	1005.598029	128.3722972	9.6490527
Estimated CO2 emitted by motorbikes per capita	Urban	192	6.800850	2.9334346	.2117024
	Rural	177	12.241060	1.8299700	.1375490
Estimated CO2 emitted by transport per capita	Urban	192	1200.038313	373.2169787	26.9346154
	Rural	177	1905.462781	244.0225842	18.3418606
Estimated £ spent on bus transport per capita	Urban	192	54.180448	14.3745243	1.0373919
	Rural	177	79.974925	9.7468816	.7326205
Estimated £ spent on diesel per capita	Urban	192	197.786718	64.2598205	4.6375531
	Rural	177	319.455736	41.6344002	3.1294332
Estimated £ spent on petrol per capita	Urban	192	314.619573	97.8260272	7.0599854
	Rural	177	499.566735	63.7735233	4.7935116
Estimated £ spent on motorbike fuel per capita	Urban	192	3.378565	1.4572884	.1051707
	Rural	177	6.081184	.9091030	.0683324
Estimated £ spent on transport per capita	Urban	192	569.965304	177.2925061	12.7949845
	Rural	177	905.078581	115.8999194	8.7115714

Spearman's rho and Pearson's correlation tests show that estimated CO_2 emitted on transport of all types increases with remoteness (table 5.4 and table 5.5).

Table 5.4: Spearman's rho for CO_2 emitted and its relation with the 6-fold rural / urban classification scheme.

			Bus transport per capita (co2)	diesel per capita (co2)	petrol (car) per capita (co2)	Petrol by motorbikes per capita (co2)	Total transport per capita (co2)
Spearman's rho	UR6FOLD	Correlation Coefficient	.812**	.849**	.849**	.848**	.849**
		Sig. (2-tailed)	.000	.000	.000	.000	.000
		N	369	369	369	369	369
		N	369	369	369	369	369

Table 5.5: Pearson's correlation for CO2 emitted and its relation with the 6-fold rural / urban classification scheme

		Bus transport per capita (co2)	diesel per capita (co2)	petrol (car) per capita (co2)	Petrol by motorbikes per capita (co2)	Total transport per capita (co2)
Distance to Cities	Pearson Correlation	.583**	.652**	.644**	.684**	.643**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	369	369	369	369	369
Distance to Towns	Pearson Correlation	.479**	.536**	.531**	.548**	.529**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	369	369	369	369	369
Distance to Villages	Pearson Correlation	.578**	.568**	.571**	.547**	.571**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	369	369	369	369	369
Population per square kilometer	Pearson Correlation	-.670**	-.695**	-.694**	-.690**	-.694**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	369	369	369	369	369
Average distance to population centers	Pearson Correlation	.664**	.711**	.707**	.720**	.706**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	369	369	369	369	369
Distance to all services	Pearson Correlation	.754**	.792**	.788**	.797**	.788**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	369	369	369	369	369

Relations between remoteness were equal for CO2 emitted and £ spent; this is because the degree to which the dwelling's locations influence the estimated amount of CO2 or £ spent are equal (table 2 and table 3, appendix III).
Relations are strongest for the distances to services. The relation for distances to population centers are weakest, but using the average distance to all population centers rather than the distance to a particular type of population center (a city, village or town) results in stronger correlations.

Estimated transportation figures were based on the LAU-1 area and the area type that a dwelling belongs to. On the one hand, LAU-1 areas are relatively large and on the other hand, area types coincide strongly with the existing classifications of remoteness. The use of LAU-1 areas is inherently related to remoteness because LAU-1 areas are larger in remote areas. Area type is inherently related to remoteness because the area type constitutes a proximity to a population center. It is therefore all the more surprising that distances to population centers are less strongly correlated with distances to all services. This may be explained either by one of two factors;

- Coincidence because dwellings that were located in data zones further from services may happen to have been located closer to small population areas (where carbon-fuelled private transport use is high) rather than high population areas (where carbon-fuelled private transport use is lower).
- The selected dwellings are close to small population area types that are located in LAU-1 areas where the fuel type of transport (for example, petrol or LPG) result in low carbon emissions and expenditure. In that case the population centers have only a limited amount of influence on expenditure and CO2 emissions but are more strongly influenced by the LAU-1 fuel types used in that area.

5.3 Heater activity

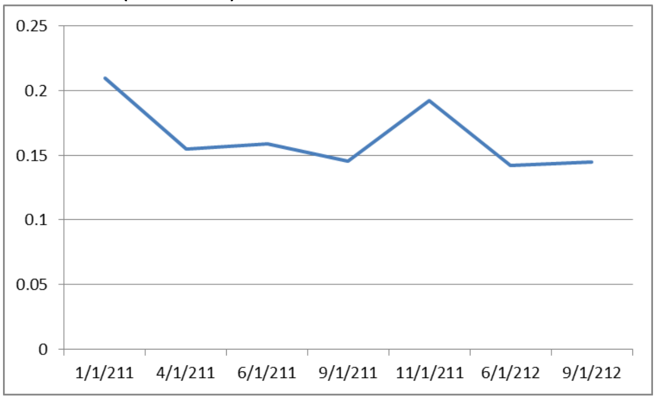
The following chapters (5.3 to 5.7) can explain how and to what extent the first research objective was reached; what useful information can be derived from temperature data provided by smart

energy monitors. Moreover it analyzes the relation between remoteness and the warmth use factors and thermal comfort.
Analyzing those factors results in an estimation of CO_2 emissions and expenditure based on warmth use (chapter 5.6, paragraph *Predicted CO2 and £ on warmth use*). With this information, it can be concluded how remoteness is related warmth use factors, and its CO_2 emission and expenditure. Adding up the CO_2 emissions and expenditure on fuel transport fulfills research goal 2.

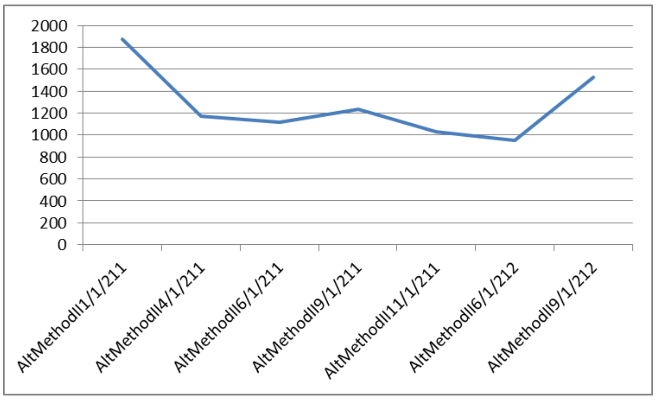
In this chapter the activity of the heater is explained using only the alternative methods for measuring heater activity. The initial method was regarded as too imprecise because of the distortions that occur due to the measurement per decimal as explained in chapter 4.7. There are apparent differences as well as similarities in the results of measured heater activity, as displayed in figure 5.1.

Figure 5.1: heater activity per month.

Method I (inverted)



Method II



For method I the results are inverted for visualization purposes; this is because initially the higher the number, the less often the heater was regarded as "on", while for the second method, the higher the number, the more often the heater was regarded as "on".
Source data: EstimatedHeaterActivity

The correlation between both methods is tested (e.g. June method I with June method II) and also the relationships between various months of the year according to the same method (e.g. June method I with January method I). The relation between the variables is linear (figure 2-4 Appendix III). Pearson's correlation tables were run for comparing the correlations between method I and method II, with all relations significantly correlated at a > 99% confidence level with the exception of the month of January (table 4 Appendix III). Average heater activity was not correlated however (table 5.6).

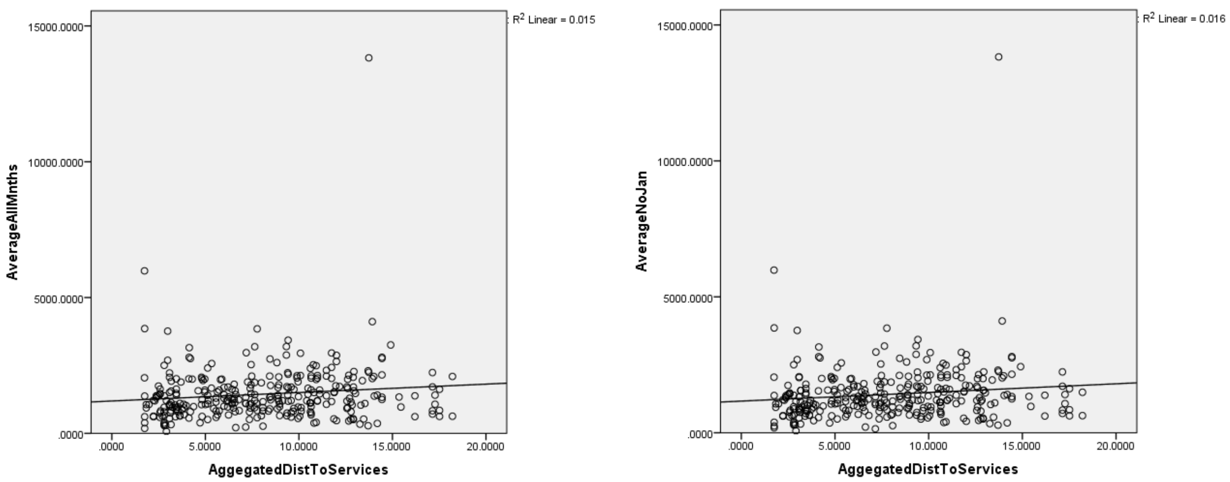
Table 5.6: Pearson's correlation for averages from all months of measuring heater activity through method I and II

		ActMethod I	ActMethod II
ActMethod I	Pearson Correlation	1	-.088
	Sig. (2-tailed)		.120
	N	315	315
ActMethod II	Pearson Correlation	-.088	1
	Sig. (2-tailed)	.120	
	N	315	639

Comparing months from method I with other months from method I, all months are correlated at a 99% confidence level, except for the relationship between the month of January and June which is correlated at the 95% confidence level (table 5 Appendix III).
Doing the same for months from method II, all months are correlated at a 99% confidence level, except for the relationship between the month of January and September which is correlated at the 95% confidence level, and the month of January and June which are not correlated at all (table 6 Appendix III). The low confidence levels for January probably are strongly explained by the lack of data, where for January and June there are N=39 cases that are measured.
Method I results in the highest Pearson's correlations, indicating that it is likely that the criteria used in this method are more related to measuring actual heater activity than the criteria used in method II. High levels of correlation among different months for both methods I and II suggest that dwellings where the heater is on relatively frequently in one month, are likely to have the heater on relatively frequently in another month as well.

It is not possible to validate the reliability of either method I or method II. The correlations between method I and method II suggest that both methods do provide some indication of the amount of time the heater was on. However, when both methods were reliable to a very high degree, it is to be expected that Pearson's correlation figures turn out significantly higher than what they do now; correlations higher than 0.8 do not occur; hence correlations cannot be regarded as strongly correlated. Hence it cannot be stated that there is clarity on the degree of accuracy in the results but it does appear that the results generally give an indication on where the heater is on more or less often relative to the other dwellings that were measured.
Due to the nature of differences with the month of January and other months it was checked whether this month may have influence on the overall results. It should be concluded that the differences in outcomes when accounting for January or not accounting for January, are negligible. Therefore January was used in all analyses (figure 5.2) (source data: EstimatedHeaterActivity).

Figure 5.2: scatterplot for correlation between distances to all services and the average of all months (left), and correlation between distances to all services and the average of all months except the month of January (right).



Method I uses an inverted method of measuring the amount of time the heater was on. A significant negative correlation exists between method I and remoteness indices (table 5.7 and table 5.8). This shows that the heater was on more often in remote dwellings than in non-remote dwellings. The relation is statistically significant for all relations.

Method II uses a method where a higher number indicates a higher number heater activity; the reverse is true for method I. The relations between the methods and remoteness indicate a higher level of heater activity for more remote dwellings. The correlations are not statistically significant for method II however, unlike method I, with the exception of population density of the data zone, which is statistically related to heater activity at the 95% confidence level (table 5.7 and table 5.8). From the maps there is no clear influence visible regarding heater activity (appendix I figure 11 and 12).

Table 5.7: Spearman's correlation for the amount of time the heater was on and its relation with ordinal remoteness indices.

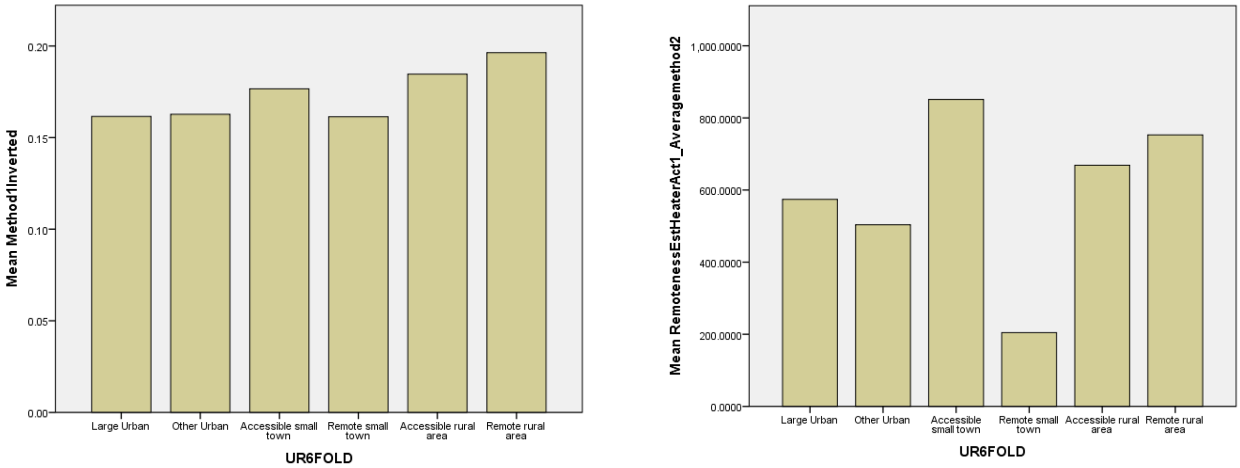
			UR6FOLD	UR2FOLD
Spearman's rho	Average method1	Correlation Coefficient	-.181**	-.159**
		Sig. (2-tailed)	.001	.005
		N	314	314
	Average method2	Correlation Coefficient	.097	.098
		Sig. (2-tailed)	.087	.083
		N	314	314

Table 5.8: Pearson's correlation for the amount of time the heater was on and its relation with interval remoteness indices.

			AvgAllDist	PopPerSqKM	AggegatedDistToServices
Spearman's rho	ActMethod I	Correlation Coefficient	-.179**	.175**	-.200**
		Sig. (2-tailed)	.001	.002	.000
		N	314	314	314
	ActMethod II	Correlation Coefficient	.046	-.120*	.104
		Sig. (2-tailed)	.418	.033	.066
		N	314	314	314

For both method I and method II it is clear that in large urban areas the heater is less often on (figure 5.3). Generally it appears that heater activity tends to increase as remoteness increases. A relatively low number for remote small towns is apparent for both methods, but is considerably clearer for method II. The apparent differences for both methods cannot be explained but is likely to be due to the limitations of reliability of method II. The fact that correlations for method I are stronger and more significant for the remoteness indices, which is in line with the assumption that remote areas tend to use more warmth, as has been proven in previous researches (chapter 2.6), seems to point towards a higher degree of reliability of method I than of method II. While there is reason to assume that remote dwellings will report higher heater activity there is no reason to assume this should be vastly different between large urban areas and small urban or remote urban areas.

Figure 5.3: Average numbers of heater activity of inverted method 1 (left) and method 2 (right) divided according to remoteness categories.



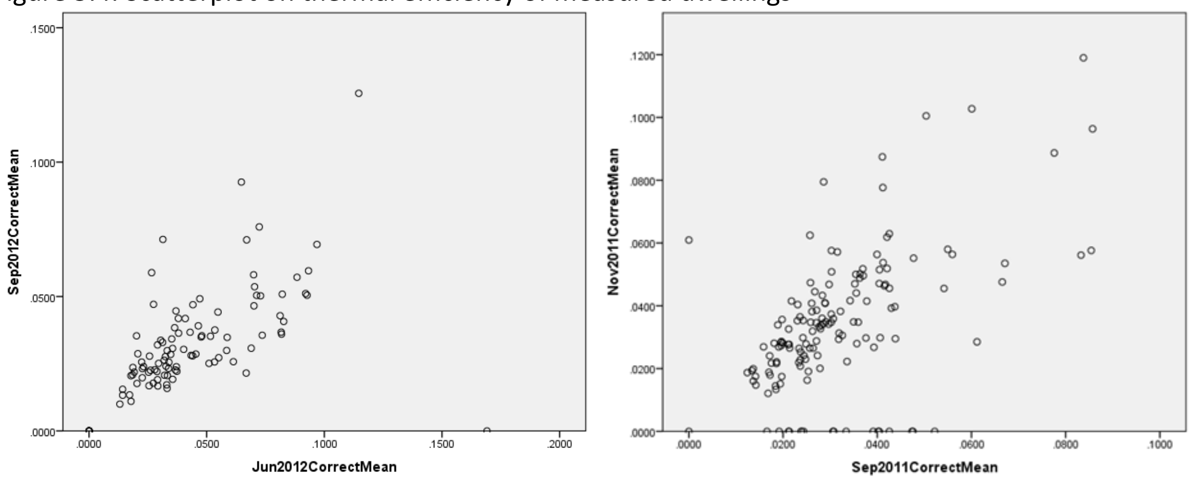
The results for method I are inverted for visualization purposes; this is because initially the higher the number, the less often the thermometer was regarded as “on”, while for the second method, the higher the number, the more often the thermometer was regarded as “on”.
Source data: EstimatedHeaterActivity

The results of method I are more in line with expectations and previous research so it is concluded that with the temperature data provided by the smart meters, information on heater activity can be derived but precise measurement of heater activity could not be validated nor made plausible. Measuring heater activity based on the conditions of method I however, results in more plausible results than using method II. In order to have more accurate results it may be suggested that more than one decimal can be recorded. When this can be done reliably, heater activity may be based on 5 minute recordings which would show temperature increases or decreases for every five minutes which may result in more accurate results.

5.4 Thermal Efficiency

Thermal efficiency measured for each month is linearly correlated (for example figure 5.4).

Figure 5.4: Scatterplot on thermal efficiency of measured dwellings



Pearson's correlation is applied to measure the correlation between the estimated thermal efficiency for each month. All correlations are significant at the 99% confidence level (table 7, appendix III). This means that dwellings that are estimated to have a low thermal efficiency in one month tend to do so in the other month as well. This is to be expected as thermal efficiency depends on the dwelling properties, and these hardly change.

However, as with heater activity, the figures rely on relative numbers so the thermal efficiency should be more or less equal (or, when completely correct and doors and windows remain closed, completely equal) for each month and for each dwelling. If the measurement of thermal efficiency were reliable to a very high degree, it is to be expected that Pearson's correlation figures turn out significantly higher than what they do now; correlations higher than 0.8 do not occur; hence strongly correlated relations are nonexistent.

Thermal efficiency is measured per month and its correlation with remoteness is calculated using Pearson's correlation (table 8 Appendix III). Criteria for measurement were that no more than N=1000 cases per dwelling per month were allowed to have recorded a thermal efficiency of 0, and no cases per dwelling per month were allowed to have recorded a thermal efficiency of either below 0 or above 1.

The direction of the relation between thermal efficiency and distances (both to services and to population centers) is positive in all but one case; January 2011 and its relation to average distances to population centers, which is not a significant relationship. Thermal efficiency and relation to population per square kilometer was negative in every case. This means that the higher the remoteness, the higher the thermal efficiency score tends to be. Since high thermal efficiency scores indicate a low actually estimated thermal efficiency, this shows that within the study area, thermal efficiency decreases as remoteness increases.

The average thermal efficiency for all months is calculated using the total of all thermal efficiencies for all months divided by the amount of months the thermal efficiency was measured while using the same criteria per month for a valid dataset (source data: AllThermalEfficiency). There is a significant relation (table 5.9 and table 5.10). When plotting the data in scatterplots the relation is not clearly visible, but the fit lines do indicate the correlation (figure 5.5 and 5.6).

