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Energy Poverty in the Dublin Region: Modelling Geographies of Risk

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Master thesis, 30 credits, in Geographical Information Science

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ABSTRACT

Energy poverty is, in the European context, defined as a household's inability to obtain a socially and materially acceptable level of energy services in the home. This is a widespread issue affecting an estimated 50 to 125 million people in Europe. Negative consequences include, but are not limited to, childhood asthma, mental health issues and in the worst case, premature death. The problem is largely under-researched and widely absent in public debates in Europe, and a common definition at the level of the EU commission is still lacking.

A big exception from this lack of attention are Ireland and the UK, where the issue has received policy recognition for decades and has been part of scholarly debates since the 1980s.

Tackling energy poverty through proactive area-based schemes has seen some successes in the UK. These schemes target groups of households in the same geographic area and can thereby assist a greater number of energy poor at a lower cost per household. The identification of the areas is often conducted with the help of energy poverty risk prediction models developed in Geographical Information Systems (GIS).

By contrast, in Ireland there is currently no area-based energy poverty alleviation programme that proactively seeks out high-risk communities. Moreover, the scholarly work in the country dedicated to risk modelling of energy poverty is, at best, nascent. Meanwhile, a growing number of Irish households are experiencing difficulties with keeping their homes adequately warm, increasing the urgency to act.

Against this backdrop, this master thesis seeks to fill a crucial, and timely, research gap. The main aims of this study are: 1) to develop a model for predicting geographic areas at high risk of energy poverty in Ireland, and validate its accuracy; 2) apply and validate the model to the Dublin region to identify high risk areas and groups of energy poor households. In achieving this, the work not only provides novel empirical insights for the selected region, but also makes methodological and theoretical advances in the field of energy poverty risk modelling.

To pursue these objectives, I apply a mixed-methods approach. A GIS-based Multi-Criteria Analysis (MCA) is used for the model design. To evaluate different approaches to energy poverty prediction modelling, three models are produced: two based on different conceptual understandings of energy poverty, and one uncalibrated test model. Census variables combined with a unique dwelling energy efficiency dataset form the input data. Finally, structured interviews with 80 households in the study area are conducted to assess the risk prediction accuracy of the models and potential differences in household experiences with energy poverty.

Notwithstanding certain limitations in terms of the households reached through the survey, these methods and research steps lead to the following major results of the study:

- Energy poverty risk prediction must be modelled considering both social and physical dimension factors in order to aptly account for the complex nature of the problem.

- Nonetheless, the results display a model of best fit which particularly emphasises social risk factors. Thus, social vulnerability is a stronger determinant of risk than the energy efficiency of the built environment.
- A distinct geography of high risk areas can be identified along the river Liffey in the Dublin City area.
- Based on the survey findings, households experiencing energy poverty can be grouped into three different types: those with low levels of employment and with existing social welfare support; those with medium levels of employment with little social welfare support; and those with high employment level, with little social welfare support in houses of extremely poor energy efficiency. This consequently means that policy needs are not homogenous for all affected households.
- Several steps by both scholars and decision-makers should be taken to improve the efficacy of current policy efforts in Ireland. Some of the major recommendations that are derived from the study results are: conducting targeted information campaigns in high risk areas to increase awareness of existing policy programmes; redesigning current financial assistance to account for the energy efficiency of dwellings and not solely rely on socio economic criteria; identifying the break-point where good energy efficiency of the dwelling becomes a negating factor for socially vulnerable households otherwise at high risk of energy poverty.

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LIST OF ABBREVIATIONS

1+ EPI	One or more energy poverty indicators
2+ EPI	Two or more energy poverty indicators
AGE	Model attribute: People aged 16 - 34
AHP	Analytical Hierarchy Process
BEC	Better Energy Communities
BAD	Model attribute: Bad/very bad health
BER	Building Energy Rating, ALSO Model attribute
CEN	Irish Census 2011 dataset
CES	Chief Economic Supporter
CHLD	Model attribute: Families with 4+ children
COD	Codema energy efficiency dataset
CSO	Irish Central Statistics Office
DCENR	Department Communications, Energy & Natural Resources
DISE	Model attribute: Divorced/separated marital status
EPI	Energy Poverty Indicator
EPR	Energy poverty Risk
FPI	Fuel Poverty Index
GIS	Geographical Information Systems
HIPO	Energy poverty type identified: High employment level poor housing
LCL	Model attribute: Local authority tenant.
LOME	Energy poverty type identified: Low employment level medium to poor housing
LONE	Model attribute: Lone parents
MCA	Multi Criteria Analysis
MEME	Energy poverty type identified: Medium employment level medium to poor housing
NOED	Model attribute: Lower than upper secondary educational attainment
OA	Census Output Areas (smallest spatial unit coming out of the UK census)
PRIV	Model attribute: Private landlord tenant
RET	Model attribute: Retired
SAPS	Small Area Population Statistics (smallest spatial unit coming out of the Irish census)
SEAI	Sustainable Energy Authority of Ireland
SIDI	Model attribute: Adult who cannot work due to sickness/disability
SING	Model attribute: Single marital status
THED	Model attribute: Completed 3rd level education

1. INTRODUCTION

1.1. ENERGY POVERTY IN EUROPE

Energy poverty is defined as a household's inability to obtain a socially and materially acceptable level of energy services in the home (Bouzarovski, 2014; Bouzarovski et al., 2012; Thomson et al., 2016). The topic has gathered increasing attention from scholars and practitioners alike, in particular as a serious challenge in the developing world, where the problem often is framed in terms of access to energy. By contrast, energy poverty in Europe is receiving much less academic and public attention – and where it does, it is primarily understood as an issue of affordability (Bouzarovski, 2014; Thomson and Snell, 2013; Thomson et al., 2016).

In fact, until recently, this was nearly exclusively discussed as an issue isolated to some parts of Europe such as the UK and Ireland. However, it is now known that the issue of energy poverty as defined above, is an EU-wide problem affecting people in all member states, with particular prominence in the Central Eastern European and the Southern parts (Bouzarovski, 2014; Thomson and Snell, 2013; Thomson et al., 2016). It is estimated that as many as 50 to 125 million people in the EU are affected (Atanasiu et al., 2014). Despite this a common definition at the level of the EU commission is still lacking (Thomson et al., 2016). Consequently, this remains a new policy area for many EU member states (Bouzarovski, 2014; Pye et al., 2015), and in some cases, for example Sweden, the issue has not been granted policy recognition (Johansson et al., 2015).

Adding to the complexity of the issue is that the definition makes the problem highly context-dependent, as what is socially and materially acceptable varies between places and people. This subjective condition notwithstanding, living with inadequate energy services often result in negative impacts relating to both health and social aspects. Households may, for example, change their habits and only use the heating when the children are home and otherwise live in the cold (Middlemiss and Gillard, 2015). In relation to health, negative effects include mental health issues (Atanasiu et al., 2014; Thomson and Snell, 2013); childhood asthma (Tod et al., 2016); cardiovascular and respiratory health issues among elderly (Healy and Clinch, 2002) and, in the worst case, premature death (Atanasiu et al., 2014; Healy, 2003b).

Causes of energy poverty are generally discussed as a result of low household income, high energy prices, and energy-inefficient housing and appliances (Healy, 2003a; Thomson et al., 2016). These three factors illustrate that the issue rests on a physical dimension relating to housing and appliances, as well as a social dimension relating to socio-economic factors that impact on a household's ability to afford sufficient energy services. However, the lack of an agreed upon approach to define and measure energy poverty at the EU level, means that efforts to appraise the problem on both national and pan-European scales have to work with various proxy indicators. This is aggravated by a lack of data on energy expenditure and building energy efficiency across the EU. Figure 1.1 highlights the overlaps between the causal building blocks of energy poverty, which represents the space where researchers are trying to identify indicators of the problem.