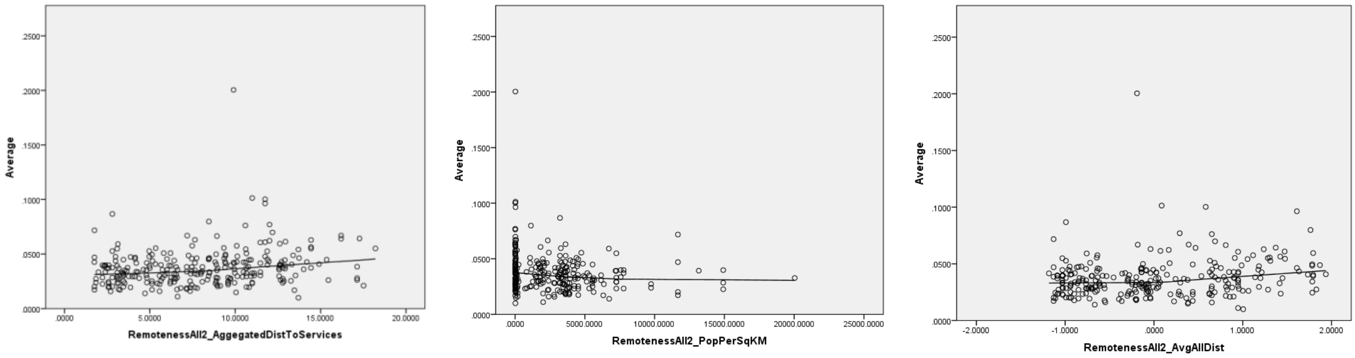
Table 5.9: Spearman's rho for thermal efficiency and classification according to the ordinal scheme from the Scottish Government.

			UR6FOLD	UR2FOLD
Spearman's rho	Average	Correlation Coefficient	.180**	.192**
		Sig. (2-tailed)	.003	.002
		N	267	267

Table 5.10: Pearson's correlation for remoteness indices and average measured thermal efficiency measured over all months.

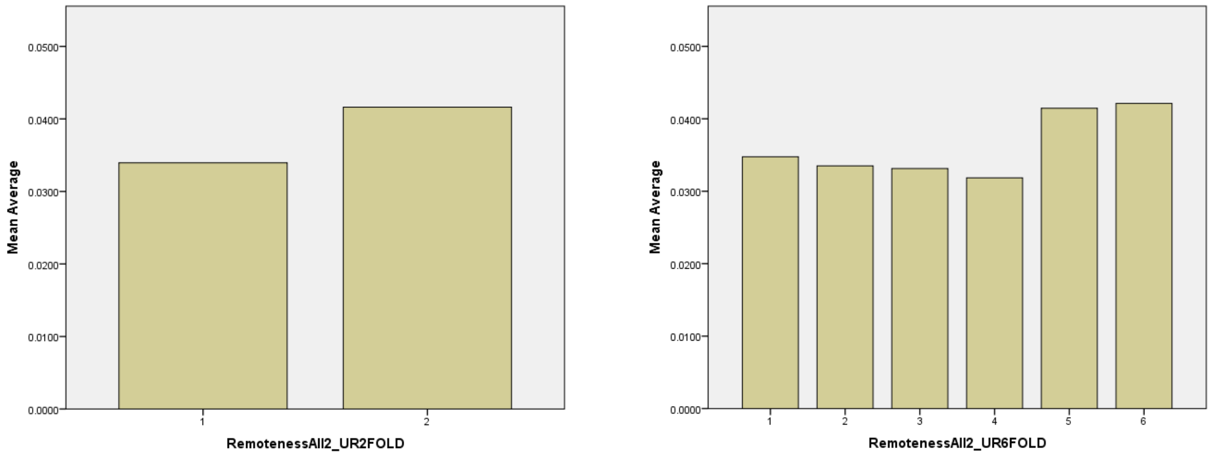
		AvgAllDist	PopPerSqKM	AggegatedDistToServices
ThermalEff	Pearson Correlation	.179**	-.168**	.215**
	Sig. (2-tailed)	.003	.006	.000
	N	267	267	267

Figure 5.5: relation between remoteness indices and average measured thermal efficiency measured over all months, visualized in scatterplots



The fit line is based on an Epanechnikov kernel with 90% points to fit

Figure 5.6: relation between categorical remoteness indices and average measured thermal efficiency measured over all months, visualized in bar charts



Thermal efficiency shows correlations with remoteness, where more remote dwellings tend to have lower thermal efficiency. This appears to be in line with the known influence of remoteness on thermal efficiency; it is known that rural dwellings are less thermally efficient. Rural areas are generally classified according to the 2-fold classification scheme; these are classes 5 and 6 in the 6-fold classification scheme. The 6-fold classification scheme suggests that thermal efficiency is negatively related with remoteness only according to the 2-fold scheme because as far as a relation exists, thermal efficiency is positively related with remoteness for the first 4 classifications (figure 5.6). However, the scatterplots suggest that such a stepwise index does not exist, as the equation tends to increase gradually in spite of the fit line being a Loess type; following the average dots rather than following the dots by a linear or quadratic equation. Regarding both the bar charts in figure 5.6 as well as the charts in figure 5.5 and their simultaneous correlations (table 5.1), it must be concluded that remoteness has no increased influence on thermal efficiency up to a point, possibly around the point where dwellings are classified as 'rural' rather than 'urban', after which thermal efficiency further decreases as remoteness increases. This is noteworthy especially for the second research goal related to remoteness and warmth use factors. Differences in thermal efficiency are not clearly visible from the map (appendix I, figure 14)

Regarding insights into what useful data can be derived from temperature data on smart meters, it seems that thermal efficiency was measured with accuracy (thermal efficiency correlated positively among months) although with limited precision (strength of thermal efficiency among months was below 0.8). It is certain that thermally inefficient dwellings were identified; both because monthly thermal efficiency figures correlated and because the results in regards with remoteness is in line with expectations (i.e. urban dwellings are significantly more thermally efficient than rural dwellings). The accuracy of the thermal efficiency indicators is unclear but may be further established by comparing total electricity use in data zones (chapter 5.8) and also explained by propensity to other buildings (chapter 5.9).

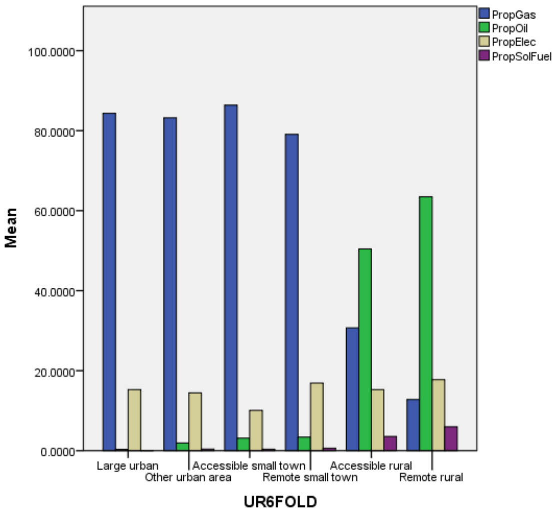
5.5 Central heating use type

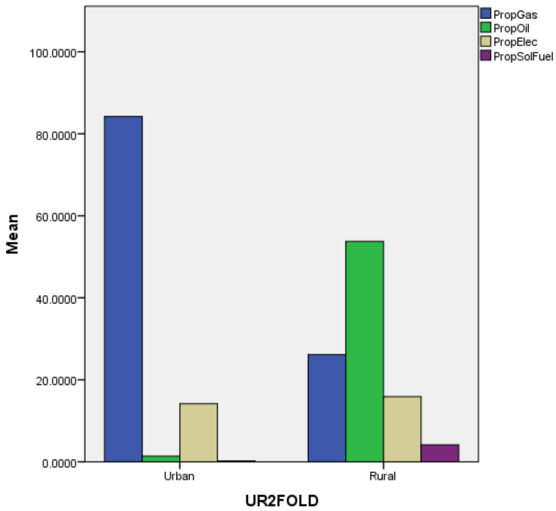
A dataset from Scotland's Census (2011c) indicating the energy use type per data zone was combined with the estimated dwelling locations. The share of energy use type was assigned to each dwelling on each location.

It is assumed that none of the dwellings had no central heating at all. Dwellings with more than one type of central heating were not used from the Scotland Census (2011c) dataset because these different types are not given, so they may be any type of fuel. "Other" types of central heating are also not accounted for. The share of energy sources not taken into account is 3.388% (source data: CentralHeatingPerDataZone). The other 96.612% were taken into account.

A contrast in oil and gas use is illustrated by the categorical classifications (figure 5.7). Rural towns in the area use gas more often than oil. Rural areas that are not within 30 minutes' drive from towns however, do not. Electricity for central heating is more equally divided among remote and non-remote areas.

Figure 5.7: Central heating use type in percentages of households in the study area according to categorical classification of the Scottish Government (2012b).





Gas and oil

The scatterplot (figure 5.8 and figure 5.9) shows that there is a clear link between remoteness to services or population centers and the use of oil and gas. A majority of dwellings in the study area use oil heating when the distance to services is larger than 10 minutes' drive. A majority of dwellings below 10 minutes' drive to services in the study area use gas.

Figure 5.8: Distance to services and oil and gas use

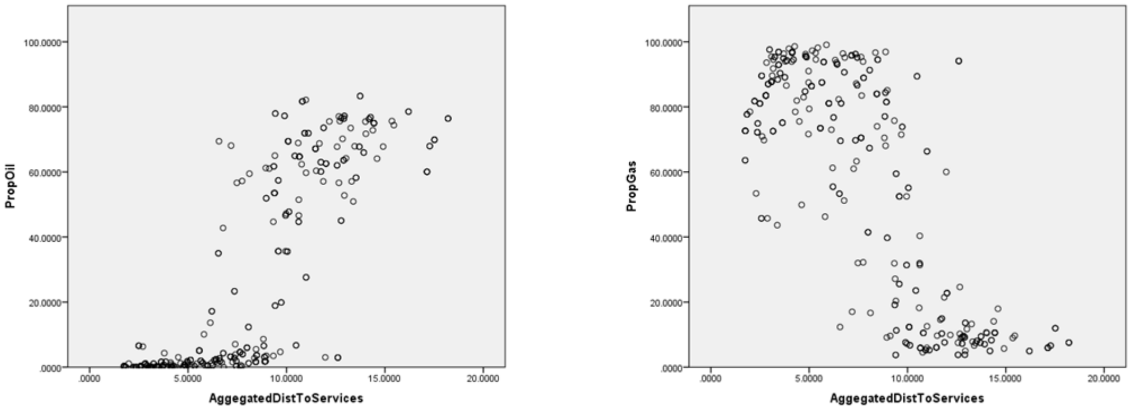
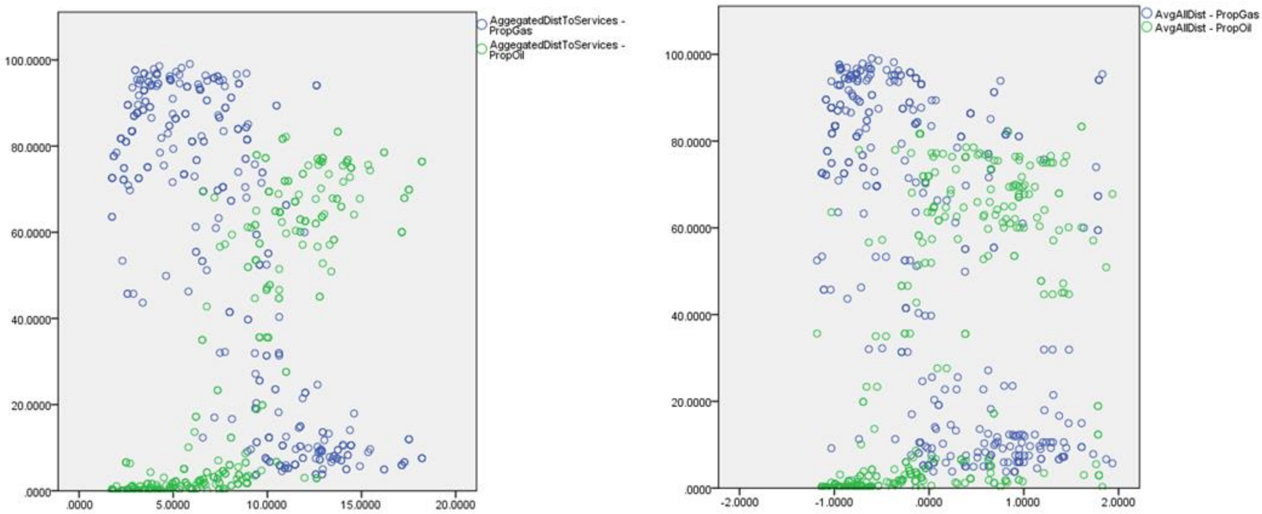


Figure 5.9: gas and oil use for central heating relative aggregated distance to services (left) and relative to average distance to villages, towns and cities in one scatterplot (right)



Solid fuels and Electricity

There exists a positive relationship between the use of solid fuels and electricity and categorized remoteness levels. The relation is strong for solid fuels while it is weak for electricity when using the 6-fold and 2-fold remoteness schemes (table 5.11 and 5.12).

Table 5.11: Biofuel and electricity use and their relation with remoteness, Spearman's Rho.

			UR6FOLD	UR2FOLD
Spearman's rho	PropSolFuel	Correlation Coefficient	.824**	.789**
		Sig. (2-tailed)	.000	.000
		N	369	369
	PropElec	Correlation Coefficient	.116*	.153**
		Sig. (2-tailed)	.026	.003
		N	369	369

Table 5.12: Biofuel and electricity use and their relation with remoteness, Pearson's correlation.

		AggegatedDistToServices	AvgAllDist	PopPerSqKM
PropSolFuel	Pearson Correlation	.698**	.655**	-.531**
	Sig. (2-tailed)	.000	.000	.000
	N	369	369	369
PropElec	Pearson Correlation	.010	.093	.130*
	Sig. (2-tailed)	.841	.075	.012
	N	369	369	369

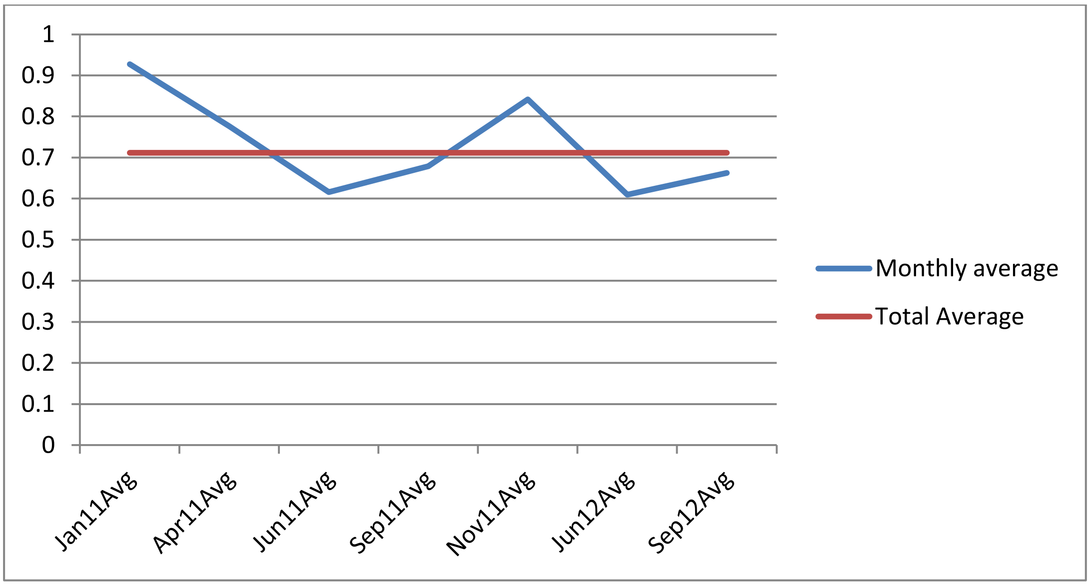
Clear positive relations exist between solid fuels and the interval remoteness levels. The relation is strongest for distances to services. For electricity there only exists a relation with population per square kilometer. The fact that this relation is positive is noticeable; it means that within the study area, electricity use is more likely to be found in more densely populated areas. This contradicts when measuring remoteness in the previous way; the 6-fold and 2-fold categorical schemes found that electricity was more likely to be found in areas categorized as 'rural'.
It can be concluded that the use of more expensive energy sources, in particular heating oil, will result in higher CO2 emissions and expenditure on warmth in more remote dwellings ceteris paribus. This conclusion shows that with regards to the second research goal, warmth use contributes to higher in CO2 emissions and expenditure in rural areas than in urban areas in the study area.

5.6 Warmth use

Heater intensity

Warmth increase in the home was highest in January 2011 and lowest in June 2012 and June 2012 (figure 5.10). There is a negative relation with warm months and warmth use.

Figure 5.10: estimated increase of the heater

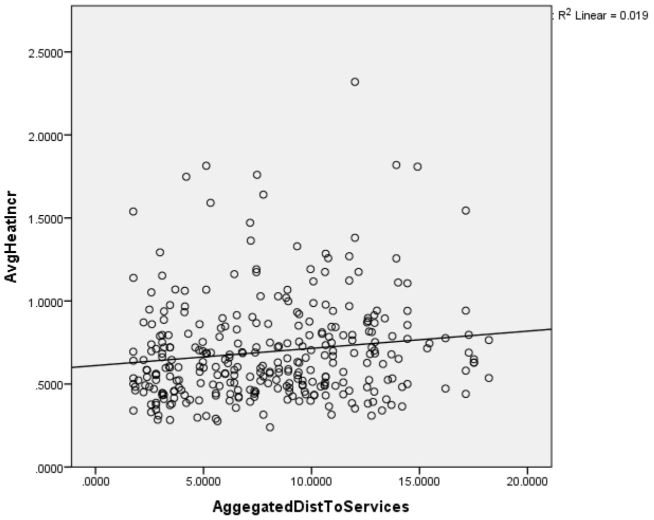


Source data: WarmthIncrease

Intensity with which the warmth in the house increases correlates significantly at the 99% confidence level for all months measured with the exception of January 2011 June 2011, which only correlates at the 95% confidence level, and January 2011 and September 2011, which don't correlate at all (appendix III, table 9). The lack of significance for these relations has probably to do with a relatively low number of matching cases (N= 39 for the former and N= 34 for the latter). The result means that high or low increases in inside temperature in a dwelling mean likely high or low increases in another month as well. This may be due to a heater being quick or slow heating up the dwelling but it may also be due to a more limited or larger amount of space that is heated. Temperature rises more quickly in a small space than in a larger space under the same conditions.

Heater intensity was found to be higher for rural areas than for urban areas, although the correlation is very weak (figure 5.11 and table 5.14 and table 5.15). Heater intensity was only recorded when the heater as off according to method II. Heater intensity measurements may be inaccurate because occasionally too few cases were measured per dwelling. In order to check if this is the case, a division is made between analyzing all cases or analyzing only cases when >1000 temperatures were reported. The upper rows show the figures when >1000 valid cases of heat increase were measured, while the lower rows show this for all temperatures. Significance and strength of the relation diminish with less cases but the direction of the relation does not. It seems that less than 1000 cases of warmth use measured per dwelling provides reliable results and number of analyzed dwellings in this case was more important than larger numbers of analyzed heat increase cases.

Figure 5.11: scatterplot for average increase and distances to services



A linear fit line type was used

Table 5.14: Spearman’s rho for average increase in temperatures inside the home and its relation with ordinal remoteness indices; all cases and cases where at least 1000 time intervals in one month were measured

			UR6FOLD	UR2FOLD
Spearman's rho	Morethan1000NAvgHeatIncr	Correlation Coefficient	.057	.080
		Sig. (2-tailed)	.354	.195
		N	263	263
	AvgHeatIncr	Correlation Coefficient	.143*	.109
		Sig. (2-tailed)	.011	.054
		N	312	312

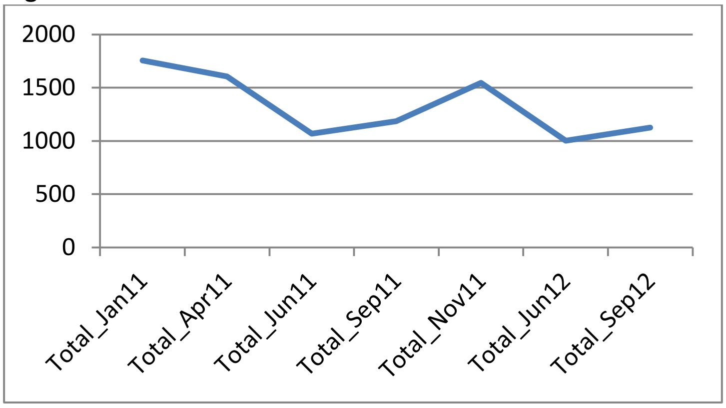
Table 5.15: Pearson's correlation for average increase in temperatures inside the home and its relation with interval remoteness indices; all cases and cases where at least 1000 time intervals in one month were measured

		PopPerSqKM	AggegatedDistToServices	AvgAllDist
Morethan1000AvgHeatIncr	Pearson Correlation	-.036	.089	.105
	Sig. (2-tailed)	.562	.149	.090
	N	263	263	263
AvgHeatIncr	Pearson Correlation	-.102	.139*	.092
	Sig. (2-tailed)	.072	.014	.103
	N	312	312	312

Warmth use

Warmth use was highest in January 2011 and lowest in June 2012 (figure 5.12). There is a negative relation with warm months and warmth use.

Figure 5.12: warmth use across various months



Source data: HeatUseCosts

Warmth use correlates significantly at the 99% confidence level for all months measured with the exception of January 2011 and June 2011 and January 2011 and September 2011, which show no correlations (table 10 Appendix III). This again is probably related to a relatively low number of cases that was measured.

Warmth use is positively correlated with remoteness (table 5.16 and table 5.17). The correlation figures are however very weak for all remoteness indicators.

Tests were run on average warmth use both including and excluding the month of January. This was done due to earlier tests showing no or low significance of correlation between January and other months. The results show that overall the difference is limited, but for population density a significant correlation was found for higher warmth use in less densely populated areas, while this result was not found as a significant correlation when taking into account the average warmth use during all months measured. Although the relation between warmth use is not immediately clear when visualized (appendixI figure 15), the estimated increased amount of warmth used from the correlation tests is apparent. Also apparent is that more remote data zones tend to use more energy (appendix I, figure 16) while another study, using samples from the same data set as this research, found no significant differences with overall electricity use and rural-urban households (Craig et al. p. 499). This makes the idea plausible that higher energy use in more remote areas is can merely be explained by the warmth use and that electricity use has a negligible effect on the variance in energy use among rural or urban dwellings. It should be noted that in the study cited, the sample of electricity heated homes was very small, so warmth consumption in this study should have had a minimal effect on electricity use (N=28 (Craig et al. p. 497)).

Concluding from the chapters 5.1 to 5.6 it can be established that the first hypothesis "*The warmth use factors increase as remoteness increases*", can be answered in the affirmative. Categorical remoteness indices suggest that this is only so for remote dwellings outside of population centers with a maximum of 3000 inhabitants. However, the interval remoteness indices simultaneously suggest that a linear equation exists for areas that can be considered to be more remote (to population, services or larger population centers), which is shown in particular by the graphs in figure 5.5. So as far as this research can tell, remoteness overall implies increased warmth use and heater activity and lower thermal efficiency, except within population centers, where a population center can be defined as having 3000 inhabitants or more.

Table 5.16: Spearman's rho for average warmth use over all months and all months with the exception of January; relation with ordinal remoteness indices.

			UR6FOLD	UR2FOLD
Spearman's rho	AvgHeatUse	Correlation Coefficient	.138*	.140*
		Sig. (2-tailed)	.015	.013
		N	314	314
	HeatUseNoJan	Correlation Coefficient	.152**	.150**
		Sig. (2-tailed)	.007	.008
		N	314	314

Table 5.17: Pearson's correlations for average warmth use over all months and all months with the exception of January; relation with interval remoteness indices.

		PopPerSqKM	AggegatedDistToServices	AvgAllDist
AvgHeatUse	Pearson Correlation	-.110	.123*	.166**
	Sig. (2-tailed)	.052	.029	.003
	N	314	314	314
HeatUseNoJan	Pearson Correlation	-.117*	.126*	.168**
	Sig. (2-tailed)	.039	.025	.003
	N	314	314	314

The variables heater increase and heater activity according to method II were taken into account when measuring warmth use. It is clear that heat increase has had a much more profound effect on the warmth use than heater activity (table 5.18).

Table 5.18: Pearson's correlations for average warmth use over all months, thermal efficiency over all months and activity of the heater measured according to method I and method II.

		ThermalEff	AvgHeatIncr	HeaterActMethod I	HeaterActMethod II
AvgHeatUse	Pearson Correlation	.595**	.717**	-.739**	.148*
	Sig. (2-tailed)	.000	.000	.000	.010
	N	299	298	299	299

Warmth use correlates positively with the variable thermal efficiency; this indicates that less thermally efficient dwellings tend to use more warmth. The variable thermal efficiency was not taken into account when measuring warmth use, but the correlation may be attributed to the fact that less thermally efficient dwellings lose more warmth, increasing its heater activity. Warmth use correlates more strongly with method I for measuring warmth use than method II, which is apparent because method I was not used for measuring warmth use.

Given the results indicating remoteness being positively correlated with warmth use and negatively correlated with thermal efficiency, it can be established that the first part of the second research goal has been achieved with a degree of accuracy and an unknown degree of precision. It was shown that using GIS and smart meter temperature data it is possible to measure the warmth use factors. As a second part of the research goal it was shown how the relation between the warmth use factors depends on remoteness types used. Given the fact that more remote dwellings use more costly and CO2 emitting energy sources it can be established that CO2 and expenditure is significantly higher in remote areas. This is further perpetuated by the fact that CO2 emissions and expenditure on transport in these areas is also higher.

The second hypothesis “*More remote areas tend to have higher warmth use, even when using various measures of remoteness”* can be answered in the affirmative, although there is an important nuance to this with regards to remoteness, which has been concluded from hypothesis 1. The degree to which this true is shown in the next paragraph.

Predicted CO2 and £ on warmth use

The estimated amount of monthly CO2 emitted for warmth use purposes per dwelling per household was 538 Kg for urban dwellings and 845 Kg for rural dwellings. Average monthly expenditure on warmth per household was estimated to be 83£ for urban and 121 £ for rural dwellings (table 5.19). For CO2 emissions, relations between all months were significant with the exception of January and June and January and September 2011 (table 11 Appendix III). For £ spent, all relations were significant (table 12 Appendix III). A weak relation exists between the amount of CO2 emitted and £ spent with remoteness (table 5.20 and table 5.21). For all remoteness indices used, the relation is stronger for emitted CO2 than for £ spent.

Table 5.19: carbon emissions in rural and urban areas.

	UR2FOLD	N	Mean	Std. Deviation
Estimated CO2 emitted on warmth use per capita	Urban	192	538.054773	424.1630303
	Rural	177	845.344744	856.7211823
Estimated £ spent on warmth use per capita	Urban	192	83.425805	65.5662422
	Rural	177	121.827640	119.0505464

Table 5.20: Spearman’s Rho for estimated CO2 emissions and estimated £ spent on heating and relation with ordinal remoteness indices

			UR6FOLD	UR2FOLD
Spearman's rho	PoundsAvgHeatUse	Correlation Coefficient	.211**	.217**
		Sig. (2-tailed)	.000	.000
		N	369	369
	KgCO2AvgHeatUse	Correlation Coefficient	.247**	.255**
		Sig. (2-tailed)	.000	.000
		N	369	369

Table 5.21: Peason's correlation for estimated CO2 emissions and estimated £ spent on heating and relation with interval remoteness indices

		AggegatedDistToServices	AvgAllDist	PopPerSqKM
PoundsAvgHeatUse	Pearson Correlation	.200**	.225**	-.156**
	Sig. (2-tailed)	.000	.000	.003
	N	369	369	369
KgCO2AvgHeatUse	Pearson Correlation	.224**	.237**	-.172**
	Sig. (2-tailed)	.000	.000	.001
	N	369	369	369

CO2 emissions and £ spent were tested for relation with the share of central heating type in each data zone where dwellings were located. Oil use as energy source for central heating has the strongest relation with CO2 emissions and £ spent (table 5.22). It can be concluded that oil use and gas use also have the largest impact on the CO2 emitted and £ spent since these are the most used central heating types in the area; 56.36% for gas, 15.01% for electric heating, 26.52% for heating oil and 2.1% for solid fuels (source data: HeatUseCosts).

Table 5.22: Pearson's correlation for estimated CO2 emissions and estimated £ spent and its relation with type of central heating.

		PropGas	PropElec	PropOil	PropSolFuel
PoundsAvgHeatUse	Pearson Correlation	-.188**	-.037	.222**	.177**
	Sig. (2-tailed)	.000	.483	.000	.001
	N	370	370	370	370
KgCO2AvgHeatUse	Pearson Correlation	-.228**	-.012	.257**	.189**
	Sig. (2-tailed)	.000	.817	.000	.000
	N	370	370	370	370

Warmth use was tested with its relation to average kWh used per household at the MSOA level (table 5.23). Earlier it was established that high energy use appears to be correlated with warmth use (chapter 5.6, paragraph warmth use) but it should be concluded that this relation is not statistically significant. Pearson's correlation does show a significant relationship at the 99% confidence level for higher energy use and higher degree of remoteness.

Table 5.23: Pearson's correlation for domestic energy consumption and interval remoteness indices

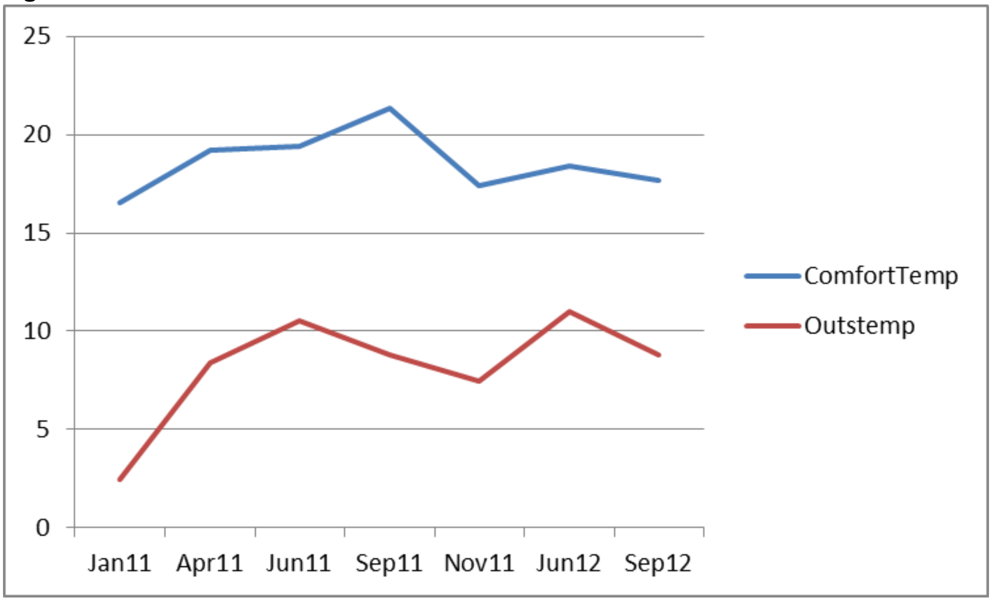
		AvgHeatUse	AvgAllDist	PopPerSqKM	AggegatedDistToServices
Average Ordinary Domestic Consumption (kWh)	Pearson Correlation	.094	.595**	-.693**	.788**
	Sig. (2-tailed)	.096	.000	.000	.000
	N	314	369	369	369
Average Economy 7 Consumption (kWh)	Pearson Correlation	.083	.623**	-.706**	.770**
	Sig. (2-tailed)	.142	.000	.000	.000
	N	314	369	369	369

The hypotheses 3 and 4 that higher degrees of remoteness result in higher degrees of CO2 emissions and expenditure in terms of money due to warmth use, transport and energy source are thereby concluded.

5.7 Thermal comfort

Using average monthly figures, thermal comfort levels appear to follow outside temperature levels (figure 5.13).

Figure 5.13



Condition was stable temperature of 0.2°C

Thermal comfort was tested for its relation with outside temperature. According to adaptive comfort theory, comfort temperatures should increase when average outside temperatures increase. Tests were conducted for assuming that the temperature should be stable and not rise or fall more than either 0.5°C or 0.2°C. The relation between comfort levels and outside temperature were positive for all months with the exception of September 2012 (table 12 appendix III). However, none of the relations were significant. Differences between a stable temperature of 0.2°C or 0.5°C have a negligible influence on the results.

In addition, the relations between average outside temperature and average inside temperature over all months were tested. Estimated comfort levels do not show a relation with the average outside temperature when taken over the year as a whole (table 5.24). This suggests that as far as this case can show, thermal comfort was dependent of monthly temperature but not of yearly temperature, so occupants are more likely to adapt to the outside temperature of their climate at that moment and less adaptive (or possibly not at all adaptive) of the general climate of their region.

Table 5.24: Pearson's correlation for average adaptive comfort levels and average outside temperature.

		AllAvgOutsTemp
AllAVG2	Pearson Correlation	.030
	Sig. (2-tailed)	.598
	N	309
AllAVG5	Pearson Correlation	.031
	Sig. (2-tailed)	.583
	N	309

Comfort levels tend to be considerably higher than expected for the dwellings in the area according to the theory of Lück on free-running buildings (2012, p. 3) (table 5.25 and table 5.26). A majority of the dwellings have an estimated comfort level above the predicted comfort level.

Table 5.25: Percentages within 90% expected adaptive comfort levels according to Lück (2012)

Month	Jan11	Apr11	Jun11	Sep11	Nov11	Jun12	Sep12
Percentages within 90% adaptive comfort level	7.14%	26.88%	27.43%	18.18%	18.63%	23.29%	14.49%
Percentage below predicted 90% comfort level	7.14%	9.38%	8.85%	6.36%	9.80%	12.33%	4.35%
Percentage above predicted 90% comfort level	85.71%	63.75%	63.72%	75.45%	71.57%	64.38%	81.16%
Average inside temperature for all dwellings	18.26	19.17	19.61	19.76	18.77	19.42	19.2
Average inside temperature 90% comfort dwellings	14.61	18.06	18.90	17.59	16.07	18.54	18.01

Table 5.26: Percentages within 90% expected adaptive comfort levels according to Lück (2012)

Month	Jan11	Apr11	Jun11	Sep11	Nov11	Jun12	Sep12
Percentages within 80% adaptive comfort level	10.71%	41.88%	36.28%	26.36%	33.33%	27.40%	26.09%
Percentages below 80% adaptive comfort level	7.14%	5.63%	7.08%	3.64%	4.90%	10.96%	2.90%
Percentages above 80% adaptive comfort level	82.14%	52.50%	56.64%	70.00%	61.76%	61.64%	71.01%
Average inside temperature for all dwellings	18.26	19.17	19.61	19.76	18.77	19.42	19.20
Average inside temperature 80% comfort dwellings	14.74	18.22	19.16	17.81	16.78	18.45	17.81

Contrary to the formula derived from Lück (2012), the predicted adaptive comfort levels of Toe & Kubota seem to overestimate the figures (table 5.27 and table 5.28). A majority of the dwellings have an estimated comfort level below the predicted comfort level. It is also possible that occupants prefer warmer temperatures than their thermostat levels indicate, but choose not to do so in order to save energy.

Table 5.27: Percentages within 90% expected adaptive comfort levels according to Toe & Kubota (2013)

Month	Jan11	Apr11	Jun11	Sep11	Nov11	Jun12	Sep12
Percentages within 90% adaptive comfort level	25.00%	38.75%	40.71%	40.91%	35.29%	32.88%	43.48%
Percentages below predicted 90% adaptive comfort level	50.00%	48.13%	41.59%	34.55%	45.10%	43.84%	33.33%
Percentages above predicted 90% adaptive comfort level	25.00%	13.13%	17.70%	24.55%	19.61%	23.29%	23.19%
Average inside temperature for all dwellings	18.26	19.17	19.61	19.76	18.77	19.42	19.20
Average inside temperature 90% comfort dwellings	19.52	20.12	20.31	20.14	19.88	20.14	19.65

Table 5.28: Percentages within 80% expected adaptive comfort levels according to Toe & Kubota (2013)

Month	Jan11	Apr11	Jun11	Sep11	Nov11	Jun12	Sep12
Percentages within 80% adaptive comfort level	50.00%	58.75%	61.06%	59.09%	50.98%	52.05%	63.77%
Percentages below 80% adaptive comfort level	32.14%	34.38%	29.20%	24.55%	36.27%	34.25%	26.09%
Percentages above 80% adaptive comfort level	17.86%	6.88%	9.73%	16.36%	12.75%	13.70%	10.14%
Average inside temperature for all dwellings	18.26	19.17	19.61	19.76	18.77	19.42	19.20
Average inside temperature 80% comfort dwellings	19.11	20.03	20.27	20.12	19.91	20.11	19.76

Spearman's Rho and Pearson's correlation were used to find whether a relation exists between thermal comfort levels and remoteness (table 5.29 and table 5.30). A correlation was found between population per square kilometer and comfort levels in September 2012. It shows a negative relation; indicating that the higher the population per square kilometer, the lower the thermal comfort level during that month. No other significant correlations were found.

Table 5.29: Spearman's correlation for comfort levels and ordinal remoteness indices

		Jan11	Apr11	Jun11	Sep11	Nov11	Jun12	Sep12	All
UR6FOLD	Correlation Coefficient	.241	-.034	-.010	-.075	.104	.011	.050	.050
	Sig. (2-tailed)	.208	.669	.914	.438	.297	.883	.684	.684
	N	29	161	114	110	102	175	69	69
UR2FOLD	Correlation Coefficient	.297	.002	-.003	-.020	.165	.050	.069	.069
	Sig. (2-tailed)	.118	.980	.975	.835	.098	.507	.576	.576
	N	29	161	114	110	102	175	69	69

Table 5.30: Pearson's correlation for comfort levels and interval remoteness indices

		Jan11	Apr11	Jun11	Sep11	Nov11	Jun12	Sep12	ALL
PopPerSqKM	Pearson Correlation	.042	.055	-.073	-.015	-.146	.162	-.287*	-.023
	Sig. (2-tailed)	.830	.485	.437	.880	.144	.172	.017	.758
	N	29	161	114	110	102	73	69	175
AggegatedDistToServices	Pearson Correlation	.174	-.036	-.027	-.043	.139	-.185	.106	.004
	Sig. (2-tailed)	.366	.646	.776	.658	.165	.117	.385	.959
	N	29	161	114	110	102	73	69	175
AvgAllDist	Pearson Correlation	-.055	-.009	.017	-.058	.197*	-.150	.149	.017
	Sig. (2-tailed)	.776	.909	.857	.544	.047	.206	.222	.826
	N	29	161	114	110	102	73	69	175

No differences were found for rural or urban dwellings and comfort temperatures are very similar (table 13, appendix III). This makes it unnecessary to test the variance in resemblance with the formulas used across different degrees of remoteness.

5.8 Demography and geographical characteristics

Demographic data per 2001 data zone were tested on their relation with the warmth use factors (thermal efficiency, heater activity according to both method I and II, and warmth use). The significant relations found are summarized in table 5.31 to 5.33 (source data: Demography (showing raw data) and FuelPAndVulnerability (summarized analysis)). No significant relations were found for warmth use and thermal comfort (source data: AdaptiveComfortDemography). For warmth use there were however individual months where significant relations were found (table 5.34 and table 5.35).

Variables for vulnerable areas are: percentage of the population above 50 with disability allowance, disability allowance in all four quartiles, percentage working / percentage pensioners, health rank, percentage of citizens without central heating.
Warmth use is higher in areas where on average more citizens are working. Thermal efficiency is lower in areas where no central heating was found. Absence of a central heater may imply that thermal efficiency in those buildings is low, but more plausible is that areas with relatively many homes where a central heater is absent, tend to contain less thermally efficient dwellings.

Variables for (fuel) poverty are: Citizen income rank, Household income rank, percentage income deprived population, gross weekly income per citizen and gross weekly income per household. No geographical data on actual fuel poverty were found.
Income rank (the higher the number, the lower the rank) is negatively related to warmth use, while income deprivation is also negatively related. This indicates that in areas where more income is earned, more warmth is used. This is in line with the general numbers from previous researches indicating that warmth use increases as income increases. It cannot predict fuel poverty based solely on the data; geographical data are needed on fuel poverty for this type of analysis.

Dwelling data that are used are: the median number of rooms, percentage detached dwellings, percentage flats, percentage semi-detached dwellings, percentage terraced dwellings, percentages 1 – 10 or more rooms.