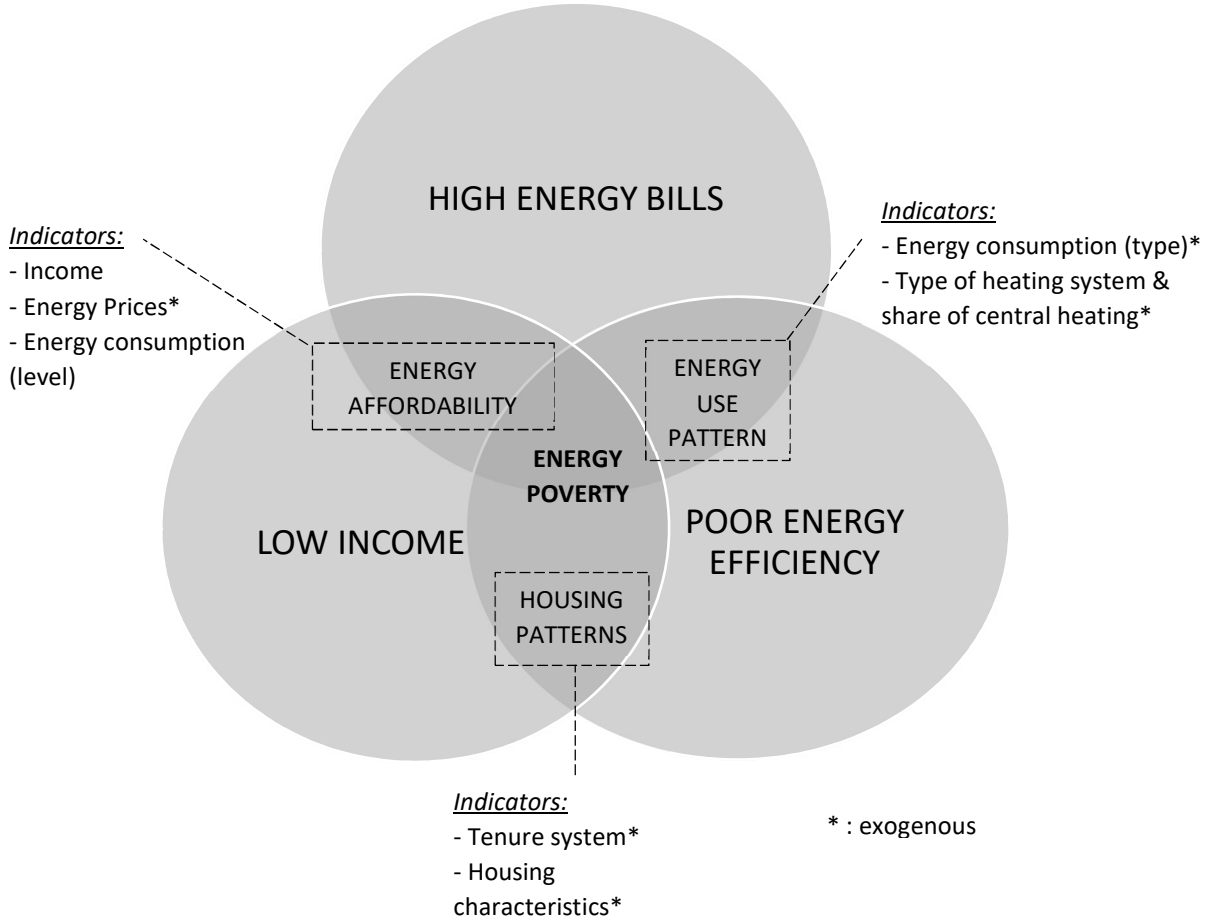


Figure 1.1. The causal building blocks of energy poverty and related indicators.
This outline commonly identified indicators from a European wide perspective and how these relate to the causes of energy poverty. Adapted from: Pye et al. (2015: 10).

1.2. THE IRISH EXPERIENCE

Ireland and the UK stand out in the energy poverty debate, as these countries have given the problem policy recognition for decades. The Irish policy efforts have roots going back to the introduction of the cheap fuel scheme in 1942 (DCENR, 2016: 8). Later, in 1977, the fuel allowance was introduced in response to the 1970s oil crisis (Healy, 2003a: 79). This is a welfare payment aimed at energy affordability still in use today (Citizens Information, 2016b). In the 1980s, scholarly debate around energy poverty emerged and, during the same time, grants were introduced specifically targeting attic insulation. These were subsequently stopped in the mid-80s as the economy of the country slowed down (Healy, 2003a). It was not until 2000 that the first national energy efficiency programs, aimed at improving the housing stock and alleviating energy poverty, were rolled out (DCENR, 2016: 8). Hence, prior to this, except for the attic insulation schemes, the issue was mainly addressed through supplementing income, thus addressing the socio-economic aspects related to affordability. Meanwhile, tackling the physical dimension that is also part of energy poverty remains an emerging field.

In 2011 the first national strategy to combat energy poverty ("Warmer Homes: A Strategy for Affordable Energy in Ireland") was launched (DCENR, 2011). This has brought progress in many regards, including that an estimated 120,000 homes in energy poverty have received free of charge retrofitting to improve their energy efficiency (DCENR, 2015). Despite these improvements, the Department of Communications, Energy and Natural Resources (DCENR) (2015) has noted an increase of households in energy poverty between 2008 and 2012. They also highlight that the targeting of policy measures can be improved to reach a greater portion of affected households. An example is that many households in the private rented sector do not avail of sufficient support, partially as one of the biggest home improvement schemes in practice only is available to homeowners (DCENR, 2015: 9). This is alarming since a growing number of people in Ireland, especially in Dublin, are living in rented accommodation where rents are increasing dramatically and putting greater strain on the economic situation of households (DCENR, 2016: 17). Additionally, about half of the private rented dwellings in Dublin city have poor energy efficiency (Codema, 2015).

There is one scheme aimed at alleviating energy poverty in Ireland that is available to all tenure statuses, the "Better Energy Communities" (BEC) scheme. This "targets interventions at all homes in a certain distinct geographic area deemed to be at particular risk of energy poverty." (DCENR, 2015: 9). Through geographical targeting, a greater number of households can receive assistance at a proportionally lower cost per household, since several dwellings can be improved at the same time in the same locale (DCENR, 2016). This method builds on evidence that poverty in the urban landscape is clustered in certain geographical areas (Walker et al., 2012). However, this is not to say that all households targeted through geographical methods are energy poor, since areas are not homogenous.

The BEC scheme in Ireland does not proactively identify areas in need. Instead, communities or community-based organisations must come together and apply to participate. This is to encourage communities to "band together to become more active and aware of the energy they use and their potential for working together to reduce it" (DCENR, 2016: 14). However, it should be noted that self-referral policies in the context of the UK have been criticised for failing to reach those most in need, since not all who are energy poor will necessarily know about the policy assistance available, or choose to apply for it. Additionally, not all energy poor will classify themselves as energy poor and hence cannot be expected to apply for assistance, even if they know it exists (Walker et al., 2013). These issues are discussed as a form of exclusion error which reduces the efficiency of the policy. This arises when households that are energy poor do not avail of the initiatives for different reasons (e.g. not knowing about the scheme or not applying for the scheme). Similarly, an inclusion error arises if those households that apply and qualify for assistance in fact are not the households in greatest need (Dubois, 2012).

Area based schemes of this sort have been implemented in the UK, for example through the Warm Zones scheme. In contrast to the Irish BEC scheme, the Warm Zones initiative targets areas at high risk of energy poverty and proactively visits households to encourage them to participate (Walker et al., 2012; Walker et al., 2013).

However, despite successes using area-based initiatives, reports have shown that the targeting needs to be improved and models to predict high-risk areas should be advanced.

Accurate targeting of policy efforts is important to ensure the policy reaches the households in greatest need. In this case, area-based policy efforts should be aimed at areas with as high portions of energy poor households as possible, to avoid spending resources on households which are not energy poor. One method widely used for targeting in the UK is geographical risk prediction modelling. This has emerged as a tool since the Fuel Poverty Index (FPI) was developed by Baker et. al. in 2003 (Fahmy et al., 2011). Since then there have been several studies seeking to improve the methodology of energy poverty prediction modelling in the UK (Fahmy et al., 2011; Morrison and Shortt, 2008; Walker et al., 2013; Walker et al., 2012). In contrast to the UK experience, the work on how to predict energy poverty risk in Ireland is still in an early stage. In fact, the first study looking at identifying areas in need of energy poverty alleviation measures is a report done in 2015 by the energy agency Codema (Gartland, 2015).

1.3. RESEARCH QUESTIONS

This highlight certain research and public policy gaps on energy poverty in Europe in general and the Irish context in particular. In light of these, the aim with this thesis is to develop a model for predicting geographic areas at high risk of energy poverty in Ireland and apply this to the Dublin Region.

This translates into the following two questions and respective sub-steps that guides the working process:

1) How should a geographical energy poverty risk prediction model be designed and validated?

- What risk factors (in terms of tenure status, dwelling type, health, income etc.) are characterising energy poor households in Ireland?
- What methods for combining these factors in a geographical model are suitable to best identify high-risk areas?
- How can the model be evaluated in terms of its ability to identify areas with high portions of energy poor households?

2) What does the application and validation of the model tell us about energy poverty in the study area?

- What are the geographical areas at high risk of energy poverty in the study area?
- Can different groups/types of households in energy poverty be identified in the study area, and if so, how do household characteristics (such as tenure status, dwelling type, health, income etc.) vary between these groups/types?

2. MAIN CONCEPT AND RESEARCH DEVELOPMENTS

This study leans on the scholarly work from several areas of research. Theoretically it looks to literature on how we can measure energy poverty and what groups in society have been identified as disproportionally affected by energy poverty. Methodologically the prediction modelling work in the UK and Ireland informs the conceptual understandings of how a geographical energy poverty prediction model can be produced.

2.1. MEASURING ENERGY POVERTY

Predicting energy poverty risk rests on the ability to assess the prevalence of the issue. Here energy poverty is a problematic issue with no uncontested means of measurement. Broadly speaking there are three different approaches: the expenditure approach; the objective approach and the consensual approach (Fahmy et al., 2011).

The expenditure approach was introduced in 1991 through the work of Boardman (Healy, 2003a), and inspires the currently used definition of a household in energy poverty in Ireland. This definition states that a household is considered energy poor when spending more than 10% of its disposable income on energy bills (Pye et al., 2015).

However, the expenditure approach has been widely criticized as it assumes all households which are energy poor spend more than 10% of their income on energy bills. Meanwhile, we know that it is not uncommon for a household to spend less on energy than needed to achieve an adequate level of warmth in the home (Thomson and Snell, 2013). For example, a study on children's asthma and energy poor households demonstrated that many households suffering from energy poverty are simply too worried about the costs of energy to turn the heating on. Instead some households choose to persevere in cold damp environments dangerous to the health of the household members (Tod et al., 2016).

The objective approach generally builds on professional assessments of the housing stock (Fahmy et al., 2011) or temperature measurements (Healy and Clinch, 2004). This method has however been criticized as it fails to consider the social exclusion and material deprivation inherent in energy poverty (Morrison and Shortt, 2008). It should also be noted that data such as indoor temperature measurements and professional building assessments are not available on the same spatial or temporal scale as national survey data.

The consensual measurement, or the subjective approach, is often applied to assess energy poverty both in Ireland and on a European scale (Atanasiu et al., 2014; Bouzarovski and Herrero, 2015; Healy, 2003a; Pye et al., 2015; Thomson and Snell, 2013; Watson and Maitre, 2015). The approach uses different combinations of self-reported proxy indicators. The most commonly used proxy indicators for this purpose are drawn from the EU Survey on Income and Living Conditions and its predecessor, the European Community Household Panel (Scott et al., 2008). The formulations of

the questions asked have varied over the years somewhat but generally captures the following elements:

- the ability to keep the home warm
- having to go without heating
- arrears in utility bills
- house inefficiencies such as rot and damp

A drawback of the consensual approach is the issue of exclusion errors, i.e. households in energy poverty which do not identify themselves as fuel poor (Dubois, 2012).

Naturally, the prevalence of energy poverty varies depending on the measurement used. Scott et al. (2008) for example note that using the expenditure approach identifies a much larger group of energy poor in Ireland than when using the consensual approach. Also, many studies have found that there is not a significant overlap between the groups identified as suffering from energy poverty under the different measures (Fahmy et al., 2011). For instance, in the study by Scott et. al. (2008) on energy poverty in Ireland, it was revealed that if energy poverty is defined using the expenditure approach, then people living in apartments are less likely to experience energy poverty. At the same time, if energy poverty is defined and assessed using the consensual approach, then households living in apartments are instead more likely to experience energy poverty. Despite these issues, many studies use the consensual approach to measure energy poverty, as it captures a broader picture than other measurements (Thomson and Snell, 2013).

2.2. PREDICTORS OF ENERGY POVERTY

To predict energy poverty, common characteristics of households and people experiencing the issue must first be identified so that these can be used as signifiers of risk. For example, a household where all adults are unemployed is at higher risk of having a low income and is therefore at higher risk of energy poverty, compared to a household where the adults are employed. Risk factors identified in studies on energy poverty frequently relate to aspects such as: tenure status (e.g. different forms of tenancy or social housing affecting the ability to make home improvements); dwelling type (e.g. detached or semi-detached housing affecting the energy efficiency of the dwelling) (Thomson and Snell, 2013); dwelling construction year (older buildings being less energy efficient than newer buildings) (Healy and Clinch, 2004); the type of heating systems (central heating being less dominant in countries with high energy poverty levels) (Pye et al., 2015), and aspects affecting the income of a household such as household size and composition; social class; employment status; educational attainment; and health status (Healy and Clinch, 2004).

Risk factors identified in energy poverty prediction modelling work in the UK are similar. The FPI developed by Baker et. al. in 2003, for instance contains eight socio-economic variables which combined are used in an energy poverty risk prediction index (Table 1.1.)

Table 2.1. Predictors of energy poverty.
Adapted from Morrison and Shortt (2008)

Predictors used in FPI
Unemployed households
Underoccupied households
Households with no access to a car
Households with no central heating
Single pensioner households
Lone parent households
Private renting households
Households including a disabled person

Later prediction modelling work from the UK, for example the study by Morrison and Shortt (2008) builds on the FPI. However, instead of the eight variables listed above the authors identify a slightly different set of variables from the census, which they use as risk factors to predict energy poverty in a small rural area in Scotland. They highlight the need to adjust the predictors used to the context of the area being studied, and for example include an indicator for single adult households (non-pensioners) which had not been included in the 2003 FPI. Another study by Fahmy et al. (2011) identifies 15 risk factors again slightly different to those used in previous studies. These captured both physical and social aspects of energy poverty, and for instance include households renting from local authority as a risk group as well as households with more than two dependent children. The works by Walker et al. (2012) and (2013), predicting energy poverty in Northern Ireland, in turn include a variable for heating burden into the risk calculation which is a new approach to energy poverty prediction modelling.

In Ireland, there are several national studies that identify characteristics of people and households associated with energy poverty in the Irish context (Healy, 2003a; Healy, 2003b; Healy and Clinch, 2002; Healy and Clinch, 2004; IPH, 2009; Scott et al., 2008; Watson and Maitre, 2015). While these studies also look at risk factors relating to unemployment, lone parenthood, large family size and likewise, they do not attempt to use these for the purpose of identifying geographical areas at risk of energy poverty.

2.3. GIS MODELLING OF ENERGY POVERTY RISK IN THE UK

With a set of indicators that can be used as risk factors, the process of combining the risk factors into a prediction model can take various forms.

Morrison and Shortt (2008) for example combine a set of social risk factors (e.g. single occupant households, low social class etc.) into a social dimension risk, and a set of physical factors (e.g. water heating system, dwelling construction year etc.) into a physical dimension risk. The two dimensions are then used to identify high-risk areas in Scotland by first identifying areas at high risk socially, and then from these find households which display high physical risk. This approach assumes that energy poverty is only found where there is high social risk.

Walker et al. (2012) also group a set of risk factors into different dimensions (heating burden, social vulnerability and built environment vulnerability) in their study on energy poverty risk in Northern Ireland. However, as opposed to Morrison and Shortt (2008), they combine all three dimensions into a composite risk index. Hence, they do not only include areas which are socially vulnerable but rather calculate an overall risk based on the combination of the social, built environment and heating burden risk profiles. A later study by the same authors similarly uses these three dimensions and combine them into an overall risk index (Walker et al., 2013). However, this later study includes different risk factors and a slightly different approach to combining these compared to the former study. When looking at the results of the two studies it is clear that the geography of risk changes. For example, some areas which are high-risk areas in the first study are low-risk areas in the second study. This illustrates that changing the risk factors and combining the risk factors in different ways, significantly impact the results. It also shows how important it is to evaluate the model results to determine the accuracy of models.

2.4. GIS MODELLING OF ENERGY POVERTY RISK IN IRELAND

The only geographical model of energy poverty risk in Ireland to date is the report by Codema (see Gartland 2015). This study maps the residential and business energy demand within the city of Dublin. In doing this it develops a unique dataset of average building energy efficiency by small area. The small area is a geographical unit consisting of 50-200 households on average and is used by the central statistics office (CSO) in Ireland (CSO, 2011a).

The energy efficiency dataset was produced based on Building Energy Ratings (BERs). This is a rating that assesses the energy demands of a building by calculating the primary energy use per floor area per year (kWh/m^2/yr) needed to keep the home at an acceptable indoor temperature (SEAI, 2008). The part of the report analysing areas at high risk of energy poverty is compiled using the average BER by small area in combination with unemployment data (Gartland, 2015).

The use of average building energy efficiency data as an indicator is a new development in energy poverty prediction modelling. In Northern Ireland for example the equivalent energy efficiency assessments on dwellings are very limited in numbers, and therefore insufficient to use for this purpose (Walker et al., 2012). The regulations in Ireland states that all dwellings put up for rent or sale must have a BER assessment done (SEAI, 2008), which means that an attractive area like Dublin has a high portion of dwellings assessed. This meant that the analysis of average BER that Codema conducted, was based on over 72,000 actual energy efficiency assessments. This represented about 35% of the dwellings in the area at the time the report was done (Gartland, 2015). Since then, Codema has extended the BER dataset which now covers the whole Dublin Region, consisting of the councils Dublin city, Dún Laoghaire–Rathdown, Fingal and South Dublin (Gartland, 2016).