Statistical tests have been colored according to the class of characteristic they belong to. Variables indicating vulnerability are colored yellow, fuel poverty red, dwelling related brown, additional other data grey

Table 5.31: significant relations between demographic and geographical characteristics and thermal efficiency

	AveragekWh OrdinaryAndEcon7	DetachedPerc	FlatPerc	NoCentralHeating (percent)
Pearson Correlation	.155**	.155**	-.115*	.169**
Sig. (2-tailed)	0.007136499	0.007	0.046	0.003

Table 5.32: significant relations between demographic and geographical characteristics and heater activity (method I)

	AveragekWh OrdinaryAndEcon7	DetachedPerc	FlatPerc	PercHH9Room
Pearson Correlation	-.139*	-.113*	.160**	-.118*
Sig. (2-tailed)	0.013935775	0.045749727	0.004543024	0.037091192

Table 5.33: significant relations between demographic and geographical characteristics and heater activity (method II)

	DetachedPerc
Pearson Correlation	.116*
Sig. (2-tailed)	0.039695045

Table 5.34: significant relations between demographic and geographical characteristics and particular months selected for measuring warmth use in June

Jun11HeatUse	GR-Percworking (notPens)	DeprivationCS-incrk(Ranknr)	DeprivationCS-housrk(Ranknr)	DeprivationCS-healrk(RankNR)	CS-prginc3b INCOMEAVG
Pearson Correlation	.246**	-.710*	-.680**	-.765**	-.743**
Sig. (2-tailed)	0.000683679	4.19606E-3	7.73851E-27	2.30736E-37	1.02957E-33
N	188	18	188	188	185

Table 5.34: significant relations between demographic and geographical characteristics and particular months selected for measuring warmth use in November

Nov11HeatUse	AveragekWhOrdinaryAndEcon 7	IncDepr2011Q4	DetachedPerc	FlatPerc	PercHH2Room	PercHH5Room
Pearson Correlation	.166*	-.141*	.189**	-.218**	-.147*	.173*
Sig. (2-tailed)	0.018998192	0.047089189	0.007511005	0.001943215	0.03735949	0.014242568
N	200	200	200	200	200	200

High thermal efficiency levels are positively correlated with detachment of dwellings and negatively correlated with flats. High thermal efficiency levels indicate a low actual thermal efficiency; hence areas with many flats tend to be more thermally efficient than areas with detached dwellings. The heater also tends to be on more often in areas with detached dwellings than in areas with flats (again, as with thermal efficiency, high numbers of heater activity for method 1 indicate low actual activity). From the month of November it appears that areas with relatively many detached dwellings are predicted to use more warmth while in areas with more rooms also more warmth is used.

Additional data used were the amount of average kWh per data zone in 2011.
Total average kWh used per citizen is correlated with both thermal efficiency and heater activity (method I) (table 5.31 and table 5.32); average kWh used is higher in those areas where the heater is on more often and in those areas where thermal efficiency is lower. This indicates that thermal efficiency and heater activity influence the energy bill. However, this should also mean that warmth use has an even more profound effect on energy bills. The lack of a significant relation between kWh used and (estimated) warmth used however, can be explained by the fact that for warmth use the thermal efficiency was not taken into account and also, that the method used for warmth use prediction was method II (which has no significant relation) and not method I.

Drive distances to public services have shown the strongest correlations with other remoteness indices as well as with warmth use factors. Distance to services by public transport, which up to now has been left aside, was therefore analyzed in addition (table 14 and table 15 appendix III). Additionally researched remoteness indices were access to the following services by public transport:

GP, higher education, JobCenterPlus facility, library, nursery, police station, post office, shopping center, ATM, bank, Citizens Advice Bureau, chemist, further education, general store and finally, aggregated average of access to all these services as was done similarly to the aggregated average drive times; all distances were added up for each dwelling individually and then divided by the number of distance to service indices.
Aggregated drive times have proven to be most significantly correlated with the warmth use indicators. Drive times are summarized individually similarly to public transport data as in table 16 appendix III. Closer examination shows that correlations tend to be stronger for public transport than for drive time data.
No data that was provided contradict the supposition that presence of physical dwelling properties which lower thermal efficiency, influence warmth use factors negatively. More clearly, that means that physical dwelling properties within the area can to some extent explain or predict the warmth use in the area. Nevertheless the significant relations with warmth use tended to only apply to individual months and correlations were not strong. This makes plausible the idea that this information, provided at the data zone level, has predicting power for dwellings but to a limited extent. The third research goal was to find what location-specific characteristics of an area have a visible impact on warmth use, and it can be concluded that these include detachment, dwelling type, amount of rooms and income. Whether absence of a central heater is a predictor of low thermal efficiency cannot be stated because there was no reason to assume causality.

Hypothesis 5 stated that a higher degree of remoteness results in a higher degree of fuel poverty due to household income levels, higher heating costs and higher fuel costs. Hypothesis 5 could not be confirmed. In particular it is apparent that warmth use coincides with higher income levels. Areas where income deprivation was relatively high did not tend to coincide with any of the warmth use factors, suggesting that fuel poverty may be an effect more of income than of warmth use. Areas where people could be considered to be particularly vulnerable were not identified either, thereby also not being able to confirm hypothesis 6, which stated that a higher degree of remoteness results in a higher degree of vulnerability due to higher fuel poverty and demography in rural areas (age, disability).

Since no relations were found for warmth use factors and vulnerability and fuel poverty, and no relations could be researched for vulnerability and fuel poverty and remoteness due to lacking data, the effect of remoteness on vulnerability and fuel poverty could not be tested. An arguable exception is de lack of central heating which is more prevalent in remote areas and also correlated with warmth use at the data zone level.

It may be concluded that research goal 4 was not achieved since it was not possible to show whether areas with high fuel poverty and existence of vulnerable households tended to coincide with high energy use.

5.9 Revision of the relation between thermal efficiency and remoteness

In chapter 5.4 it was established that estimated thermal efficiency figures tended to decrease as remoteness increased up to category 4 (see also: Figure 5.6 in chapter 5.4).
Category 5 and 6 had higher numbers, which indicates that the fact that remoteness correlated with higher thermal efficiency figures is due to these categories but not the increasingly less thermally efficient dwellings in category 1-4. Thus it may be said that remoteness is an indicator for lower thermal efficiency figures only in accessible rural and remote rural areas, but not in (small) towns, villages, or cities, even when the towns are remote.

Through chapter 5.4 to chapter 5.8 it became clear that remoteness as a contributor to warmth use depends on a variety of factors related to physical dwelling properties (number of rooms and dwelling type). These dwelling properties tend to coincide with the building density of the area; denser areas have fewer rooms per occupant and are less often completely detached.

A striking conclusion of this research would be that thermal efficiency as measured here can be fully explained by the amount of buildings in the close vicinity of the dwelling. Buildings in the vicinity may increase the capacity to insulate the dwelling and share warmth across the attached dwellings. Dwellings nearby may also provide some 'shelter' against wind. This assumption is derived from the idea that in category 1-4 many buildings are still close to each other or detached to each other while in category 5-6 more buildings are significantly further away from each other, or simply not detached.
To confirm this supposition and to improve the explanatory power of remoteness as an indicator for thermal efficiency and warmth use factors in general, an indicator is created for how large the area of built-up sites is in square meters in the area. It is not possible to calculate or estimate the amount of buildings attached to the dwelling since the location of dwellings is unknown. Estimations on the location have been made however, and both the original location data as well as estimated locations are used in order to test the supposition.

Method
For the initially given location, the amount of built up area is calculated within its square kilometer. Since the dwelling can be anywhere within the square kilometer, it is not possible to establish with certainty the amount of built up area in its closer vicinity.
As explained in chapter 4.1, dwellings have been relocated according to the data zone where the amount of population within the square kilometer was highest. It is assumed that dwellings are more likely to be located there than on their initially given location. The degree to which this is true however remains unknown and impossible to control. Nonetheless it is possible to compare the built up vicinity of the originally provided location data with the built up vicinity of relocated dwellings, and find which of both has higher explanatory power regarding thermal efficiency of the dwellings.
Two different parameters are used in order to estimate the approximate amount of built up area around the relocated dwelling; the area 200 meters around the dwelling and the area 500 meters around the dwelling. For the initial data, an area of 1 km² is used. Some of the dwellings never were relocated because for some cases, no other data zones were close than the data zone within it was located initially, thereby not being possible to be relocated at the basis of more densely populated data zones nearby. Other dwellings never were relocated because they already were located in the area with the highest population density within their km².

The built up area data was retrieved from Ordnance Survey (2015), providing polygons for built up area. Polygons indicating a built up area were selected based on 200m, 500m and 1km² buffer zones. The total amount of square meters of built up area selected per buffer zone was calculated using 'calculate geometry' tool in ESRI's ArcMap. Polygons that were only partially within the buffer zone area were not cut off; since no justification could be found for either cutting off the part of the polygon falling outside the buffer nor taking into account the whole polygon, the latter option was chosen because this required one less task (clip) to be carried out.

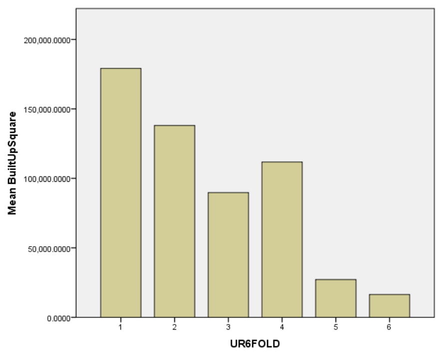
The hypothesis is that the amount of built up area is negatively correlated with the thermal efficiency figure attributed to it. If this hypothesis is correct, this would mean that more built up area in the vicinity results in a lower thermal efficiency figure, which means higher actual thermal efficiency.
The built up area data was retrieved from Ordnance Survey (2015). Maps on national grid reference squares NO, NJ and NK were merged. A model was built in ESRI's ArcMap modelbuilder (appendix II,

figure 2) to select the buildings within the mentioned radii (1 km², 200m circles and 500m circles) and report the number of buildings and the amount of m² of built up area; the sum of that is reported in excel along with the ID of the dwelling that belongs to the amount of built up m². These numbers are joined in a table with the remoteness indices, thermal efficiency and warmth use.

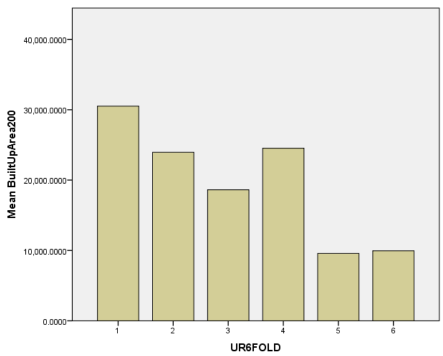
Results
The amount of built-up area is highest in large urban areas (figure 5.14). Accessible rural and remote rural dwellings (class 5 and 6) have the least built-up area in the neighborhood, but the difference with class 1 to 4 is less for the relocated dwellings (200m buffers and 500m buffers) than for the initial locations. The difference is also less for 200m buffers than for 500m buffers (figure 5.14). Note that class 1 to 4 is equal to class 1 in the 2-fold classification scheme while class 5 and 6 are equal to class 2 in this scheme.

Figure: 5.14: bar chart indicating the relation between the average amount of built-up area within the different radii in relation to the 6-fold classification scheme of the Scottish Government.

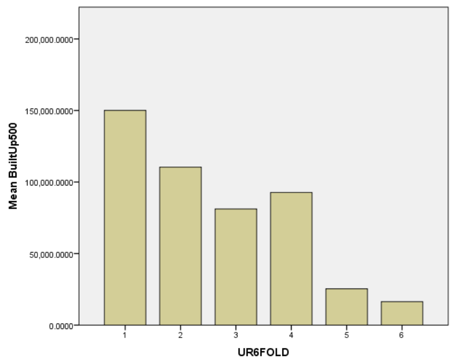
Km² buffers



200m buffers (radii)



500m buffers (radii)



More built-up area results in lower thermal efficiency figures; i.e. higher actual thermal efficiency, and the correlation is strongest for the smallest buffers (200m radius) measured (table 5.35). No correlations were found for warmth use. When calculating these relations among class 1-4, the thermal efficiency figure even becomes positive, showing lower thermal efficiency in larger urban areas, although not to a statistically significant extent (table 5.36). The opposite is true for class 5 and 6 where higher remoteness coincides with lower thermal efficiency, while additionally for buffer areas of 200m measured, the correlation is significant (table 5.37).

Table 5.35: Pearson's correlations between the amount of built up area in the estimated vicinity and remoteness indices, thermal efficiency and warmth use.

		BuiltUpSquare	BuiltUpArea200	BuiltUp500	AvgAllDist	PopPerSqKM	DistToServices	ThermalEff	HeatUse
BuiltUpSquare	Pearson Correlation	1	.750**	.968**	-.549**	.762**	-.758**	-.150*	-.051
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.014	.371
	N	368	368	368	367	367	367	266	314
BuiltUpArea200	Pearson Correlation	.750**	1	.774**	-.385**	.653**	-.520**	-.163**	-.059
	Sig. (2-tailed)	.000		.000	.000	.000	.000	.008	.300
	N	368	368	368	367	367	367	266	314
BuiltUp500	Pearson Correlation	.968**	.774**	1	-.546**	.769**	-.762**	-.146*	-.037
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.017	.513
	N	368	368	368	367	367	367	266	314

Table 5.36: Pearson's correlations between the amount of built up area in the estimated vicinity and remoteness indices, thermal efficiency and warmth use when selecting only remoteness class 1 to 4.

		ThermalEff	HeatUse
BuiltUpSquare	Pearson Correlation	.106	.111
	Sig. (2-tailed)	.216	.165
	N	137	158
BuiltUpArea200	Pearson Correlation	.069	.094
	Sig. (2-tailed)	.420	.242
	N	137	158
BuiltUp500	Pearson Correlation	.122	.130
	Sig. (2-tailed)	.154	.104
	N	137	158

Table 5.37: Pearson's correlations between the amount of built up area in the estimated vicinity and remoteness indices, thermal efficiency and warmth use when selecting only remoteness class 5 and 6.

		ThermalEff	HeatUse
BuiltUpSquare	Pearson Correlation	-.137	-.012
	Sig. (2-tailed)	.121	.880
	N	129	155
BuiltUpArea200	Pearson Correlation	-.174*	-.074
	Sig. (2-tailed)	.049	.362
	N	129	155
BuiltUp500	Pearson Correlation	-.114	.020
	Sig. (2-tailed)	.196	.802
	N	129	155

The causal relation between thermal efficiency and warmth use has been empirically proven in previous researches. Whether this relation is also causal for the study area cannot be proven because sufficient data is lacking. Most importantly lacking may be the exact locations and their propensity to built-up areas. It can nevertheless be assumed that the amount of built-up area is indeed an explanatory factor for lower thermal efficiency in more remote areas. Assuming this causal relation, a stepwise multiple regression is conducted in order to find whether the correlations with thermal efficiency and remoteness can be explained through factors other than their distance from and amount of built-up areas in the vicinity (table 5.38). Since 200m buffer zones showed the highest correlations, and assuming the built-up area is a causal factor, it is most likely that 200m buffers provide the highest amount of explanatory power among the different buffer types that were used previously. It is assumed that for the independent variable built up area, the dependent variable thermal efficiency is normally distributed (figure 5 appendix III).

Table 5.38: multiple regression on interval remoteness indices and thermal efficiency when controlling for the amount of built-up area within 200m from the estimated dwelling location.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.215[a]	.046	.043	.0175661

a. Predictors: (Constant), AggegatedDistToServices
b. Dependent Variable: ThermalEff

ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	.004	1	.004	12.810	.000[b]
	Residual	.081	264	.000		
	Total	.085	265			

a. Dependent Variable: ThermalEff
b. Predictors: (Constant), AggegatedDistToServices

Excluded Variables[a]

Model		Beta In	T	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	BuiltUpArea200	-.055[b]	-.744	.458	-.046	.652
	AvgAllDist	.056[b]	.657	.512	.040	.504
	PopPerSqKM	-.028[b]	-.320	.749	-.020	.486

a. Dependent Variable: ThermalEff
b. Predictors in the Model: (Constant), AggegatedDistToServices
Output tables of the coeffiecients and Entered variables were not included here. The complete tables were added in table 17 appendix III.

The results show that the amount of built-up area cannot explain the lower thermal efficiency in rural areas other than the fact that remote areas tend to have lower thermal efficiency. This may be either because other factors than the amount of nearby dwellings play a role in thermal efficiency or it may be attributed to the fact that exact dwelling locations are unknown and thus the propensity of built-up area and detachment of the dwellings is unknown and cannot be taken into account.

6. Discussion

Evaluation
The first step in the analysis using outside and inside climate data for estimating various warmth use factors was interpolation of climate data. Outside climate was estimated using kriging data. It should be noted that the use of inverse distance weighting (IDW) is still a matter of discussion in research on weather data, although kriging tends to provide more accurate results, and in particular co-kriging. When time and resources allow for it, it would be recommendable to control whether IDW may in a particular case provide better results than kriging. This was not done in this research. Although it is clear that the interpolated weather data indirectly provided results that were in line with the hypothesis that warmth use is related to remoteness, it is possible that IDW would have provided more accurate results. It is also possible that taking into account other factors by using co-kriging, such as proximity to the sea, may have provided more reliable results on outside weather. Wind and humidity were not used in the analysis. Both factors are known to be of high importance for thermal comfort (chapter 2.10 and De Dear et al. 1997) and thermal efficiency (Chapter 2.9 and Lück 2012). This may explain the limited coherence of comfort temperature across months.

Useful information can be derived from temperature data provided by smart energy monitors, which means that the first research goal was achieved; a degree of thermal efficiency, comfort temperature, heater activity and warmth use were measured, although the latter two only to a limited extent.

The reliability of thermal efficiency over the months was evaluated measuring the coherence of thermal efficiency figures over several months. The correlations between months suggest that thermal efficiency was measured, but with limited accuracy, arguably due to absence of wind and humidity used in the analysis.
Warmth use was estimated in this research but findings appear to be too inaccurate in order to draw strong conclusions on the numbers. The accuracy of warmth use estimates was evaluated by testing the geographical relation between the dwelling's estimated warmth use and known kWh used at the 2011 data zone level. With accurate warmth use estimates on 314 cases in different 192 different data zones it would be expected that warmth use should show a significant relation with energy use per data zone if warmth use was accurately measured, especially when thermal efficiency and kWh per data zone do correlate. Lack of accuracy for warmth use is likely to have been caused by lack of accounting for interfering factors, one of these being the thermal efficiency of the dwellings. However, it may be that using more dwellings, warmth use and average energy use per data zone would be more strongly correlated. Now however, some outliers in some data zones where there are no other dwellings in that same data zone, have a strong effect on the correlation between kWh and estimated warmth used.
Secondly, inaccurate warmth use data may be related to the method used for heater activity, which was the alternative method II.
To measure the heater activity, two different methods were used. Both methods coincided to some extent but their average figures were not correlated. This suggests that at least one of the methods used was flawed. The first method showed more significant relations among months and more strongly with remoteness indices, suggesting this method was more accurate than method II. Alternative measures for measuring warmth use had to be developed in addition to the initial method, which required more precise temperature data (with at least two decimals recorded). This may have improved the outcomes of heater activity and related to it, warmth use.
Differences in warmth use are, as far as the research can show, not related to comfort temperatures, nor do comfort temperatures appear to differ across geographies within the study area. The lack of correlation of thermal comfort levels between months might suggest that actual thermal comfort levels have not been measured because thermal comfort does not vary widely from

month to month within one household. Thermostat levels however may vary much more; hence the use of thermostat levels in dwellings (as was done in this research) may not give an effective way to measure thermal comfort. It may also be that more cases are needed in order to find significant correlations; the research of Toe & Kubota (2013) found r^2 levels as low as 0.09 for moderate climates. The relation may not be clear with a lower number of cases (3213 cases were used in the study of Toe & Kubota (2013)).

As far as CO_2 emissions and expenditure on energy are concerned, the research identified a variety of variables that may be combined to estimate CO_2 levels and expenditure, but the results were not verified. However since these figures are based on warmth use levels, which are unlikely to be accurate, these numbers should be taken with a large grain of salt. For this part the research merely achieved to show that it was possible estimating CO_2 emissions and expenditure based on empirical data; its validity was however not proven.
For CO_2 emissions and cost in transportation data, several variables had to be assumed. Certain vehicles, for example new buses, light duty vehicles were assumed to be used in the study area but the specifics for light duty vehicle used in the study of Schlömer et al. (2014) were not researched or evaluated on the degree to which these vehicle types coincided with the specifics of buses used for public transport in the data of Department of Energy and Climate Change (2012). It was also not researched whether the car types varied over different geographies or what types of cars are most commonly used in Scotland, so the most common car type was assumed for all areas. It was pointed out in the literature that households in more remote areas often have more than one car. This was not taken into account in the analysis, although more cars per household may result in more car purchases, which also increases the amount of CO_2 emitted (due to more cars being produced).