The geographical models that predict areas at risk of energy poverty in the UK discussed above, also assesses the physical dimension of dwelling energy efficiency. However, these indicators have a greater causal distance to the issue of energy efficiency. Examples include: dwelling type (detached dwellings tend to require more energy to heat); size (larger dwellings require more energy); lack of central heating (lacking central heating indicates a less efficient heating system which indicates greater energy demand); dwelling age (older dwellings tend to be less energy efficient); and property value (lower valued properties tend to be less energy efficient) (Fahmy et al., 2011; Walker et al., 2013). The contribution of the study by Gartland (2015) therefore adds a new risk indicator to studies on energy poverty prediction.

3. METHODOLOGY

This study uses Multi-Criteria Analysis (MCA) methods in GIS to model energy poverty risk in the Dublin region in Ireland. Three models are created based on different conceptual understandings of energy poverty risk modelling. The performance of the models is assessed through structured interviews with households in the study area.

3.1. MULTI CRITERIA ANALYSIS

GIS is an analysis support system, which enables users to analyse spatially referenced data. Because of the flexibility a GIS offers this analysis uses this environment to produce the energy poverty prediction models. The UK studies on energy poverty prediction modelling which this study draws on, have also been conducted in a GIS (Morrison and Shortt, 2008; Fahmy et al., 2011; Walker et al., 2012; Walker et al., 2013).

However, a GIS is a toolset and must be applied in an appropriate manner to ensure reliability and validity. Here I use MCA, which provides the user with a set of procedures that make the analytical process coherent, structured and transparent. A GIS-based MCA is a method through which geographical data is integrated with knowledge and judgements of the analyst to solve a spatial problem (Malczewski, 2006). In its simplest form, this is accomplished by combining a set of input maps, resulting in an output map (Malczewski, 2010). The GIS-based MCA approach has a set of building blocks which structures the problem, and a set of techniques used to solve that problem. These building blocks include 1) defining the objective of the analysis, 2) determining the model components and its attributes (e.g. risk factors), 3) standardizing these (scoring), then 4) combining (weighting) the components and finally 5) validating the model. These steps will be explained in detail in the below sections.

Previous studies modelling energy poverty risk do not explicitly apply MCA methods, but share many similarities with these since they identify a set of risk factors which are scored and combined into a risk value. In MCA, the scoring (standardizing of risk factors and converting these into attributes) and weighting (method for combining the attributes) is the most crucial step in the model creation (Linkov and Moberg, 2011). These steps require careful consideration of how the attributes relate to the objective (Eastman, 2001), which in this case is to identify areas at high risk of energy poverty. To assign the scores and weights the user therefore has specific techniques referred to as decision rules.

To benefit from previous studies as well as the rigorousness that MCA offers, this analysis applies a combined approach. It learns from the UK studies outlined above conceptually, but rests on MCA procedures for scoring and weighting. The decision rules used are weighted summation of standardized attributes which are combined using weights calculated through a pairwise comparison procedure. These are popular techniques in GIS-based MCA as they are easy to understand and easy to use (Malczewski, 2006).

As there are no clear procedures for energy poverty prediction modelling, this study develops three models and test these against survey results to evaluate the best approach and the model of best fit. Model A groups the attributes into either a physical or a social dimension and ensures that both dimensions are equally represented in the final risk score. To do this, the two dimensions are given equal weights, similar to the method Walker et al. (2013) use. This rationale rests on a conceptual understanding that the physical and social dimensions of energy poverty are equally important in determining risk. Each of the attributes within the two dimensions are given a weight through a pairwise comparison procedure.

Model B also applies weights to the attributes with a pairwise comparison. However, in this approach, in contrast to Model A, the attributes are not grouped into a social and a physical dimension. Instead, conceptually this model replicates a pattern of risk across a geographical space. This is achieved by assigning a weight to each attribute which reflects how much the odds of being in energy poverty increase with the presence of that attribute. This attribute-focused design is similar to the method Fahmy et al. (2011) apply where the weights are assigned to the identified attributes without differentiating between physical and social risk factors. The weights for each attribute, and the determination thereof, is clarified below in section 3.6.

A third uncalibrated model is also created (Model C) in which all attributes are equally weighted. This is a form of sensitivity testing of the models to display the difference between carrying out a weighting procedure and not. The models are conceptually depicted in figures 3.1 and 3.2.

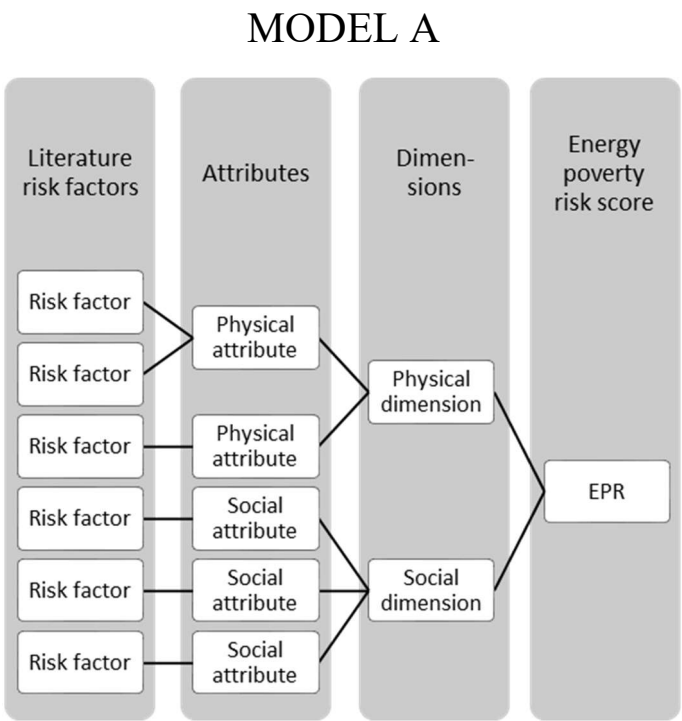


Figure 3.1. Conceptual diagram of Model A.
The attributes are combined into a social and physical dimension which ensure both building blocks are equally weighted.

MODEL B & C

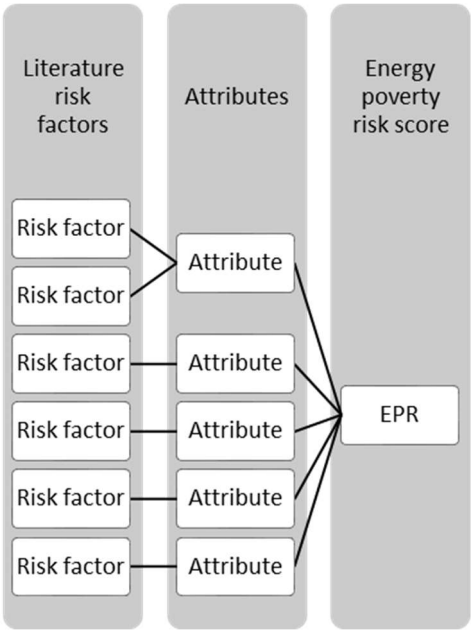


Figure 3.2. Conceptual diagram of Model B and C.
The attributes are combined without being placed into a social and physical dimension. The difference between Model B and Model C is that in Model B the attributes have differentiated weights while in Model C all attributes are equally weighted.

3.2. CASE SELECTION, UNIT OF ANALYSIS AND SPATIAL DATASETS

The Dublin region is the ideal location to advance energy poverty modelling due to the opportunity of using the energy efficiency dataset from Codema (Gartland, 2015), and because this type of work is an emerging field in Ireland. Therefore, while the general focus of this thesis is on energy poverty prediction modelling, the case selection for the prediction models is limited to the area of the Dublin Region. This region consists of the councils Dún-Laoghaire-Rathdown, Fingal, South Dublin as well as the Dublin city (map 3.1).

The Codema dataset is produced at the unit of the Small Area Population Statistics (SAPS) which contain 50-200 households. These units are also the finest resolution spatially referenced data in the Irish Census (CSO, 2011a), making them the best unit of analysis for the purpose of this study. Naturally, the finer the scale of the dataset, the more precise can the prediction model be.

In terms of spatial datasets, the Census 2011 is the most recent census available and the output of this is the largest set of spatially referenced socio-economic data in Ireland. Therefore, the Census 2011 together with the Codema dataset form the data sources relied on for the building of the prediction models.

Map 3.1. The study area: The Dublin region, Ireland

3.3. DATA COLLECTION

Risk factors for the model are identified by reviewing national studies which outline characteristics of groups/households vulnerable to energy poverty in the Irish context. As discussed, energy poverty can be measured in different ways (the expenditure/ objective/consensual measures), and we know that the groups/households identified as at higher risk of energy poverty depend on the measurement used (Fahmy et al., 2011; Scott et al., 2008).

Since the consensual measure generally is considered the most holistic measure for energy poverty (Thomson and Snell, 2013), and as it is commonly used in Irish national studies on the issue (Healy, 2003a; Healy and Clinch, 2004; Scott et al., 2008; Watson and Maitre, 2015), this study relies on the consensual measure of energy poverty. Consequently, the risk factors identified for the prediction models are taken from studies which also use the consensual measure of energy poverty to identify risk groups/households.