For fuel poverty, no relations at all were found with warmth use. This is not because the research implies that high warmth use and higher incomes means that fuel poor areas are not in need of warmer dwellings. What the research does imply is that low income areas have not been found to be less thermally efficient, and neither have lower income areas been found to demand higher comfort temperatures. On the other hand, the opposite cannot be proven either.
This shows one of the shortcomings of the research; no data were obtained from the dwellings' properties or its residents. It remains unclear whether fuel poverty and vulnerability are related to thermal efficiency or thermal comfort. But the strong correlations for warmth use and income do suggest that income is a factor that is of high significance for the eventual warmth use, (and warmth use was proven to occur more in less thermally efficient dwellings) while demographic data are of lower significance in explaining warmth use than income.

The initial scope of the research was to find whether the thermometer data could provide valuable information for smart grids. The research has not found a cause to make this argument. Prediction or at least correlation of warmth use with certain geographical areas is a precondition for its value for smart grids. However, the research does show that this information may well be of value when it is possible to use the information on thermal efficiency (derived from the temperature data) in order to combine this with more of the data which is necessary to be acquired in order to estimate warmth use. Thermal efficiency is difficult to measure for individual dwellings; this is shown by the variety of energy efficiency bands that result in different outcomes (in Scotland most importantly SAP and NHER). The research shows that thermal efficiency starts to increase from a certain degree of remoteness. Further research into this area may be able to identify what precisely causes this, which can be valuable information into the use of smart grids.

Recommendations for further research
Furthermore, related to both smart grids and this research would be to make a weighted overlay predicting warmth use for areas by a variety of factors that tend to coincide with warmth use or

thermal efficiency. Some of these factors have been identified in this research; Dwelling type, number of rooms, remoteness, income, outside temperature and vicinity to buildings all impact the use of warmth. These factors are of course intertwined and should be controlled for the degree to which these interfere with each other. The strength of relations with warmth use varied strongly per month. Although it has been noted that warmth use in this research has not been proven to give reliable figures, it should come to the researcher's attention that with a weighted overlay as described here, the factors involved for predicting warmth use may vary per month.
Secondly, for measuring whether the heater is on, method I may be a more recommendable approach than method II; this may also improve the reliability of the warmth use measurements (which relied on method II in this research). In addition to that it may be recommendable to use the initial method for measuring heater activity, which was eventually disregarded, but may be used effectively when east 2 decimals of inside temperature are recorded.
Regarding the primary influences on warmth use as defined by Harvey (2006), a recommendation is to add the influence of humidity, wind speed and wind direction; these data are all available through the Meteorological Office (2013). With the data available two of the five primary influences of thermal efficiency may be explained; resistance to moisture migration and rate of exchange of inside air with outside air.
Certain data are not to be accessed by the researcher but almost certainly are available to some public researchers, who may research the extent to which the thermal efficiency of the analyzed dwellings coincides with SAP and NHER bands at large scale geographical levels such as 2011 data zones or postcode levels. A higher amount of dwellings to be analyzed may also reveal more information on the relation of the warmth use factors and geographical criteria other than remoteness and information of thermal comfort levels, and adaptability thereof, across Scotland. This may result in more information on what location-specific characteristics of an area have a visible impact on warmth use factors, as an addition to what the third research goal has achieved. Data on fuel poverty and vulnerability, either at the individual level or at large scale geographical levels, may also shed light on causes of fuel poverty and vulnerability; this was the fourth research goal, which was not achieved. Data on fuel poverty and vulnerability, either at the individual level or at large scale geographical levels, may also shed light on causes of fuel poverty and vulnerability; this was the fourth research goal, which was not achieved. These figures could prove to be particularly useful for public actions for decreased fuel poverty and increased thermal efficiency. The effects of area-based schemes such as HEEPS:ABS (2013) may be improved using spatial autocorrelation to identify areas of low thermal efficiency, high fuel poverty and high vulnerability. This is a way the issues addressed in this research may be applied in practice. Also the costs of these schemes may be lowered using a second spatial autocorrelation analysis to identify where dwellings with low thermal efficiency may be most proximate to other dwellings to be prioritized, since insulation on several buildings in the same area can be more economically beneficial (Consumer Focus Scotland 2012, p. 4).This is especially relevant for remote areas, where insulation measures have been less applied but more badly needed, and where economies of scale are more challenging to achieve due to the low proximity of other dwellings.

7. Conclusion

Lowering energy use may be an effective to tackle many of the concerns that exist today with regards to energy use. In Scotland, warmth use is a large contributor to both pollution and expenditure for households. For rural households this is more so than for urban households, due to dwelling's physical properties in rural areas (SHCS 2009, SHCS 2011a). Measuring the thermal efficiency of dwellings however is not a straightforward issue and neither is measuring the causes for warmth use in different areas; the reasons for why warmth use has gone up in the past decades are disputed (Shipworth 2011).

The first research question addressed whether temperature data derived from energy monitors could be useful in monitoring warmth use factors (thermal efficiency, heater activity and warmth use) and thermal comfort temperatures. Development of a method was successful in estimating these factors and to distinguish these factors among the tested dwellings. Correlations were not strong enough to make predictions on eventual warmth use within an area.
For establishing whether the heater was on or off, two different methods were used, the first suggesting more reliable results than the second. The first method suggested more reliable results due to its stronger and more often significant correlations with remoteness indices, which is to be expected since remote dwellings are likely to have a significantly different heater activity than urban dwellings primarily due to their higher warmth use (this has been proven to be the case in previous research). So although the claim that method I is an effective way to measure heater activity cannot be proven, it is suggested to be so due to its significant correlation with other variables that according to theory indeed should correlate. For both methods heater activity was higher in colder months than in warmer months, which similarly is to be expected according to theory.
Thermal efficiency was measured when the heater was off according to method I for measuring heater activity. For thermal efficiency it was proven that thermal efficiency in one month also coincides with thermal efficiency in another month. In theory, thermal efficiency should remain equal regardless of the outside temperature. The correlations from one month to the other were, although highly significant, not very strong, so the method does provide some information on the thermal efficiency but the method is simultaneously limited in its accuracy.
Warmth use was estimated using the activity of the heater according to method II combined with increases in temperature when the heater was regarded as on. Thermal efficiency was not taken into account while estimating warmth use, and this may explain why warmth use showed weaker relations with remoteness and other geographical factors than thermal efficiency. In addition to that, the weakness of relations may be explained by the use of measuring heater activity according to method II.
Comfort temperatures were estimated in order to find whether discrepancies in warmth use and thermal efficiency may be the result of differing demand inside temperature in the house. Comfort temperature levels did not vary across various levels of geography. Thermal comfort changed throughout the year along with the monthly temperature. This coincides with theory on adaptive comfort. Nonetheless thermal comfort did not coincide with the predicted comfort levels of previous research; thermal comfort levels tended to be underestimated by research assuming thermal comfort levels for occupants of free running buildings while it tended to be overestimated for occupants of heated and cooled buildings. Possible explanations may be that for the dwellings in this study it was unknown whether buildings were free-running or not, thus the combination of both cases distorted the data for both analyses, while another explanation may be that actual thermal comfort levels were not measured since it was unknown whether the stable temperature levels in dwellings were comfortable to the occupant or only thermostat levels (which were possibly not directly related to thermal comfort).

Estimating the warmth use allowed for estimating the CO_2 emissions and expenditure on warmth. Since transport and housing are both primary contributors to CO_2 emissions and expenditure, transportation figures per measured dwelling were estimated.
Through this information, the research goals 2a and 2b were achieved. For 2a; developing a GIS-based methodology for finding heat loss and fuel consumption, the method has proven to be able to show that CO_2 emissions and expenditures on both warmth use and fuel are influenced by the remoteness of an area by a variety of factors. A GIS method called kriging was used to interpolate weather data. The significance and correlations that were found by achieving research goal 1 show that this method was successful in achieving its goal. GIS was also used for establishing the area type of each dwelling, which allowed for estimating their fuel consumption. The validity of this outcome however, was not tested to empirical data.

In addition, GIS was essential for research goal 2b in finding how different measures of remoteness influence CO_2 emissions, thermal efficiency and warmth use. It was shown that GIS can be used successfully in estimating remoteness at the hand of distance to population centers; using network analysis, network distance to population centers showed significant correlations with warmth use, thermal efficiency and heater activity. However, the known indicators for distances to services showed to be a better predictor for warmth use than distance to population centers, while these are merely derived as attribute data rather than obtained through a GIS-based methodology.
Pearson's correlations between remoteness factors were at a minimum of -0.424 (population per square kilometer and its relation to distance to population centers) and a maximum of 0.864 (drive distance to services and its relation to Scottish Government classification). The correlations suggest that there is sufficient reciprocity among the remoteness indices while the indices are simultaneously dissimilar enough to justify the use of various indicators. Using the various remoteness degrees it was shown that warmth use factors start to increase only when dwellings are located outside of populated areas (containing more than 3000 inhabitants).
Distances to individual population centers (villages, towns or cities) were regarded as having too little correlation with other remoteness indicators in order to be useful for further analysis on its relation to warmth use factors. The aggregate of distances to all population centers combined showed a stronger correlation than the individual distances and therefore this aggregate figure was used.

Related to research objective 2 was research objective 3; to find what location-specific characteristics of an area have a visible impact on warmth use. Demographic data were usually not significantly correlated with warmth use. Important exceptions were the variables ratio workers / pensioners and the ranking of income deprivation. It is very likely that both variables are related to each other as workers may have more disposable income, which for both previous researches and this research have shown to result in less warmth use on average. Dwelling type was correlated with warmth use in some months, while dwelling type was correlated with heater activity and thermal efficiency for the average of all months; Pearson's correlation for presence of detached dwellings showed a significant correlation of 0.155 and flats -0.155 with thermal efficiency. Heater activity was significantly higher for detached dwellings (Pearson's correlation = -0.113 for detached dwellings while 0.160 for percentage of flats) Number of rooms was only occasionally significantly correlated; this suggests that house type is a better predictor of the used warmth use factors than number of rooms or demographic data.

The fourth objective was related to fuel poverty and vulnerability of households. These coincide with the data used for research objective 3. It could not be proven that factors related to warmth use related to fuel poverty. No actual data on fuel poverty were available and therefore income data were used instead. Higher incomes correlated with higher warmth use while presence of income deprivation showed no correlations. A likely explanation is that fuel poverty is more determined by

income than by warmth use factors of the dwelling. It is also possible that fuel poor households happen to be located in data zones with relatively high incomes or on average low income deprivation. Another explanation may be that poverty and fuel poverty overall are low in the study area and more present in other parts of Scotland.
For vulnerability, no demographic relations were found with any of the factors influencing either uncomfortably low temperatures (taken into account by adaptive comfort temperature) or a high energy bill for warmth use (warmth use and heater activity) or a factor that may influence both (thermal efficiency). Thermal efficiency however tended to be larger in areas where no central heating was found; this may imply (although it does not necessarily do so) that dwellings that already are more vulnerable due to lack of central heating also have less ability to keep any warmth that the dwelling may have otherwise, inside, perpetuating the vulnerability of its residents. If the contrary to this implication is not disproven, it may reasonably alarm Scottish citizens and policy makers that the vulnerability of these factors tends to coincide.

The main goal of this research was to develop a method to measure domestic warmth use from inside temperature data and to find how various degrees of remoteness influence energy use for households and to analyze the implications on CO_2 emissions, fuel poverty and vulnerability of households.
Monthly CO_2 emitted by transport per household came down to 1200 Kg for urban areas and 1905 Kg for rural areas. Yearly expenditure on transport per household was estimated to be 570 £ for urban and 905 £ for rural areas. The estimated amount of monthly CO_2 emitted for warmth use purposes per dwelling per household was 538 Kg for urban dwellings and 845 Kg for rural dwellings. Average monthly expenditure on warmth per household was estimated to be 83£ for urban and 121 £ for rural dwellings. For transport, higher figures on CO_2 and expenditure for remote areas were explained by the drive distances and used fuel types. For dwellings, higher figures on CO_2 and £ expenditure on warmth use were partially explained by the type of central heating used and partially by the amount of warmth used.
The validity and accuracy of the model can only be tested to a limited extent with the data available. Considering that earlier research found no correlation between electricity use and rural or urban households (Craig et al. 2014), it is likely that differences in energy use can by and large be attributed to warmth use. For the month of November it was shown that higher warmth use was correlated with areas with higher average energy use. Although the average yearly warmth use was not correlated significantly with energy use in kWh per data zone, average thermal efficiency was. This suggests that thermal efficiency was measured more accurately than warmth use. In addition, thermal efficiency was not taken into account while measuring warmth use due to lacking data on the heater's properties (primarily the intensity with which the heater was functioning) and therefore inherent errors of measurement were assumed for warmth use. In total 369 dwellings were analyzed across 7 months in two years, some of which lacked data on inside temperature for some of these months and occasionally, for data missed for all months analyzed for some dwellings. The amount of dwellings and months analyzed showed sufficient to both draw reliable conclusions on the significance and direction of the relation between warmth use factors and remoteness. The amount of analyzed dwellings was also high enough on many occasions to find relations between warmth use factors and geographical information on the data zone level.
The research has shown that inside temperature data can provide information along with geographical information through which estimates can be made on the thermal efficiency in dwellings. With enough data, patterns in various geographies can be found as well. Geographies may be based on statistical data known at the geographical level but may also be based on remoteness indices, the latter being more strongly correlated with warmth use factors than the former for this study area with this amount of analyzed dwellings. The method was able to find possible areas of particular vulnerability, but only regarding dwellings with no central heating. The method was not able to explain fuel poverty or find areas of possible fuel poverty.

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Appendix I: Maps and visualization

Figure 1: remoteness according to a 2-fold classification scheme

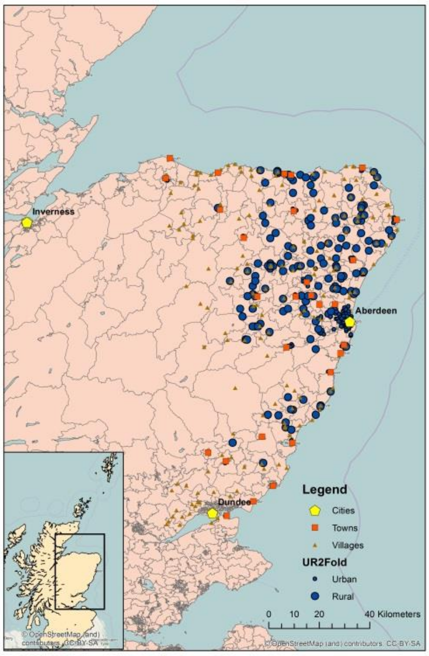


Figure 2: remoteness according to a 3-fold classification scheme

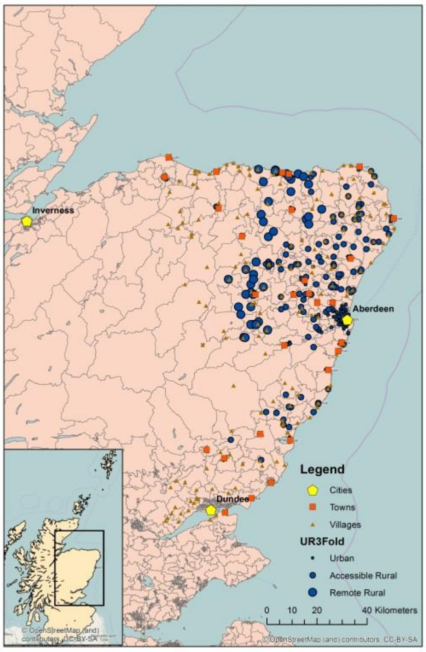


Figure 3: remoteness according to the 6-fold classification scheme

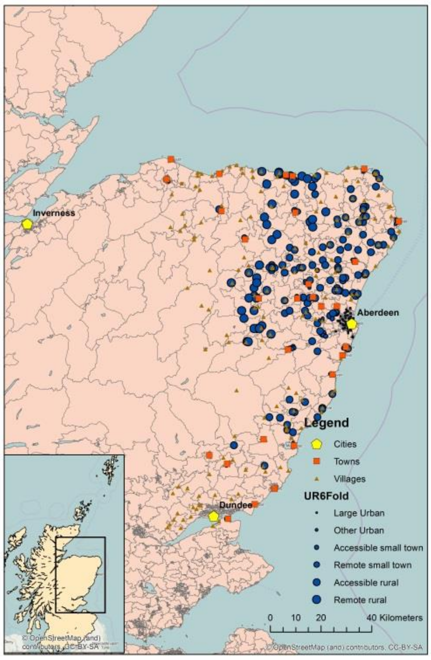
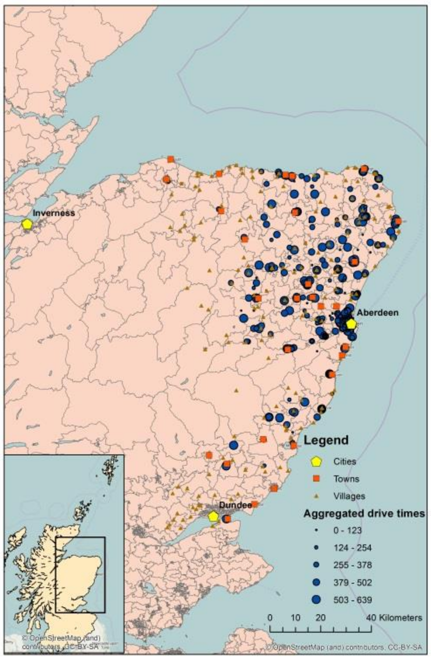


Figure 4: remoteness according to distance to drive times to services

Figure 5: remoteness according to population per square kilometer



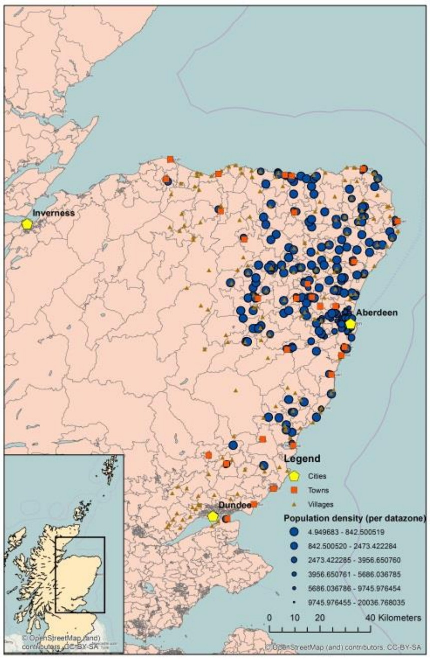
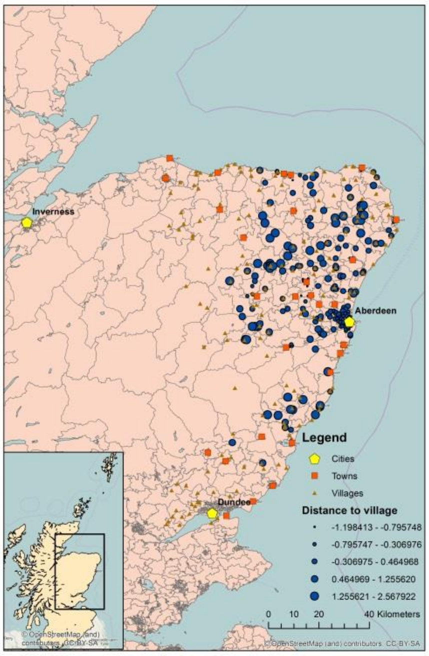