To select the risk factors for the prediction models, this analysis draws on Morrison and Shortt (2008) as well as Fahmy et al. (2011). These studies measure energy poverty and subsequently analyse the characteristics of households identified as energy poor to determine risk factors. For example, assume lone parent households are identified as a risk group disproportionally affected by energy poverty. This leads to lone parenthood being determined to be a risk factor, and through the use of spatially referenced data areas with high portions of lone parents can be identified. The identified areas are then assumed to have higher concentrations of energy poor households than areas with lower portions of lone parent households.

To identify risk factors relevant to Ireland, this study uses four national studies which establish factors relevant to the risk of experiencing energy poverty in Ireland. All four studies use the consensual measure to identify energy poverty and associated risk factors: Healy (2003a); Healy and Clinch (2004); Scott et al. (2008); Watson and Maitre (2015). Short descriptions of each of the studies are noted in APPENDIX 1.

3.3.1. IRISH RISK FACTORS

Each of the four studies (Healy, 2003a; Healy and Clinch, 2004; Scott et al., 2008; Watson and Maitre, 2015), contain statistical analysis investigating the association between various characteristics (e.g. marital status, dwelling type, education, health etc.), and the likelihood of being energy poor. In this thesis, the results of these statistical analysis are used to determine the risk factors to include. This means only factors found to have a statistically significant correlation to households in energy poverty are considered.

Factors that are not classified the same way in all four studies are simplified. For instance, the study by Healy (2003a) uses the categories of ‘separated’ and ‘divorced’ as two separate factors, while Watson and Maitre (2015) and Scott et al. (2008) use one single category of ‘divorced/separated’. For such factors, the simpler form (‘divorced/separated’) is used.

Through this process, a total of 35 risk factors relevant to the experience of energy poverty in Ireland were identified from the four studies. Table 3.1. lists these and the studies they are drawn from.

- Risk factors which are significant are marked with a tick (✓).
- Risk factors which are significant in one study (i.e. qualify to be included in the database), but are insignificant in another study, are marked with a cross (×).
- A risk factor which is significant in a study (i.e. qualify to be included in the database) but is not considered in the analysis of another study, is left blank.

The risk factor selection process can be followed with the example of the risk factor 'lone adult' households. This factor is not included in the studies Healy (2003a) or Healy and Clinch (2004), therefore the space in the table has been left blank for these two studies. In Scott et. al. (2008) the factor is included but found insignificant, hence the field is marked with a cross (×). Lastly, in the study by Watson and Maitre (2015) the factor is found to affect the likelihood of a household experiencing energy poverty so the field is marked with a tick (✓).

The 35 risk factors were also reviewed in terms of their importance and consistency to decide which factors should be included in the prediction model. This qualitative review process is detailed in APPENDIX 2. The right-hand column of Table 3.1. shows the 21 of the 35 risk factors that were found consistent and deemed important for inclusion.

Table 3.1. The 35 risk factors identified as significant in one or more of the four studies on energy poverty in Ireland.

Factor group	Factor name	Healy (2003a)	Healy and Clinch (2004)	Scott et al. (2008)	Watson and Maitre (2015)	Status
Tenure	Rented dwelling	✓	✓	✓	✓	Include
	Rent Free/ Local authority	✓	✓	✓	✓	Include
	Own with mortgage		×		✓	Exclude
Dwelling type	Semidetached/ Terraced	✓			✓	Exclude
	Apartment/ Flat	✓		✓	×	Exclude
	Other	✓				Exclude
Marital status	Single	✓		✓	✓	Include
	Widow/ Widower	✓	×	×	×	Exclude
	Divorced/ Separated	✓	×	✓	✓	Include
Household composition	Lone parents			✓	✓	Include
	Alone adult			×	✓	Exclude
	Being in a couple reduces risk		✓	×		Exclude
	Number of children	✓	×	✓	✓	Include
	Multiple adults	✓	×			Exclude
	Other adult with disability				✓	Include
Income status	Retired/Inactive in other way	✓		✓		Include
	Self employed	✓			×	Exclude
	Unemployed	✓		✓	✓	Include
	Student			✓		Include
	Other benefit recipient	✓				Include
	Home duties			✓		Include

Factor group	Factor name	Healy (2003a)	Healy and Clinch (2004)	Scott et al. (2008)	Watson and Maitre (2015)	Status
	Ill/Disabled			✓		Include
	Private income	✓				Exclude
Health	Bad/Very bad	✓				Include
Education	No education/ Primary only/ Secondary not finished/ Education other/Not stated	✓	×	✓	✓	Include
	Secondary finished	✓	×	✓	×	Exclude
	Having a degree reduces risk		✓	×	×	Include
Personal data	Age	✓	×	✓	✓	Include
	Sex	.		×	✓	Exclude
Dwelling	Dwelling built year		✓		×	Include
	Leaks /Too dark				✓	Include
	Lack central heating				✓	Include
Social Class	Social class unknown			×	✓	Exclude
	Unskilled / Low. Service/ Manual / Intermediate			×	✓	Exclude
Other	Housing allowance recipient	✓				Include

3.4. FROM RISK FACTOR TO ATTRIBUTE

To spatially predict energy poverty risk, the 21 identified risk factors are matched with variables in the spatial datasets, the Census 2011 (CSO, 2011b) and the energy efficiency dataset (Gartland, 2016). To use GIS-based MCA terminology, the spatial dataset variables are hereafter referred to as attributes.

An example of a matching risk factor-attribute relationship is health status. Studies on energy poverty in Ireland, as noted in Table 3.1., shows a positive correlation between bad health status and energy poverty prevalence. In the Census 2011 datasets, there are area-based data on self-reported health status of individuals by small area. I.e. the number of people in a particular small area that report having very bad health. This risk factor can therefore be directly matched and used in the model.

Risk factors which could not be directly matched to attributes in the spatial datasets were assessed to determine if there are possible proxy indicators that could be used instead. For instance, physical dwelling characteristics relating to damp and rot are not available in the spatial datasets. However, the reason these risk factors are included in some studies on energy poverty is because they are proxy indicators for dwelling energy inefficiencies and poor dwelling standards. Here the new dataset on energy efficiency of residential buildings produced by Codema presents an opportunity to capture some of the physical components better than previously. Therefore, for risk factors relating to building qualities, the energy efficiency dataset is used instead.

Another example of adjustments made in the matching process relates to some of the measurements of low income, as the categories the four studies use to assess the economic status of the households vary. Scott et al. (2008) for example, only assess household income based on the Chief Economic Supporter (CES), which does not

exist as a variable in the spatial datasets. The Census 2011 reports some statistics of the 'Reference Person' of the household. However, the 'Reference Person' is the person in the household with the lowest personal number which is not necessarily the same as the CES of the household (CSO, 2012). Watson and Maitre (2015) in turn only use the category 'Jobless household' and do not differentiate between different categories of non-working status (e.g. looking for first job, student, unemployed etc.). Finally, Healy (2003a) includes different income statuses but has slightly different categories to those used by Scott et al. (2008). Hence some decisions were made when selecting the attributes from the spatial datasets, and at times some attributes are grouped to correspond to one or more identified risk factors.

An important decision this study makes is to represent all physical dimension risk factors (e.g. dwelling age, dwelling type etc.) with the energy efficiency (BER) dataset. The BER represents the complete energy efficiency profile of a building, including its heating system, insulation, size and related factors. It is hence a more complete indicator of energy efficiency compared to the use of partial energy efficiency parameters such as heating system for instance.

Additionally, when designing the BER dataset Codema used the energy efficiency assessments in each small area to create energy efficiency area profiles. These profiles are constructed based on the housing type, dwelling age, energy efficiency and location. For the Dublin city council area, that has resulted in 448 different energy efficiency profiles (Gartland, 2015). This means the BER attribute is spatially variable and more appropriate to use for risk prediction than, for example, spatially invariable attributes such as dwelling age.

A detailed description of how each of the 21 risk factors were matched, grouped or excluded is outlined in APPENDIX 3, and Table 3.2. summarises the process. In total 14 model attributes have been created from the 21 risk factors. Out of these, 13 are socio-economic attributes coming from the Census 2011, and the 14th attribute is the energy efficiency attribute from the Codema dataset.

To streamline the attribute datasets and make the data between the small areas comparable, the 13 social dimension attributes were converted from absolute numbers (e.g. number of unemployed adults in each small area) into portions (e.g. % of unemployed adults in each small area). The energy efficiency (BER) attribute dataset is expressed as average dwelling energy efficiency (kWh/m^2/yr) by small area. Hence the BER values did not need to be converted since they in their raw data form are comparable between the areas. Table 3.3. details the final 14 attributes.

Table 3.2. Conversion of risk factors to model attributes.
The 'Dataset match' indicates the spatial dataset used to form a match (Codema = COD, or the Census 2011 = CEN). The 'Attribute name(s)' notes the statistics gathered from the spatial datasets. The 'Abbreviation' is the abbreviation used for the attribute in the model creation. Finally, the 'Status' notes if the risk factor is included, grouped or excluded.

Factor group	Factor name	Dataset match	Attribute name(s)	Abbreviation	Status
Tenure	Rented dwelling	CEN	Private renting households	PRIV	Include
	Rent Free/ Local authority	CEN	Local authority and Rent free households	LCL	Include
Marital status	Single	CEN	Single people	SING	Include
	Divorced/ Separated	CEN	Divorced and Separated people	DISE	Include
Household composition	Lone parents	CEN	Lone parent families	LONE	Include
	Number of children	CEN	4+ children families	CHLD	Include
	Other adult with disability	See SIDI			Grouped
Income status	Retired/Inactive in other way	CEN	Retired and otherwise inactive people	RET	Include
	Unemployed	CEN	People unemployed or looking for 1st job	UNEM	Include
	Student	Spatial data on CES is not available			Excluded
	Other benefit recipient	Spatial data on benefit recipients is limited			Excluded
	Home duties	Spatial data on CES is not available			Excluded
	Ill/Disabled	CEN	People unable to work due to sickness/disability	SIDI	Include
Health	Bad/Very bad	CEN	People reporting bad and very bad health status	BAD	Include
Education	No education/ Primary only/ Secondary not finished/ Education other/Not stated	CEN	People with below upper secondary qualifications & those not stated	NOED	Include
	Having a degree reduces risk	CEN	People with completed bachelor degrees and higher	THED	Include
Personal data	Age	CEN	People aged 16-35	AGE	Include
Dwelling	Dwelling built year	COD	Average residential building energy efficiency by small area	BER	Include
	Leaks /Too dark	See BER			Grouped
	Lack central heating	See BER			Grouped
Other	Housing allowance recipient	Spatial data on benefit recipients is limited			Exclude

Table 3.3. The final 14 attributes included in the energy poverty prediction models.
The table details the unit of the raw data; the conversion applied to the raw data before scoring it; and the dimension of energy poverty the attribute relates to (physical or social).

Factor group	Attribute	Explanation	Unit of raw data (number of)	Conversion	Dimension
Tenure	PRIV	Private renter	Households	% of households	Social
	LCL	Local authority renter / Rent free	Households	% of households	Social
Marital status	SING	Single	People	% of people	Social
	DISE	Divorced / Separated	People	% of people	Social
Household composition	LONE	Lone parent	Families	% of families	Social
	CHLD	Number of children	4+ children families	% of families	Social
Income status	RET	Retired	People	% of people	Social
	UNEM	Unemployed	People	% of people	Social
	SIDI	Sickness / Disability	People	% of people	Social
Health	BAD	Bad / Very Bad health	People	% of people	Social
Education	NOED	No education/ Primary only/ Secondary not finished/ Not stated	People	% of people	Social
	THED	Completed 3rd level education	People	% of people	Social
Personal data	AGE	Age, 16-34	People	% of people	Social
Dwelling characteristics	BER	BER rating	Average BER by small area	N/A	Physical

3.5. SCORING

3.5.1. NORMALIZE THE ATTRIBUTES

MCA evaluations can be made based on attributes expressed in their original units. However, to apply a full MCA, where the attributes are weighted and combined, the scores must first be normalized (Dodgson et al., 2009; Eastman, 2001). Normalizing does not mean that the attributes simply are expressed in the same unit (e.g. %), but that they are comparable to each other. While simple in principle, it is a common error in GIS-based MCA that attribute maps are combined without being commensurate (Malczewski, 2006).

To give an example of the problem, assume a risk index of 0 - 100 where 0 is no risk and 100 is greatest risk possible. Also assume that we have two attributes in our model which are equally weighted at 0.5. We also have an area with 2%

unemployment (which is low), and 2% of the population reporting very bad health (which is high). Even if both criteria are expressed in percentages, their meaning is different. If we simply multiply the percentages by the weights without first scoring the attributes, we obtain the value 0.02 (0.02 * 0.5 + 0.02 * 0.5 = 0.02). If instead we give 2% unemployment a low score of 5 and we give 2% bad health a high score of 80, then using the same weights the risk value calculated is 42.5 (5*0.5 + 80*0.5 = 42.5). On a risk scale of 0 – 100, a score of 42.5 could be considered indicating a medium risk.

What the user determines as low- and high-risk respectively, depends on how the attributes are scored. Here a degree of judgement from the researcher is required, but with standardised attributes that are scored using a uniform approach the results are easier to interpret. A common way of scoring attributes, is to use function scores where for example 0 represents lowest risk and 100 represents highest risk.

3.5.2. SCORING FUNCTIONS

The scoring function chosen, requires careful consideration of how the attributes relate to the objective, which in this case is to identify areas at high risk of energy poverty. This is because an attribute might have a range where it is suitable for fulfilling a certain objective, while values above and below this range are less suitable.

When applying scores to an attribute with such characteristics the most common approach in GIS is to use fuzzy membership functions (Eastman, 2006). Such functions allow for the score to gradually increase and decrease, according to the preferences set by the user.

Take for example a GIS MCA problem of identifying a suitable location for a school. Assume the school should preferably be at least 50 meters away from a main road for safety reasons, and assume it should preferably not be more than 150 meters from a main road for accessibility reasons. This creates a criterion ‘distance from main road’, which can have a bell curve like scoring function. The scores assigned would indicate less suitability up to the distance 50 meters, greater suitability 50 – 150 meters and less suitability again when it is more than 150 meter away from a main road. Figure 3.3. depict this graphically with the dot marking the point where the distance from the road is 100 meter, and hence the optimal distance in this example.

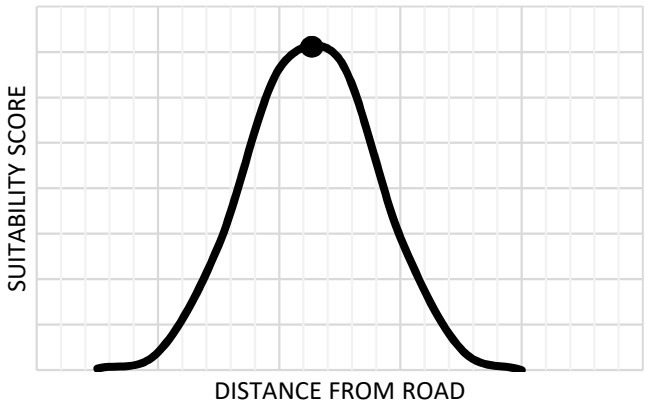


Figure 3.3. A membership function example: Bell curve.
This displays an attribute which has suitability increasing up to a certain point and then decreasing again.

However, in this study, the attributes are all characteristics that should be either maximized (e.g. higher unemployment means higher risk) or minimized (higher portion with third level education means lower risk). As a method, this assumes that risk continues to increase/decrease and does not flatten out. For example, it assumes that an area with 40% unemployment is at higher risk than an area with 30% unemployment. This is similar to the approach a Gomes and Lins (2002) apply in their study on living conditions in different neighbourhoods in Rio de Janeiro.

A common method to scoring such attributes are simple linear scoring functions that draw a straight line between the lowest/highest values in the data and the associated scores. In its simplest form, it is expressed as $S_i = \frac{R_i - R_{min}}{R_{max} - R_{min}} * S_{max}$ where S is the standardized risk score and R is the raw score (Eastman, 2006). Figure 3.4 illustrates this simplest form for an attribute which is positively correlated with the objective and has a lowest data value of 0 and a highest data value of 62.

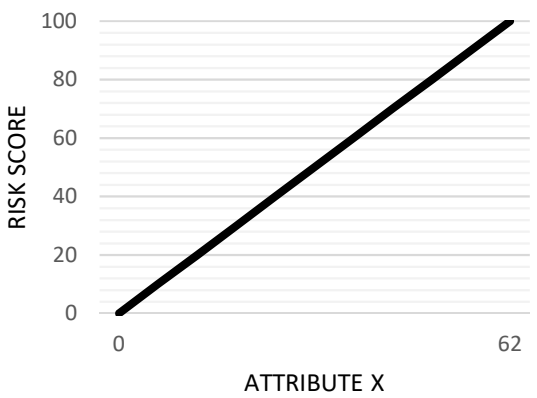


Figure 3.4. A simple linear scoring function.
This scoring function applies lowest risk to the lowest attribute value and the highest risk to the highest attribute value.

This simple linear scoring method fits the relationship between the attribute data used in the model and the model objective in this study. But, it does not consider the distribution of the data. Indeed, (Eastman, 2006) highlights that blindly applying a linear scoring function without understanding the meaning of different data values is ill advised.