Figure 6: remoteness according to distance to villages

Figure 7: remoteness according to distance to towns



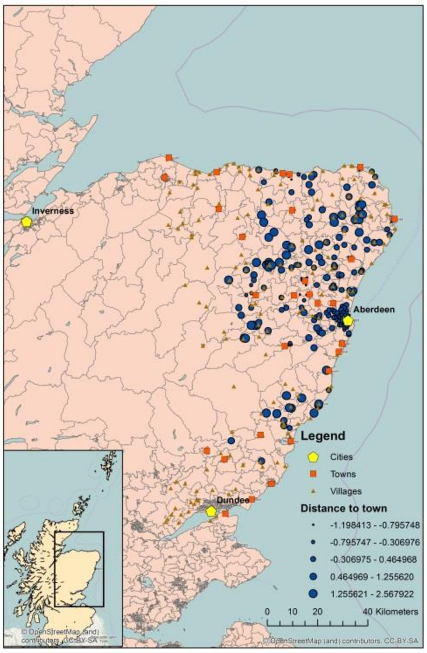


Figure 8: remoteness according to distance to cities

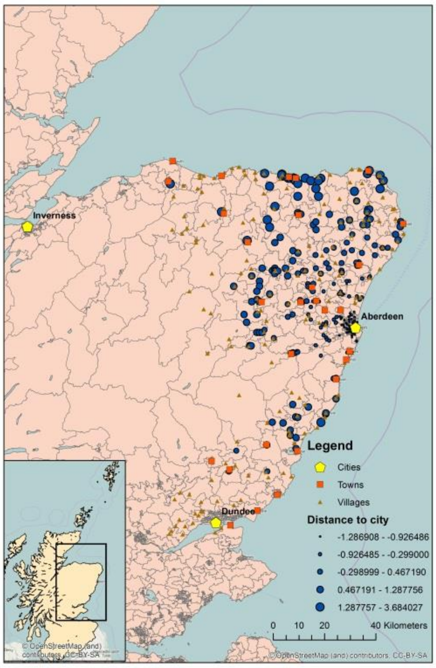


Figure 9: remoteness according to distance to all population centers

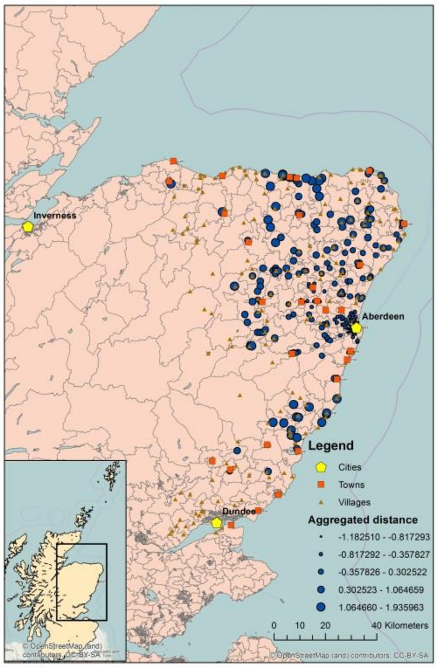


Figure 10: CO2 emissions for transportation

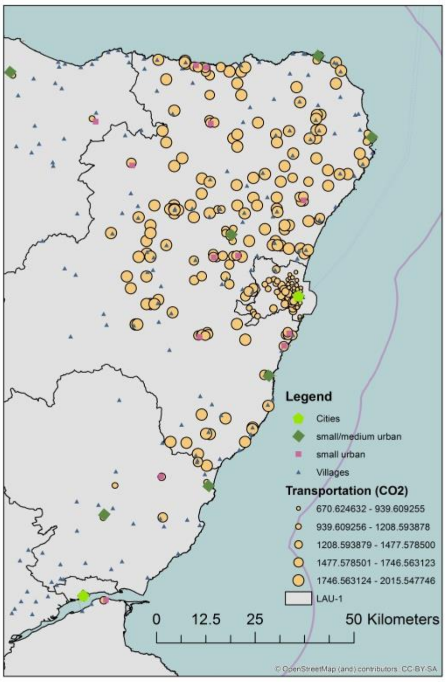


Figure 11: Heater activity 1

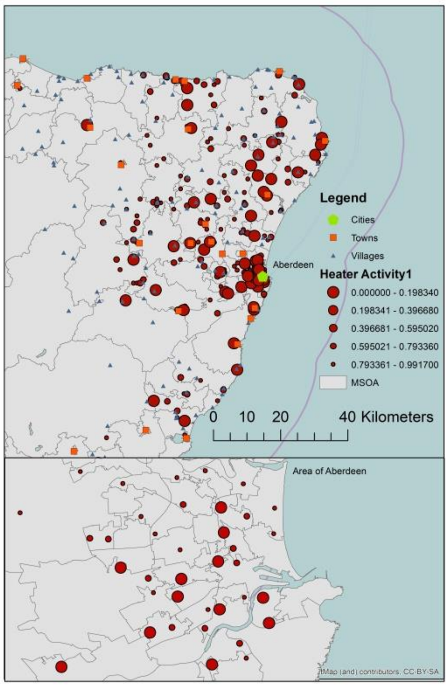


Figure 13: Heater activity 2

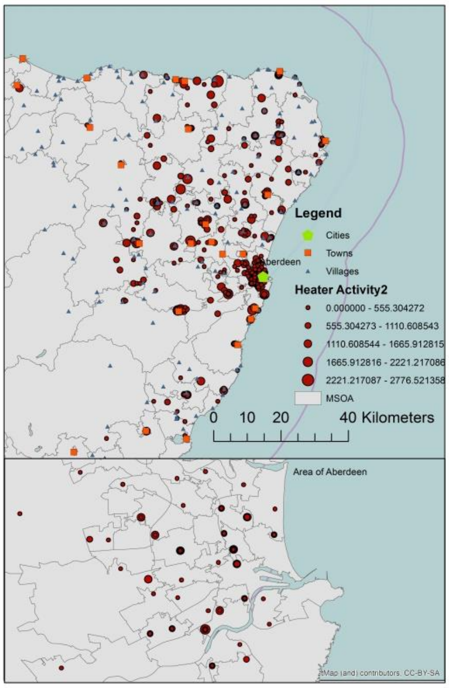


Figure 14: Thermal efficiency

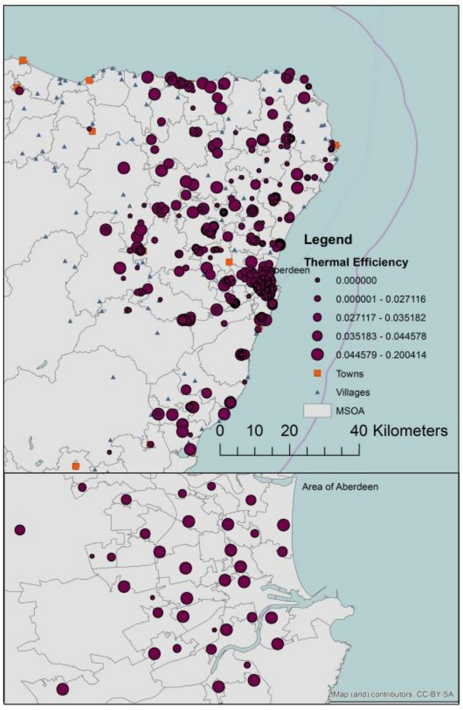


Figure 15: warmth use

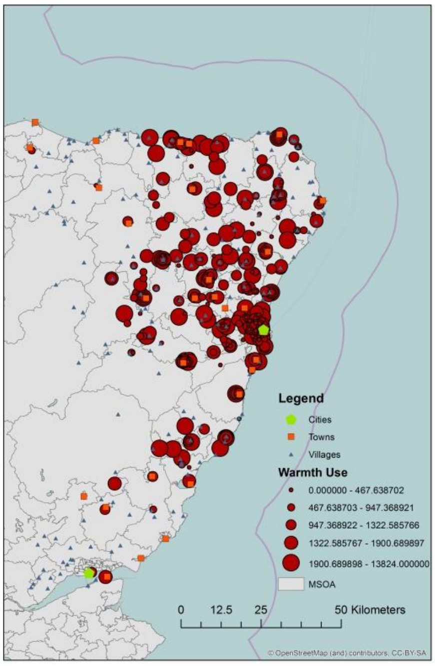
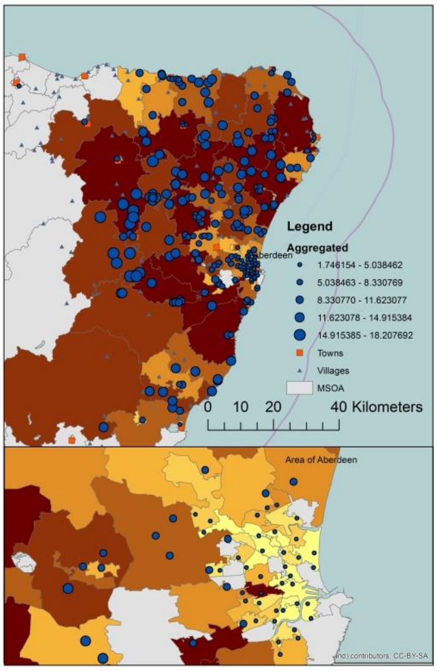


Figure 16: average energy use per MSOA per household (dots represent distance to services)



Appendix II: Tables and figures for clarification of data analysis

Figure 1:

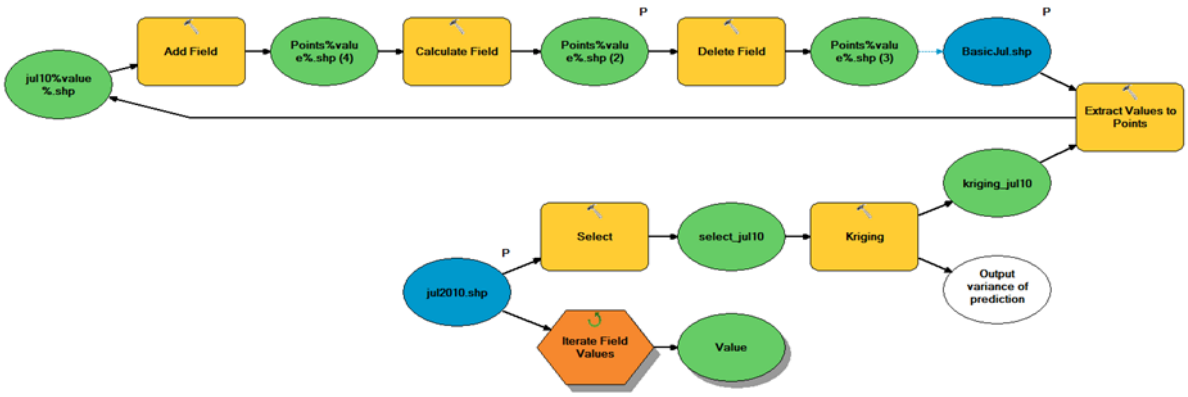
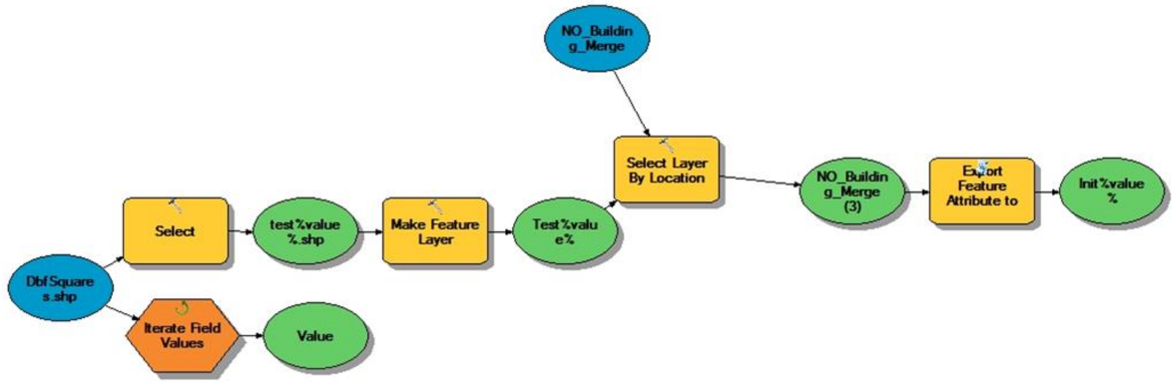


Table 1: temporal interpolation of outside temperatures belonging to TimeIDs. April 2011, dwelling 4

Date	Outside TimeID	TimeID	Temporal interpolation formula	OutsTemp	InsTemp
1/4/11 0:00	1	1	Temperature measured as a result from interpolation of meteorological data	5.19555	
1/4/11 0:05		2	TimeID1-((TimeID1- TimeID13)/12)	5.173960833	17.5
1/4/11 0:10		3	TimeID2-((TimeID1- TimeID13)/12)	5.152371667	17.3
1/4/11 0:15		4	TimeID3-((TimeID1- TimeID13)/12)	5.1307825	17.3
1/4/11 0:20		5	TimeID4-((TimeID1- TimeID13)/12)	5.109193333	17.2
1/4/11 0:25		6	TimeID5-((TimeID1- TimeID13)/12)	5.087604167	17.2
1/4/11 0:30		7	TimeID6-((TimeID1- TimeID13)/12)	5.066015	17.2
1/4/11 0:35		8	TimeID7-((TimeID1- TimeID13)/12)	5.044425833	17.1
1/4/11 0:40		9	TimeID8-((TimeID1- TimeID13)/12)	5.022836667	17
1/4/11 0:45		10	TimeID9-((TimeID1- TimeID13)/12)	5.0012475	16.9
1/4/11 0:50		11	TimeID10-((TimeID1- TimeID13)/12)	4.979658333	16.9
1/4/11 0:55		12	TimeID11-((TimeID1- TimeID13)/12)	4.958069167	
1/4/11 1:00	2	13	Temperature measured as a result from interpolation of meteorological data	4.93648	

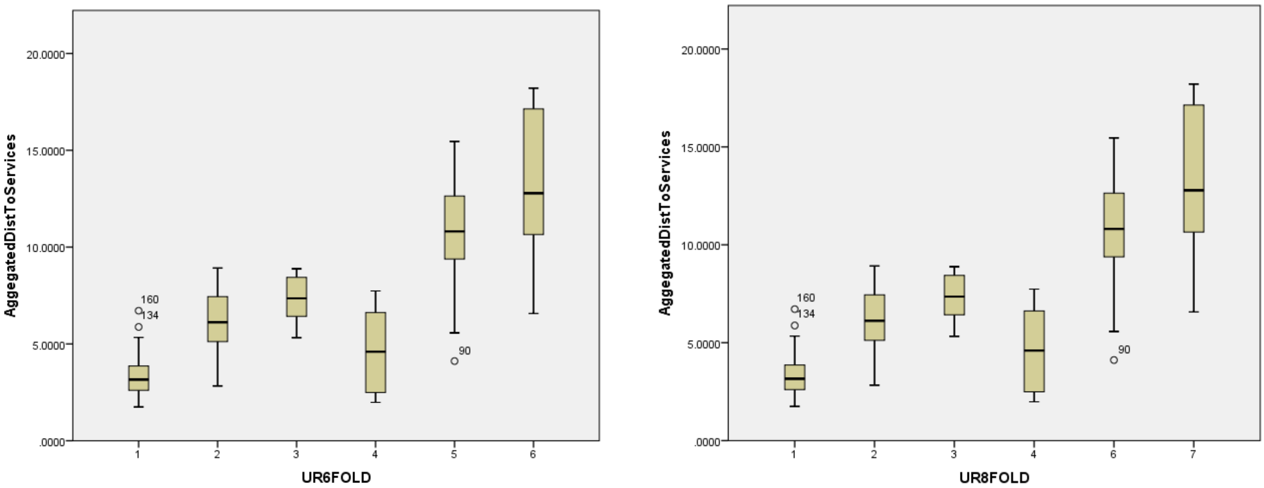
Figure 2: Model for reporting the amount of m^2 of built up area around the data point



Appendix III: Statistical tests

5.1 Remoteness

Figure 1: boxplot of 6-fold and 8-fold classification scheme and its dispersion compared to aggregated distance to services.



5.2 Transportation

Table 1: t-test Table 5.4: t-test for CO2 emitted and £ spent by rural / urban classification, significance.

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Estimated CO2 emitted by bus transport per capita	Equal variances assumed	63.998	.000	-20.006	367	.000	-57.3210600	2.8651319	-62.9551957	-51.6869243
	Equal variances not assumed			-20.311	337.833	.000	-57.3210600	2.8222352	-62.8724271	-51.7696929
Estimated CO2 emitted by diesel per capita	Equal variances assumed	52.789	.000	-21.388	367	.000	-270.3755964	12.6414261	-295.2343154	-245.5168774
	Equal variances not assumed			-21.747	330.239	.000	-270.3755964	12.4325837	-294.8326447	-245.9185481
Estimated CO2 emitted by petrol per capita	Equal variances assumed	55.979	.000	-21.319	367	.000	-372.2876014	17.4623756	-406.6264715	-337.9487312
	Equal variances not assumed			-21.673	331.287	.000	-372.2876014	17.1774882	-406.0783065	-338.4968962
Estimated CO2 emitted by motorbikes per capita	Equal variances assumed	97.640	.000	-21.166	367	.000	-5.4402108	.2570291	-5.9456455	-4.9347762
	Equal variances not assumed			-21.549	323.696	.000	-5.4402108	.2524631	-5.9368865	-4.9435352
Estimated CO2 emitted by transport per capita	Equal variances assumed	55.887	.000	-21.297	367	.000	-705.4244684	33.1238729	-770.5608734	-640.2880635
	Equal variances not assumed			-21.648	331.788	.000	-705.4244684	32.5867666	-769.5271892	-641.3217477
Estimated £ spent on bus transport per capita	Equal variances assumed	63.998	.000	-20.006	367	.000	-25.7944770	1.2893094	-28.3298381	-23.2591160
	Equal variances not assumed			-20.311	337.833	.000	-25.7944770	1.2700058	-28.2925922	-23.2963618
Estimated £ spent on diesel per capita	Equal variances assumed	52.789	.000	-21.388	367	.000	-121.6690184	5.6886417	-132.8554420	-110.4825948
	Equal variances not assumed			-21.747	330.239	.000	-121.6690184	5.5946627	-132.6746901	-110.6633467
Estimated £ spent on petrol per capita	Equal variances assumed	55.979	.000	-21.319	367	.000	-184.9471619	8.6750588	-202.0062220	-167.8881017
	Equal variances not assumed			-21.673	331.287	.000	-184.9471619	8.5335307	-201.7339015	-168.1604223
Estimated £ spent on motorbike fuel per capita	Equal variances assumed	97.640	.000	-21.166	367	.000	-2.7026190	.1276884	-2.9537117	-2.4515263
	Equal variances not assumed			-21.549	323.696	.000	-2.7026190	.1254201	-2.9493604	-2.4558777
Estimated £ spent on transport per capita	Equal variances assumed	55.879	.000	-21.298	367	.000	-335.1132763	15.7343445	-366.0540616	-304.1724911
	Equal variances not assumed			-21.649	331.759	.000	-335.1132763	15.4791184	-365.5628738	-304.6636789

Table 2: Spearman's correlation for £ spent and its relation with the 6-fold rural / urban classification scheme.