Taking unemployment as an example, the highest portion unemployment in any small area in the study is 62% and the lowest is 1.5%. If we apply the risk score using the above function, an area with 29% unemployment obtains a risk score of 46.22 ($\frac{29-1.5}{62-1.5} * 100 = 46.22$). On a risk index from 0 – 100, 46.22 is likely deemed a moderate level of risk. However, the data distribution for the attribute reveals that 29% unemployment is in the upper segment of the distribution (Figure 3.5.).

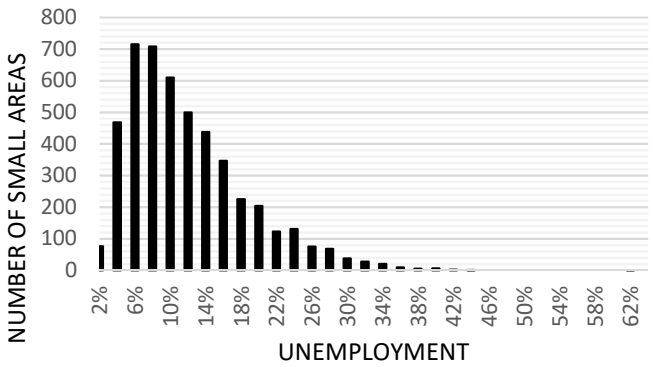


Figure 3.5. The data distribution of the attribute unemployment.
The figure displays that an area with 29% unemployment is in the upper end of the data distribution and thus is extremely high.

This stresses that the method of simple linear scoring, only considering minimum and maximum values of the raw data, is not appropriate for attributes where extreme values can result in the scores giving inaccurate indications of relative risk.

Working around this issue, we can instead use the data distribution in combination with minimum and maximum scores to identify areas at higher risk relative to other areas. One way to look at the distribution of the data is to divide each attribute data distribution into percentiles which displays the portion of the small areas that fall under a certain threshold. Table 3.4. demonstrates how this can be done for the unemployment attribute. This shows that only 10% of the small areas in the study region have an unemployment level of 4% or less. Unemployment levels of 13% or less are seen in 70% of the areas. Looking at the threshold of 29% unemployment, we can see that 98% of the areas have unemployment levels below this. Consequently, a 29% unemployment level is extreme in the study area.

Table 3.4. Percentiles of the attribute unemployment

Unemployment	Percentile
4%	10th
5%	20th
7%	30th
8%	40th
9%	50th
11%	60th
13%	70th
16%	80th
21%	90th
25%	95th
29%	98th
61%	100th

The values are divided into percentiles which create natural data intervals that can be used for scoring the attributes. Creating intervals is a common simplification method in MCA (Dodgson et al., 2009) that divides the raw data into groups of values rather than working with continuous data.

Naturally, the intervals can be created in many ways. They can simply detail every 10th percentile and through that split the study area into groups of 10% of the areas in each group. However, since this model strives to detect areas at high risk of energy poverty, it is not important to differentiate between areas in the lowest 0-10 percentiles but it is important to differentiate between the areas falling in the higher 90-100 percentiles. It is easier to identify the areas at most risk by distinguishing between high, very high and extreme relative risk for each attribute. This motivates applying coarser intervals for lower percentiles and finer intervals for the higher percentiles as exemplified in Table 3.4.

Applying this to the example of unemployment results in the scores outlined in Table 3.5. Here the intervals over the 50th percentile are finer and the intervals over the 90th percentile are finer still. The lowest interval is scored 0 and the highest is scored 100 to maintain the 0 – 100 scoring scale. The other intervals are scored per the median percentile of the interval (e.g. the interval of the 10th - 30th percentile is scored 20).

This results in the small areas in the lowest 10th percentile obtaining a score of 0, the areas in the 50th - 60th percentile obtain a score of 55 etc. For the attribute unemployment, this means areas with an unemployment level of 1.5 – 4 % are scored 0, and areas with unemployment levels of 9 – 11% are scored 55.

Table 3.5. Scores assigned based on the percentiles of the attribute unemployment.

Unemployment (%)	Percentile	Risk Score
1.5 - 4	0 - 10th	0
4 - 7	10th - 30th	20
7 - 9	30th - 50th	40
9 - 11	50th – 60th	55
11 - 13	60th – 70th	65
13 - 16	70th - 80th	75
16 - 21	80th – 90th	85
21 - 24	90th – 94th	92
24 - 29	94th – 98th	96
29 - 62	98th – 100th	100

3.6. WEIGHTING

The weighting of the attributes in MCA is a process normally informed by stakeholders. In this case, the four national studies used to identify the risk factors also guides the weighting of the attributes.

This was done by looking at how much each factor increases or decreases the risk of experiencing energy poverty according to each of the four studies. The method draws partially on Fahmy et al. (2011) who use regression weights from energy poverty vulnerability models, and apply these to census data to replicate the observed pattern of vulnerability at the small area level.

Since the regression models from all four studies are used in this analysis, the weights are not directly transferred into model weights. Instead each study is considered a source of input which guides a ranking of the attributes through a "pairwise comparison".

The pairwise comparison technique is an MCA method coming from the analytical hierarchy process (AHP). Here, it is used to apply weights to the attributes in Model A and Model B (the un-calibrated test Model C has equal weights). The technique, developed by T.L. Saaty, employs an index scale (Table 3.6.) to assess how important each attribute is in comparison to all other attributes. The comparison results in a ratio scale matrix that in turn forms the basis for the weight calculation (Saaty, 1987).

Table 3.6. The index scale used to rank attributes in a pairwise comparison.
Adapted from: Dodgson et al. (2009).

How important is A relative to B?	Preference index assigned
Equally important	1
Moderately more important	3
Strongly more important	5
Very strongly more important	7
Overwhelmingly more important	9

The pairwise comparison process is demonstrated easily using dummy attributes A, B and C. If we compare attribute A to B and determine that A is 'very strongly more important' than B, then we give the relationship A/B a preference index score of 7 for A and 1/7 for B. We then judge the relationship between A and C to be 'equally important' and assign it a simple 1 for both attributes. Finally, we decide that C is 'strongly more important' than B and assign the score 5 to C and 1/5 to B. The scores are entered in a matrix:

Attribute	**A**	**B**	**C**
A	1	7	1
B	1/7	1	1/5
C	1	5	1

With the index scores the user can then calculate the weights. One straightforward approach to do this is to first calculate the geometrical mean for each attribute and thereafter divide this by the sum of all geometric means.

In this example, the geometric mean of attribute A is: $(1 * 7 * 1)^{\frac{1}{3}} = 1.9129$. This is divided by the sum of all geometric means (3.2986) to get the weight (0.487) (Table 3.7.). The sum of the weights is always equal to one (Dodgson et al., 2009).

Table 3.7. Example of how weights are calculated in a pairwise comparison matrix.

Attribute	**A**	**B**	**C**	$\bar{X}geom$	**Weight**
A	1	7	1	1.9129	0.487
B	1/7	1	1/5	0.3057	0.078
C	1	5	1	1.7099	0.435
∑				3.2986	1.000

Table 3.9. outlines the pairwise comparison matrix used to assign weights for Model B.

Model A uses the same pairwise comparison but removes the physical dimension attribute (BER) into its own dimension to create the discussed social and physical dimensions this model applies. Consequently, the weights from the pairwise comparison for the 13 social dimension attributes in Model A are slightly different to those calculated for Model B.

The dimensions in Model A are equally weighted by assigning the 13 attributes in the social dimension a weight of 0.5, and assigning the physical dimension attribute (BER) a weight of 0.5 (Figure 2.1).

Table 3.8. details the weights for all attributes in each of the three models. Table 3.9. depicts the full pairwise comparison matrix (Model B). Lastly, the model algorithms are diagrammatically illustrated in figures 3.6 – 3.8.

Table 3.8. The attribute weights for the three models.
The weights listed for Model A and B are calculated through a pairwise comparison. For Model C the weights are equal for all 14 attributes.

Factor group	Attribute	Model A	Model B	Model C
Tenure	LCL	0.062	0.050	0.071
	PRIV	0.052	0.043	0.071
Marital status	SING	0.020	0.017	0.071
	DISE	0.101	0.083	0.071
Household composition	LONE	0.019	0.017	0.071
	CHLD	0.011	0.010	0.071
Income status	RET	0.028	0.024	0.071
	UNEM	0.265	0.230	0.071
	SIDI	0.074	0.061	0.071
Health	BAD	0.171	0.146	0.071
Education	NOED	0.132	0.109	0.071
	THED	0.011	0.010	0.071
Personal data	AGE	0.053	0.045	0.071
Dwelling	BER	1.000	0.154	0.071

Table 3.9. The pairwise comparison matrix and weights.
The weights in the right-hand column are the weights applied in Model B. See Table 3.8. for the weights applied for all three models.