Correlations

			Bus transport per capita (£)	diesel per capita (£)	petrol (car) per capita (£)	Petrol by motorbikes per capita (£)	Total transport per capita (£)
Spearman's rho	UR6FOLD	Correlation Coefficient	.812**	.849**	.849**	.848**	.849**
		Sig. (2-tailed)	.000	.000	.000	.000	.000
		N	369	369	369	369	369

Table 3: Pearson's correlation for £ spent and its relation with distance to population centers

Correlations

		Bus transport per capita (£)	diesel per capita (£)	petrol (car) per capita (£)	Petrol by motorbikes per capita (£)	Total transport per capita (£)	Bus transport per capita (£)
Distance to Cities	Pearson Correlation	.643**	.583**	.652**	.644**	.684**	.643**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000
	N	369	369	369	369	369	369
Distance to Towns	Pearson Correlation	.529**	.479**	.536**	.531**	.548**	.529**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000
	N	369	369	369	369	369	369
Distance to Villages	Pearson Correlation	.571**	.578**	.568**	.571**	.547**	.571**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000
	N	369	369	369	369	369	369
Population per square kilometer	Pearson Correlation	-.694**	-.670**	-.695**	-.694**	-.690**	-.694**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000
	N	369	369	369	369	369	369
Average distance to population centers	Pearson Correlation	.706**	.664**	.711**	.707**	.720**	.706**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000
	N	369	369	369	369	369	369
Distance to all services	Pearson Correlation	.788**	.754**	.792**	.788**	.797**	.788**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000
	N	369	369	369	369	369	369

5.3 Heater activity

Figure 2: correlation between April 2011 according to method I and April 2011 according to method II

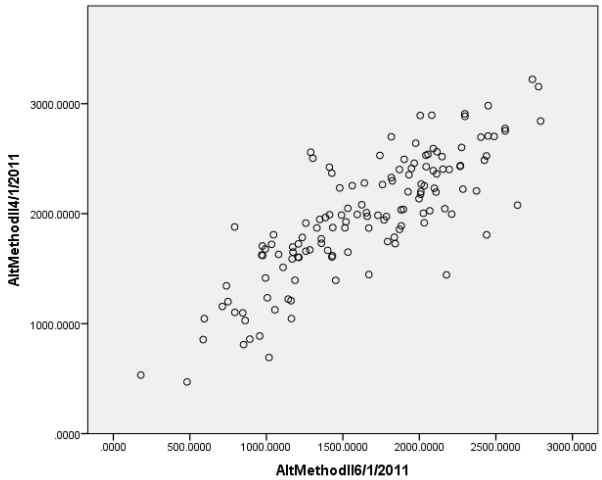


Figure 3: correlation between June 2011 and April 2011 according to method I

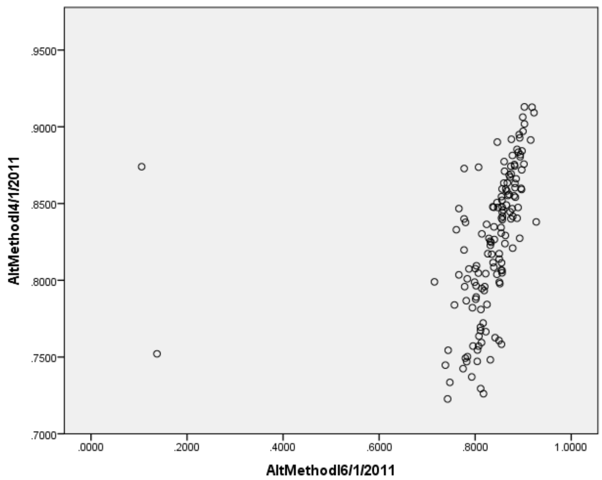


Figure 4: correlation between June 2011 and April 2011 according to method II

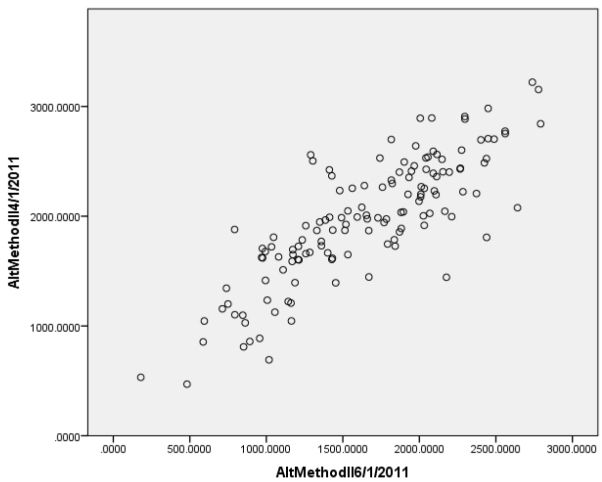


Table 4: Pearson's correlation for heater activity according to method I and method II

Correlations

		ActMethodI4/1/2011	ActMethodII4/1/2011
ActMethodI4/1/2011	Pearson Correlation	1	-.713**
	Sig. (2-tailed)		.000
	N	287	287
ActMethodII4/1/2011	Pearson Correlation	-.713**	1
	Sig. (2-tailed)	.000	
	N	287	287

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		ActMethodI6/1/2011	ActMethodII6/1/2011
ActMethodI6/1/2011	Pearson Correlation	1	-.416**
	Sig. (2-tailed)		.000
	N	187	187
ActMethodII6/1/2011	Pearson Correlation	-.416**	1
	Sig. (2-tailed)	.000	
	N	187	187

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		ActMethodI1/1/2011	ActMethodII1/1/2011
ActMethodI1/1/2011	Pearson Correlation	1	-.363*
	Sig. (2-tailed)		.012
	N	47	47
ActMethodII1/1/2011	Pearson Correlation	-.363*	1
	Sig. (2-tailed)	.012	
	N	47	47

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

		ActMethodI9/1/2011	ActMethodII9/1/2011
ActMethodI9/1/2011	Pearson Correlation	1	-.698**
	Sig. (2-tailed)		.000
	N	211	211
ActMethodII9/1/2011	Pearson Correlation	-.698**	1
	Sig. (2-tailed)	.000	
	N	211	211

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		ActMethodI11/1/2011	ActMethodII11/1/2011
ActMethodI11/1/2011	Pearson Correlation	1	-.542**
	Sig. (2-tailed)		.000
	N	199	199
ActMethodII11/1/2011	Pearson Correlation	-.542**	1
	Sig. (2-tailed)	.000	
	N	199	199

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		ActMethodI6/1/2012	ActMethodII6/1/2012
ActMethodI6/1/2012	Pearson Correlation	1	-.397**
	Sig. (2-tailed)		.000
	N	137	137
ActMethodII6/1/2012	Pearson Correlation	-.397**	1
	Sig. (2-tailed)	.000	
	N	137	137

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		ActMethodI9/1/2012	ActMethodII9/1/2012
ActMethodI9/1/2012	Pearson Correlation	1	-.674**
	Sig. (2-tailed)		.000
	N	136	136
ActMethodII9/1/2012	Pearson Correlation	-.674**	1
	Sig. (2-tailed)	.000	
	N	136	136

**. Correlation is significant at the 0.01 level (2-tailed).

Table 5: testing Pearson's correlation for warmth use of each month mutually with two other months. Measurement of heater activity according to method I

Correlations

		ActMethodI4/1/2011	ActMethodI6/1/2011
ActMethodI4/1/2011	Pearson Correlation	1	.268**
	Sig. (2-tailed)		.000
	N	185	185
ActMethodI6/1/2011	Pearson Correlation	.268**	1
	Sig. (2-tailed)	.000	
	N	185	185

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		ActMethodI6/1/2011	ActMethodI1/1/2011
ActMethodI6/1/2011	Pearson Correlation	1	.393*
	Sig. (2-tailed)		.012
	N	40	40
ActMethodI1/1/2011	Pearson Correlation	.393*	1
	Sig. (2-tailed)	.012	
	N	40	40

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

		ActMethodI1/1/2011	ActMethodI9/1/2011
ActMethodI1/1/2011	Pearson Correlation	1	.445**
	Sig. (2-tailed)		.007
	N	35	35
ActMethodI9/1/2011	Pearson Correlation	.445**	1
	Sig. (2-tailed)	.007	
	N	35	35

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		ActMethodI9/1/2011	ActMethodI11/1/2011
ActMethodI9/1/2011	Pearson Correlation	1	.374**
	Sig. (2-tailed)		.000
	N	173	173
ActMethodI11/1/2011	Pearson Correlation	.374**	1
	Sig. (2-tailed)	.000	
	N	173	173

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		ActMethodI11/1/2011	ActMethodI6/1/2012
ActMethodI11/1/2011	Pearson Correlation	1	.592**
	Sig. (2-tailed)		.000
	N	110	110
ActMethodI6/1/2012	Pearson Correlation	.592**	1
	Sig. (2-tailed)	.000	
	N	110	110

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		ActMethodI6/1/2012	ActMethodI9/1/2012
ActMethodI6/1/2012	Pearson Correlation	1	.687**
	Sig. (2-tailed)		.000
	N	105	105
ActMethodI9/1/2012	Pearson Correlation	.687**	1
	Sig. (2-tailed)	.000	
	N	105	105

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		ActMethodI4/1/2011	ActMethodI9/1/2012
ActMethodI4/1/2011	Pearson Correlation	1	.612**
	Sig. (2-tailed)		.000
	N	129	129
ActMethodI9/1/2012	Pearson Correlation	.612**	1
	Sig. (2-tailed)	.000	
	N	129	129

**. Correlation is significant at the 0.01 level (2-tailed).

Table 6: testing Pearson's correlation for each month mutually with two other months. Measurement of heater activity according to method II

Correlations

		ActMethodII4/1/2011	ActMethodII6/1/2011
ActMethodII4/1/2011	Pearson Correlation	1	.788**
	Sig. (2-tailed)		.000
	N	175	175
ActMethodII6/1/2011	Pearson Correlation	.788**	1
	Sig. (2-tailed)	.000	
	N	175	175

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		ActMethodII6/1/2011	ActMethodII1/1/2011
ActMethodII6/1/2011	Pearson Correlation	1	.131
	Sig. (2-tailed)		.426
	N	39	39
ActMethodII1/1/2011	Pearson Correlation	.131	1
	Sig. (2-tailed)	.426	
	N	39	39

Correlations

		ActMethodII1/1/2011	ActMethodII9/1/2011
ActMethodII1/1/2011	Pearson Correlation	1	.371*
	Sig. (2-tailed)		.034
	N	33	33
ActMethodII9/1/2011	Pearson Correlation	.371*	1
	Sig. (2-tailed)	.034	
	N	33	33

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

		ActMethodII9/1/2011	ActMethodII11/1/2011
ActMethodII9/1/2011	Pearson Correlation	1	.574**
	Sig. (2-tailed)		.000
	N	163	163
ActMethodII11/1/2011	Pearson Correlation	.574**	1
	Sig. (2-tailed)	.000	
	N	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		ActMethodII11/1/2011	ActMethodII6/1/2012
ActMethodII11/1/2011	Pearson Correlation	1	.531**
	Sig. (2-tailed)		.000
	N	107	107
ActMethodII6/1/2012	Pearson Correlation	.531**	1
	Sig. (2-tailed)	.000	
	N	107	107

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		ActMethodII6/1/2012	ActMethodII9/1/2012
ActMethodII6/1/2012	Pearson Correlation	1	.814**
	Sig. (2-tailed)		.000
	N	103	103
ActMethodII9/1/2012	Pearson Correlation	.814**	1
	Sig. (2-tailed)	.000	
	N	103	103

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		ActMethodII4/1/2011	ActMethodII9/1/2012
ActMethodII4/1/2011	Pearson Correlation	1	.633**
	Sig. (2-tailed)		.000
	N	127	127
ActMethodII9/1/2012	Pearson Correlation	.633**	1
	Sig. (2-tailed)	.000	
	N	127	127

**. Correlation is significant at the 0.01 level (2-tailed).

5.4 Thermal efficiency

Table 7: correlations on estimated thermal efficiency per month.

Correlations

		Apr2011 Mean	Jun2011 Mean
Apr2011ThermalEff	Pearson Correlation	1	.605**
	Sig. (2-tailed)		.000
	N	162	162
Jun2011ThermalEff	Pearson Correlation	.605**	1
	Sig. (2-tailed)	.000	
	N	162	162

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		Jan2011ThermalEff	Jun2011ThermalEff
Jan2011ThermalEff	Pearson Correlation	1	.639**
	Sig. (2-tailed)		.000
	N	40	40
Jun2011ThermalEff	Pearson Correlation	.639**	1
	Sig. (2-tailed)	.000	
	N	40	40

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		Jan2011 Mean	Jun2011 Mean
Jan2011 Mean	Pearson Correlation	1	.391
	Sig. (2-tailed)		.065
	N	23	23
Jun2011 Mean	Pearson Correlation	.391	1
	Sig. (2-tailed)	.065	
	N	23	23

Correlations

		Jan2011 Mean	Sep2011 Mean
Jan2011 Mean	Pearson Correlation	1	.425**
	Sig. (2-tailed)		.009
	N	37	37
Sep2011 Mean	Pearson Correlation	.425**	1
	Sig. (2-tailed)	.009	
	N	37	37

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		Nov2011 Mean	Sep2011 Mean
Nov2011 Mean	Pearson Correlation	1	.550**
	Sig. (2-tailed)		.000
	N	178	146
Sep2011 Mean	Pearson Correlation	.550**	1
	Sig. (2-tailed)	.000	
	N	146	146

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		Nov2011 Mean	Jun2012 Mean
Nov2011 Mean	Pearson Correlation	1	.505**
	Sig. (2-tailed)		.000
	N	123	108
Jun2012 Mean	Pearson Correlation	.505**	1
	Sig. (2-tailed)	.000	
	N	108	108

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		Sep2012 Mean	Jun2012 Mean
Sep2012 Mean	Pearson Correlation	1	.591**
	Sig. (2-tailed)		.000
	N	112	103
Jun2012 Mean	Pearson Correlation	.591**	1
	Sig. (2-tailed)	.000	
	N	103	103

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		Sep2012 Mean	Apr2011 Mean
Sep2012 Mean	Pearson Correlation	1	.595**
	Sig. (2-tailed)		.000
	N	107	107
Apr2011 Mean	Pearson Correlation	.595**	1
	Sig. (2-tailed)	.000	
	N	107	107

**. Correlation is significant at the 0.01 level (2-tailed).

Table 8: thermal efficiency and aggregated remoteness indices

Correlations

		AggegatedDistToServices	AvgAllDist	PopPerSqKM
Apr2011	Pearson Correlation	.153	.138	-.053
	Sig. (2-tailed)	.059	.089	.517
	N	153	153	153

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		AggegatedDistToServices	AvgAllDist	PopPerSqKM
	Pearson Correlation	.123	-.004	-.188
Jan2011	Sig. (2-tailed)	.422	.977	.217
	N	45	45	45

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		AggegatedDistToServices	AvgAllDist	PopPerSqKM
	Pearson Correlation	.048	.057	-.072
Jun2011	Sig. (2-tailed)	.669	.610	.519
	N	83	83	83

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		AggegatedDistToServices	AvgAllDist	PopPerSqKM
	Pearson Correlation	.337*	.333*	-.168
Jun2012	Sig. (2-tailed)	.011	.012	.217
	N	56	56	56

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		AggegatedDistToServices	AvgAllDist	PopPerSqKM
	Pearson Correlation	.238**	.177*	-.156
Nov2011	Sig. (2-tailed)	.006	.043	.074
	N	131	131	131

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

		AggegatedDistToServices	AvgAllDist	PopPerSqKM
	Pearson Correlation	.122	.239*	.010
Sep2011	Sig. (2-tailed)	.215	.014	.922
	N	105	105	105

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		AggegatedDistToServices	AvgAllDist	PopPerSqKM
	Pearson Correlation	.069	.214*	-.066
Sep2012	Sig. (2-tailed)	.520	.044	.539
	N	89	89	89

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

5.6 Warmth Use

Table 9: Pearson's correlation for average increase in temperatures inside the home; relation between months.

Correlations

		Apr11AvgHeatIncr	Jun11AvgHeatIncr
Apr11AvgHeatIncr	Pearson Correlation	1	.602**
	Sig. (2-tailed)		.000
	N	175	175
Jun11AvgHeatIncr	Pearson Correlation	.602**	1
	Sig. (2-tailed)	.000	
	N	175	175

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		Jun11AvgHeatIncr	Jan11AvgHeatIncr
Jun11AvgHeatIncr	Pearson Correlation	1	.336*
	Sig. (2-tailed)		.037
	N	39	39
Jan11AvgHeatIncr	Pearson Correlation	.336*	1
	Sig. (2-tailed)	.037	
	N	39	39

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

		Jan11AvgHeatIncr	Sep11AvgHeatIncr
Jan11AvgHeatIncr	Pearson Correlation	1	.111
	Sig. (2-tailed)		.533
	N	34	34
Sep11AvgHeatIncr	Pearson Correlation	.111	1
	Sig. (2-tailed)	.533	
	N	34	34

Correlations

		Sep11AvgHeatIncr	Nov11AvgHeatIncr
Sep11AvgHeatIncr	Pearson Correlation	1	.457**
	Sig. (2-tailed)		.000
	N	163	163
Nov11AvgHeatIncr	Pearson Correlation	.457**	1
	Sig. (2-tailed)	.000	
	N	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		Jun12AvgHeatIncr	Nov11AvgHeatIncr
Jun12AvgHeatIncr	Pearson Correlation	1	.484**
	Sig. (2-tailed)		.000
	N	108	108
Nov11AvgHeatIncr	Pearson Correlation	.484**	1
	Sig. (2-tailed)	.000	
	N	108	108

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		Jun12AvgHeatIncr	Sep12AvgHeatIncr
Jun12AvgHeatIncr	Pearson Correlation	1	.651**
	Sig. (2-tailed)		.000
	N	104	104
Sep12AvgHeatIncr	Pearson Correlation	.651**	1
	Sig. (2-tailed)	.000	
	N	104	104

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		Apr11AvgHeatIncr	Sep12AvgHeatIncr
Apr11AvgHeatIncr	Pearson Correlation	1	.595**
	Sig. (2-tailed)		.000
	N	128	128
Sep12AvgHeatIncr	Pearson Correlation	.595**	1
	Sig. (2-tailed)	.000	
	N	128	128

**. Correlation is significant at the 0.01 level (2-tailed).

Table 10: Pearson's correlation for average warmth use; relation between months.

Correlations

		Apr11HeatUse	Jun11HeatUse
Apr11HeatUse	Pearson Correlation	1	.718**
	Sig. (2-tailed)		.000
	N	176	176
Jun11HeatUse	Pearson Correlation	.718**	1
	Sig. (2-tailed)	.000	
	N	176	176

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		Jun11HeatUse	Jan11HeatUse
Jun11HeatUse	Pearson Correlation	1	.260
	Sig. (2-tailed)		.101
	N	41	41
Jan11HeatUse	Pearson Correlation	.260	1
	Sig. (2-tailed)	.101	
	N	41	41

Correlations

		Jan11HeatUse	Sep11HeatUse
Jan11HeatUse	Pearson Correlation	1	.151
	Sig. (2-tailed)		.395
	N	34	34
Sep11HeatUse	Pearson Correlation	.151	1
	Sig. (2-tailed)	.395	
	N	34	34

Correlations

		Sep11HeatUse	Nov11HeatUse
Sep11HeatUse	Pearson Correlation	1	.511**
	Sig. (2-tailed)		.000
	N	163	163
Nov11HeatUse	Pearson Correlation	.511**	1
	Sig. (2-tailed)	.000	
	N	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		Jun12HeatUse	Nov11HeatUse
Jun12HeatUse	Pearson Correlation	1	.518**
	Sig. (2-tailed)		.000
	N	107	107
Nov11HeatUse	Pearson Correlation	.518**	1
	Sig. (2-tailed)	.000	
	N	107	107

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		Jun12HeatUse	Sep12HeatUse
Jun12HeatUse	Pearson Correlation	1	.793**
	Sig. (2-tailed)		.000
	N	103	103
Sep12HeatUse	Pearson Correlation	.793**	1
	Sig. (2-tailed)	.000	
	N	103	103

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		Apr11HeatUse	Sep12HeatUse
Apr11HeatUse	Pearson Correlation	1	.618**
	Sig. (2-tailed)		.000
	N	127	127
Sep12HeatUse	Pearson Correlation	.618**	1
	Sig. (2-tailed)	.000	
	N	127	127

**. Correlation is significant at the 0.01 level (2-tailed).

Table 11: Pearson's correlation for CO_2 emissions for heating; relation between months.

Correlations

		KgCO2Apr11HeatUse	KgCO2Jun11HeatUse
KgCO2Apr11HeatUse	Pearson Correlation	1	.733**
	Sig. (2-tailed)		.000
	N	175	175
KgCO2Jun11HeatUse	Pearson Correlation	.733**	1
	Sig. (2-tailed)	.000	
	N	175	175

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		KgCO2Jun11HeatUse	KgCO2Jan11HeatUse
KgCO2Jun11HeatUse	Pearson Correlation	1	.325*
	Sig. (2-tailed)		.041
	N	40	40
KgCO2Jan11HeatUse	Pearson Correlation	.325*	1
	Sig. (2-tailed)	.041	
	N	40	40

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

		KgCO2Jan11HeatUse	KgCO2Sep11HeatUse
KgCO2Jan11HeatUse	Pearson Correlation	1	.227
	Sig. (2-tailed)		.196
	N	34	34
KgCO2Sep11HeatUse	Pearson Correlation	.227	1
	Sig. (2-tailed)	.196	
	N	34	34

Correlations

		KgCO2Sep11HeatUse	KgCO2Nov11HeatUse
KgCO2Sep11HeatUse	Pearson Correlation	1	.528**
	Sig. (2-tailed)		.000
	N	163	163
KgCO2Nov11HeatUse	Pearson Correlation	.528**	1
	Sig. (2-tailed)	.000	
	N	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		KgCO2Jun12HeatUse	KgCO2Nov11HeatUse
KgCO2Jun12HeatUse	Pearson Correlation	1	.512**
	Sig. (2-tailed)		.000
	N	107	107
KgCO2Nov11HeatUse	Pearson Correlation	.512**	1
	Sig. (2-tailed)	.000	
	N	107	107

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		KgCO2Jun12HeatUse	KgCO2Sep12HeatUse
KgCO2Jun12HeatUse	Pearson Correlation	1	.812**
	Sig. (2-tailed)		.000
	N	103	103
KgCO2Sep12HeatUse	Pearson Correlation	.812**	1
	Sig. (2-tailed)	.000	
	N	103	103

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		KgCO2Apr11HeatUse	KgCO2Sep12HeatUse
KgCO2Apr11HeatUse	Pearson Correlation	1	.660**
	Sig. (2-tailed)		.000
	N	127	127
KgCO2Sep12HeatUse	Pearson Correlation	.660**	1
	Sig. (2-tailed)	.000	
	N	127	127

**. Correlation is significant at the 0.01 level (2-tailed).

Table 12: Pearson's correlation for estimated £ spent heating; relation between months.

Correlations

		PoundsApr11HeatUse	PoundsJun11HeatUse
PoundsApr11HeatUse	Pearson Correlation	1	.730**
	Sig. (2-tailed)		.000
	N	175	175
PoundsJun11HeatUse	Pearson Correlation	.730**	1
	Sig. (2-tailed)	.000	
	N	175	175

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		PoundsJun11HeatUse	PoundsJan11HeatUse
PoundsJun11HeatUse	Pearson Correlation	1	.463**
	Sig. (2-tailed)		.001
	N	47	47
PoundsJan11HeatUse	Pearson Correlation	.463**	1
	Sig. (2-tailed)	.001	
	N	47	47

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		PoundsJan11HeatUse	PoundsSep11HeatUse
PoundsJan11HeatUse	Pearson Correlation	1	.601**
	Sig. (2-tailed)		.000
	N	181	181
PoundsSep11HeatUse	Pearson Correlation	.601**	1
	Sig. (2-tailed)	.000	
	N	181	181

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		PoundsSep11HeatUse	PoundsNov11HeatUse
PoundsSep11HeatUse	Pearson Correlation	1	.507**
	Sig. (2-tailed)		.000
	N	107	107
PoundsNov11HeatUse	Pearson Correlation	.507**	1
	Sig. (2-tailed)	.000	
	N	107	107

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		PoundsJun12HeatUse	PoundsNov11HeatUse
PoundsJun12HeatUse	Pearson Correlation	1	.879**
	Sig. (2-tailed)		.000
	N	120	120
PoundsNov11HeatUse	Pearson Correlation	.879**	1
	Sig. (2-tailed)	.000	
	N	120	120

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		PoundsJun12HeatUse	PoundsSep12HeatUse
PoundsJun12HeatUse	Pearson Correlation	1	.562**
	Sig. (2-tailed)		.000
	N	139	139
PoundsSep12HeatUse	Pearson Correlation	.562**	1
	Sig. (2-tailed)	.000	
	N	139	139

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		PoundsApr11HeatUse	PoundsSep12HeatUse
PoundsApr11HeatUse	Pearson Correlation	1	.649**
	Sig. (2-tailed)		.000
	N	127	127
PoundsSep12HeatUse	Pearson Correlation	.649**	1
	Sig. (2-tailed)	.000	
	N	127	127

**. Correlation is significant at the 0.01 level (2-tailed).

5.7 Thermal comfort

Table 12: Pearson's correlations for thermal comfort and average outside temperature

Correlations

		JanAVG2	JanAvgOutsTemp
JanAVG2	Pearson Correlation	1	.179
	Sig. (2-tailed)		.246
	N	44	44
JanAvgOutsTemp	Pearson Correlation	.179	1
	Sig. (2-tailed)	.246	
	N	44	44

Correlations

		JanAVG5	JanAvgOutsTemp
JanAVG5	Pearson Correlation	1	.179
	Sig. (2-tailed)		.244
	N	44	44
JanAvgOutsTemp	Pearson Correlation	.179	1
	Sig. (2-tailed)	.244	
	N	44	44

Correlations

		AprAVG2	AprAvgOutsTemp
AprAVG2	Pearson Correlation	1	.105
	Sig. (2-tailed)		.080
	N	278	278
AprAvgOutsTemp	Pearson Correlation	.105	1
	Sig. (2-tailed)	.080	
	N	278	278

Correlations

		AprAVG5	AprAvgOutsTemp
AprAVG5	Pearson Correlation	1	.104
	Sig. (2-tailed)		.084
	N	278	278
AprAvgOutsTemp	Pearson Correlation	.104	1
	Sig. (2-tailed)	.084	
	N	278	278

Correlations

		Jun11AVG2	Jun11AvgOutsTemp
Jun11AVG2	Pearson Correlation	1	.094
	Sig. (2-tailed)		.201
	N	189	189
Jun11AvgOutsTemp	Pearson Correlation	.094	1
	Sig. (2-tailed)	.201	
	N	189	189

Correlations

		Jun11AVG5	Jun11AvgOutsTemp
Jun11AVG5	Pearson Correlation	1	.090
	Sig. (2-tailed)		.217
	N	189	189
Jun11AvgOutsTemp	Pearson Correlation	.090	1
	Sig. (2-tailed)	.217	
	N	189	189

Correlations

		Sep11AVG2	Sep11AvgOutsTemp
Sep11AVG2	Pearson Correlation	1	.084
	Sig. (2-tailed)		.232
	N	204	204
Sep11AvgOutsTemp	Pearson Correlation	.084	1
	Sig. (2-tailed)	.232	
	N	204	204

Correlations

		Sep11AVG5	Sep11AvgOutsTemp
Sep11AVG5	Pearson Correlation	1	.086
	Sig. (2-tailed)		.223
	N	204	204
Sep11AvgOutsTemp	Pearson Correlation	.086	1
	Sig. (2-tailed)	.223	
	N	204	204

Correlations

		Nov11AVG2	Nov11AvgOutsTemp
Nov11AVG2	Pearson Correlation	1	.060
	Sig. (2-tailed)		.413
	N	190	190
Nov11AvgOutsTemp	Pearson Correlation	.060	1
	Sig. (2-tailed)	.413	
	N	190	190

Correlations

		Nov11AVG5	Nov11AvgOutsTemp
Nov11AVG5	Pearson Correlation	1	.060
	Sig. (2-tailed)		.408
	N	190	190
Nov11AvgOutsTemp	Pearson Correlation	.060	1
	Sig. (2-tailed)	.408	
	N	190	190

Correlations

		Jun12AVG2	Jun12AvgOutsTemp
Jun12AVG2	Pearson Correlation	1	.092
	Sig. (2-tailed)		.290
	N	133	133
Jun12AvgOutsTemp	Pearson Correlation	.092	1
	Sig. (2-tailed)	.290	
	N	133	133

Correlations

		Jun12AVG5	Jun12AvgOutsTemp
Jun12AVG5	Pearson Correlation	1	.094
	Sig. (2-tailed)		.283
	N	133	133
Jun12AvgOutsTemp	Pearson Correlation	.094	1
	Sig. (2-tailed)	.283	
	N	133	133

Correlations

		Sep12AVG2	Sep12AvgOutsTemp
Sep12AVG2	Pearson Correlation	1	-.014
	Sig. (2-tailed)		.873
	N	128	128
Sep12AvgOutsTemp	Pearson Correlation	-.014	1
	Sig. (2-tailed)	.873	
	N	128	128

Correlations

		Sep12AVG5	Sep12AvgOutsTemp
Sep12AVG5	Pearson Correlation	1	-.015
	Sig. (2-tailed)		.866
	N	128	128
Sep12AvgOutsTemp	Pearson Correlation	-.015	1
	Sig. (2-tailed)	.866	
	N	128	128

Table 13: Student's T test for urban (category 1) and rural (category 2) thermal comfort.

Group Statistics

	UR2FOLD	N	Mean	Std. Deviation	Std. Error Mean
DifferenceALLThermComf	Urban	91	-.058139	2.2245116	.2331922
	Rural	84	.062460	2.2377903	.2441629

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	Df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
DifferenceALLThermComf	Equal variances assumed	.001	.981	-.357	173	.721	-.1205993	.3375493	-.7868446	.5456459
	Equal variances not assumed			-.357	171.716	.721	-.1205993	.3376302	-.7870392	.5458405

5.8 Demography and geographical characteristics

Table 14: Pearson's correlations for warmth use, adaptive comfort, thermal efficiency, ActMethod I and method II and their relations with distances to services by public transport. Data are from 2009.

		ThermalEff	AvgHeatIncr1	AvgHeatIncr2	ActMethod I	ActMethod II	WarmthUse
CS-publicgp	Pearson Correlation	.249**	.176**	.131*	-.189**	0.098506948	0.083613
	Sig. (2-tailed)	1.29E-05	0.004926	0.024083	0.00104022	0.0890656	0.149226
	N	299	255	298	299	299	299
CS-publichiedu1	Pearson Correlation	.211**	.165**	.126*	-.225**	.123*	.124*
	Sig. (2-tailed)	0.000239	0.008261	0.030294	8.47633E-05	0.033280759	0.032081
	N	299	255	298	299	299	299
CS-publicjcp1	Pearson Correlation	.179**	.129*	0.071817	-0.10975675	.204**	0.013823
	Sig. (2-tailed)	0.001918	0.038789	0.216406	0.05800596	0.000392113	0.811855
	N	299	255	298	299	299	299
CS-publiclibrary1	Pearson Correlation	.191**	.223**	.140*	-.162**	0.107247578	0.057566
	Sig. (2-tailed)	0.000921	0.000339	0.015909	0.004910924	0.064017026	0.321167
	N	299	255	298	299	299	299
CS-publicnursery1	Pearson Correlation	.144*	.173**	.140*	-.155**	0.077741669	0.05798
	Sig. (2-tailed)	0.0128	0.00559	0.01557	0.007219522	0.18002495	0.317692
	N	299	255	298	299	299	299
CS-publicpolice1	Pearson Correlation	.207**	.231**	.138*	-.175**	0.099441076	0.083718
	Sig. (2-tailed)	0.000309	0.0002	0.017366	0.002411776	0.086061135	0.148715
	N	299	255	298	299	299	299
CS-publicpost	Pearson Correlation	.166**	.209**	.124*	-.140*	.126*	0.059878
	Sig. (2-tailed)	0.004093	0.000784	0.032682	0.015770806	0.029680304	0.302085
	N	299	255	298	299	299	299
CS-publicshopping	Pearson Correlation	.189**	.220**	.131*	-.176**	.119*	0.086304
	Sig. (2-tailed)	0.001034	0.000412	0.023749	0.002290549	0.039558037	0.136522
	N	299	255	298	299	299	299
CS-publicatm1	Pearson	0.086333	.176**	0.031534	-	-9.14094E-05	-0.00705

	Correlation				0.023533137		
	Sig. (2-tailed)	0.136389	0.004751	0.587678	0.68527344	0.998744134	0.903372
	N	299	255	298	299	299	299
CS-publicbank1	Pearson Correlation	.213**	.198**	.167**	-.182**	.140*	0.084976
	Sig. (2-tailed)	0.000208	0.001521	0.003803	0.001554033	0.015608306	0.142685
	N	299	255	298	299	299	299
CS-publiccas1	Pearson Correlation	.130*	0.107319	0.111521	-.156**	.198**	0.060726
	Sig. (2-tailed)	0.024555	0.087217	0.054472	0.006817509	0.00059042	0.295273
	N	299	255	298	299	299	299
CS-publicchemist1	Pearson Correlation	0.039579	.129*	0.054492	-0.019205538	-0.006392595	0.004667
	Sig. (2-tailed)	0.495372	0.038885	0.348543	0.740845214	0.912348766	0.935944
	N	299	255	298	299	299	299
CS-publicfuredu1	Pearson Correlation	.255**	.125*	0.097186	-.212**	.148*	0.083406
	Sig. (2-tailed)	8.08E-06	0.045628	0.094012	0.000216705	0.010251482	0.150237
	N	299	255	298	299	299	299
CS-publicgenstore1_1	Pearson Correlation	.168**	.185**	.121*	-.147*	.156**	0.065599
	Sig. (2-tailed)	0.003602	0.003067	0.036501	0.011112878	0.006949412	0.258148
	N	299	255	298	299	299	299
aggregatedAll	Pearson Correlation	.214**	.206**	.137*	-.187**	.147*	0.078411
	Sig. (2-tailed)	0.000189	0.000942	0.017764	0.00115408	0.010941123	0.176292
	N	299	255	298	299	299	299

Table 15: Pearson's correlations for warmth use, adaptive comfort, thermal efficiency, heater activity Method I and method II and their relations with distances to services by drive times. Data are from 2009.

		Thermal Eff	AvgHeat Inr1	AvgHeat Inr2	Average method1	Average method2	WarmthUse
CS-drivegp1	Pearson Correlation	0.22	0.119936	0.090033	-0.151	0.048321	0.063177
	Sig. (2-tailed)	0.000122	0.055783	0.120942	0.008808	0.405111	0.27618
	N	299	255	298	299	299	299
CS-drivehiedu1	Pearson Correlation	0.163	0.110348	0.084383	-0.184	0.075473	0.110344
	Sig. (2-tailed)	0.004834	0.078606	0.146185	0.001412	0.193108	0.056668
	N	299	255	298	299	299	299
CS-drivejcp1	Pearson Correlation	0.123	0.019001	-0.00359	-0.03849	0.163	-0.02469
	Sig. (2-tailed)	0.034186	0.762679	0.950756	0.507295	0.004641	0.670686
	N	299	255	298	299	299	299
CS-drivelibrary1	Pearson Correlation	0.195	0.198	0.132	-0.137	0.079201	0.055181
	Sig. (2-tailed)	0.000693	0.001446	0.022702	0.017554	0.171964	0.341661
	N	299	255	298	299	299	299
CS-drivenursery1	Pearson Correlation	0.266	0.217	0.156	-0.193	0.04457	0.075838
	Sig. (2-tailed)	3.20E-06	0.000492	0.006927	0.000803	0.442583	0.190954
	N	299	255	298	299	299	299
CS-drivepolice1	Pearson Correlation	0.202	0.198	0.132	-0.161	0.053601	0.099276
	Sig. (2-tailed)	0.000453	0.001446	0.022755	0.005285	0.355678	0.086587
	N	299	255	298	299	299	299
CS-drivepost1	Pearson Correlation	0.153	0.209	0.102776	-0.116	0.073567	0.038701
	Sig. (2-tailed)	0.00819	0.000778	0.076489	0.045635	0.204628	0.504993
	N	299	255	298	299	299	299
CS-driveshopping1	Pearson Correlation	0.145	0.172	0.087911	-0.13	0.08241	0.076576

	Sig. (2-tailed)	0.012031	0.005847	0.12999	0.024386	0.155183	0.186664
	N	299	255	298	299	299	299
CS-driveatm1	Pearson Correlation	0.189	0.218	0.162	-0.174	0.117	0.099784
	Sig. (2-tailed)	0.001054	0.000468	0.005137	0.002532	0.043406	0.08498
	N	299	255	298	299	299	299
CS-drivebank1	Pearson Correlation	0.192	0.142	0.155	-0.143	0.096954	0.087256
	Sig. (2-tailed)	0.00087	0.02299	0.00747	0.013095	0.094247	0.132236
	N	299	255	298	299	299	299
CS-drivecas1	Pearson Correlation	0.069616	-0.01215	0.060989	-0.08822	0.182	0.035862
	Sig. (2-tailed)	0.230064	0.846885	0.294002	0.12799	0.001545	0.536767
	N	299	255	298	299	299	299
CS-drivechemist1	Pearson Correlation	0.209	0.17	0.116	-0.14	0.099006	0.067334
	Sig. (2-tailed)	0.000271	0.006426	0.04462	0.01573	0.087452	0.245744
	N	299	255	298	299	299	299
CS-drivefuredu1	Pearson Correlation	0.217	0.013414	0.036577	-0.167	0.124	0.068546
	Sig. (2-tailed)	0.000157	0.831198	0.529365	0.003705	0.032393	0.237323
	N	299	255	298	299	299	299
CS-drivegenstore1	Pearson Correlation	0.117	0.115689	0.072448	-0.09246	0.156	0.054069
	Sig. (2-tailed)	0.042724	0.065106	0.21239	0.110616	0.006707	0.351488
	N	299	255	298	299	299	299
AllDrive2	Pearson Correlation	0.214	0.131	0.102989	-0.175	0.145	0.082816
	Sig. (2-tailed)	0.000197	0.035932	0.075879	0.002346	0.01181	0.153155
	N	299	255	298	299	299	299

Table 16: differences in strength of correlations with variables related to warmth use: public transport (blue, positive numbers) and drive times by car (red, negative numbers). Empty cells indicate that no significant correlations existed for both public transport data and drive time data.

	Thermal Eff	AvgHeatIn cr1	AvgHeatIn cr2	ActMeth od I	ActMetho d II	Warmth Use
CS-publicgp	0.029	0.056064	0.040967	0.038		
CS-publichiedu1	0.048	0.054652	0.041617	0.041	0.047527	0.013656
CS-publicjcp1	0.056	0.109999			0.041	
CS-publiclibrary1	-0.004	0.025	0.008	0.025		
CS-publicnursery1	-0.122	-0.044	-0.016	-0.038		
CS-publicpolice1	0.005	0.033	0.006	0.014		
CS-publicpost	0.013		0.021224	0.024	0.052433	
CS-publicshopping	0.044	0.048	0.043089	0.046	0.03659	
CS-publicatm1	-0.102667	-0.042	-0.130466	-0.15047	-0.116909	
CS-publicbank1	0.021	0.056	0.012	0.039	0.043046	
CS-publiccas1	0.060384			0.06778	0.016	
CS-publicchemist1	-0.169421	-0.041	-0.061508	-0.12079		
CS-publicfuredu1	0.038	0.111586		0.045	0.024	
CS-publicgenstore1_1	0.051	0.069311	0.048552	0.05454		
Aggregated Drive Times to above services		0.075	0.034011	0.012	0.002	
Aggregated Drive Times to above and other services	-0.001	0.067	0.048	-0.013	0.043	-0.044589
Amount of times public services has a stronger correlation than drive times	4	7	7	7	7	0

Figure 5: histogram of dependent variable thermal efficiency and amount of built-up area as in dependent variable

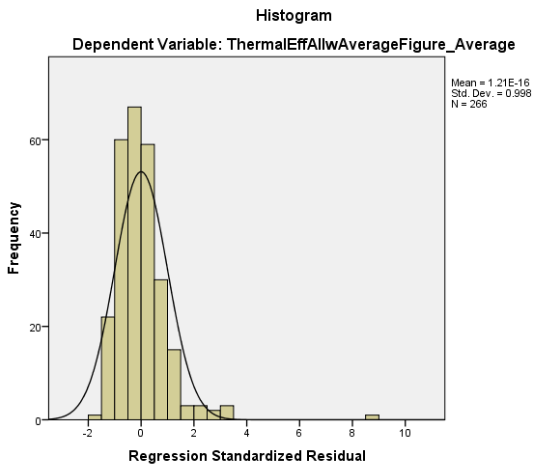


Table 17: stepwise linear regression on remoteness indices including amount of built up area within a 200m radius.

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	AggegatedDistToServices	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

a. Dependent Variable: ThermalEff

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.215[a]	.046	.043	.0175661

a. Predictors: (Constant), AggegatedDistToServices
b. Dependent Variable: ThermalEff

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.004	1	.004	12.810	.000[b]
	Residual	.081	264	.000		
	Total	.085	265			

a. Dependent Variable: ThermalEff
b. Predictors: (Constant), AggegatedDistToServices

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.030	.002		12.302	.000
	AggegatedDistToServices	.001	.000	.215	3.579	.000

a. Dependent Variable: ThermalEff

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	BuiltUpArea200	-.055[b]	-.744	.458	-.046	.652
	AvgAllDist	.056[b]	.657	.512	.040	.504
	PopPerSqKM	-.028[b]	-.320	.749	-.020	.486

a. Dependent Variable: ThermalEff
b. Predictors in the Model: (Constant), AggegatedDistToServices

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.031592	.047753	.037673	.0038553	267
Residual	-.0333438	.1608172	-.0000133	.0175013	267
Std. Predicted Value	-1.574	2.611	.001	.998	267
Std. Residual	-1.898	9.155	-.001	.996	267

a. Dependent Variable: ThermalEff