Criteria	LCL	PRIV	SING	DISE	LONE	CHLD	RET	UNEM	SIDI	BAD	NOED	THED	AGE	BER	$\bar{X}geom$	Weight
LCL	1	2	5	1/2	5	7	3	1/7	1/2	1/5	1/3	7	1	1/5	1.094	0.050
PRIV	1/2	1	5	1/3	5	7	3	1/7	1/2	1/5	1/4	7	1	1/5	0.943	0.043
SING	1/5	1/5	1	1/5	1	3	1/2	1/8	1/4	1/7	1/6	3	1/3	1/7	0.379	0.017
DISE	2	3	5	1	6	8	5	1/4	1	1/2	1/2	8	3	1/3	1.795	0.083
LONE	1/5	1/5	1	1/6	1	3	1/2	1/8	1/5	1/7	1/6	3	1/4	1/7	0.361	0.017
CHLD	1/7	1/7	1/3	1/8	1/3	1	1/4	1/9	1/6	1/8	1/7	1	1/5	1/8	0.219	0.010
RET	1/3	1/3	2	1/5	2	4	1	1/7	1/4	1/6	1/5	5	1/3	1/6	0.524	0.024
UNEM	7	7	8	4	8	9	7	1	6	3	4	9	6	2	5.002	0.230
SIDI	2	2	4	1	5	6	4	1/6	1	1/4	1/3	7	1	1/4	1.316	0.061
BAD	5	5	7	2	7	8	6	1/3	4	1	2	8	4	1	3.163	0.146
NOED	3	4	6	2	6	7	5	1/4	3	1/2	1	8	4	1/2	2.375	0.109
THED	1/7	1/7	1/3	1/8	1/3	1	1/5	1/9	1/7	1/8	1/8	1	1/4	1/8	0.215	0.010
AGE	1	1	3	1/3	4	5	3	1/6	1	1/4	1/4	4	1	1/4	0.967	0.045
BER	5	5	7	3	7	8	6	1/2	4	1	2	8	4	1	3.352	0.154
∑															21.704	1.000

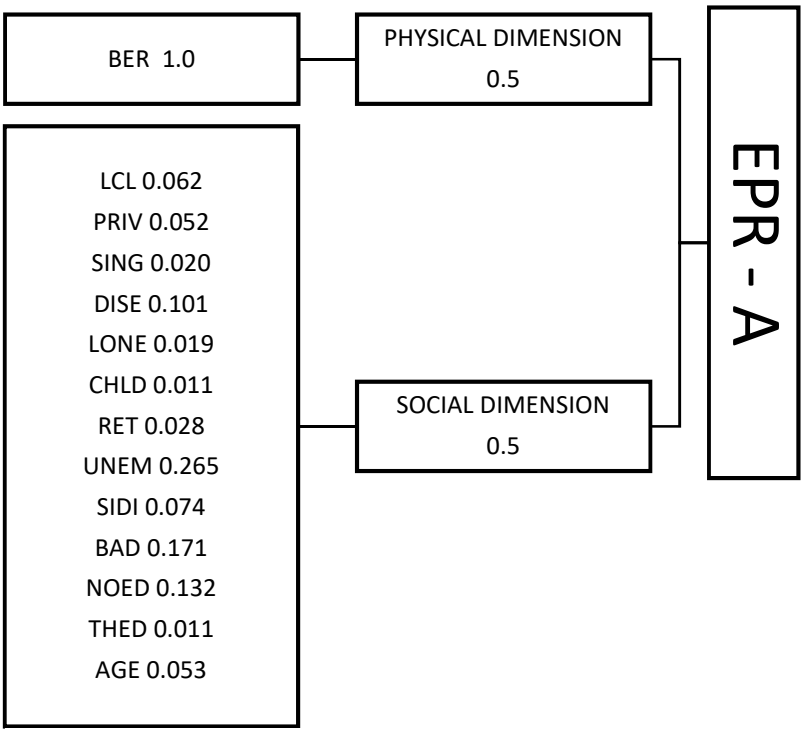


Figure 3.6. Algorithm for Model A
The figure displays how the energy poverty risk (EPR) score is calculated for Model A.

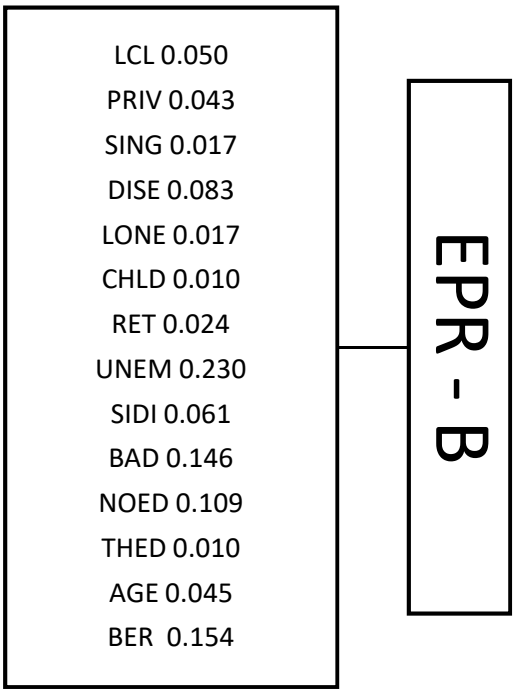


Figure 3.7. Algorithm for Model B.
The figure displays how the energy poverty risk (EPR) score is calculated for Model B.

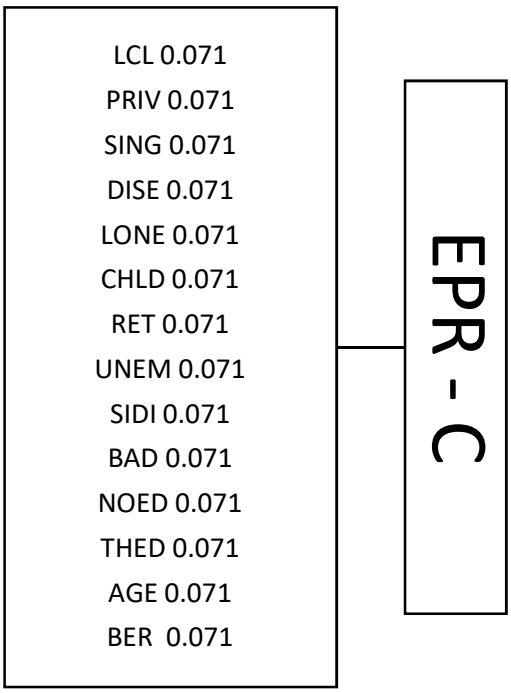


Figure 3.8. Algorithm for Model C.
The figure displays how the energy poverty risk (EPR) score is calculated for Model C.

3.7. GIS PROCESSES

GIS software ArcMap 10.3. was used for the modelling process. Figure 3.9. outlines the model creation processing steps that are described in the following sections.

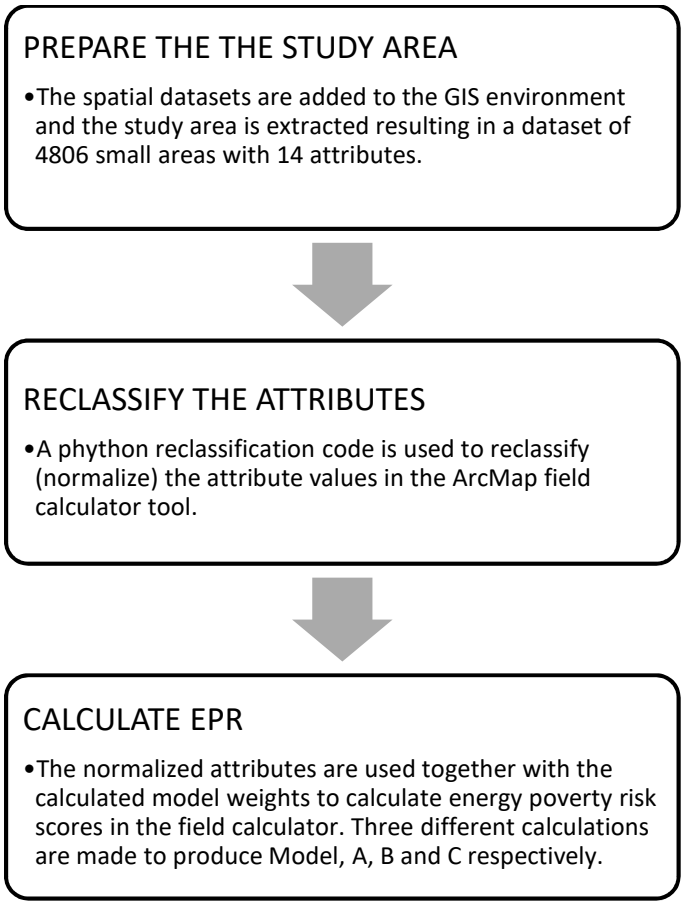


Figure 3.9. GIS processing steps

3.7.1. PREPARE THE STUDY AREA

The study area shapefiles were obtained from the CSO website (CSO, 2011a). The attribute datasets from CSO and from Codema contains the same unique small area identifiers as the shapefiles which allowed for easy integration of these into the GIS environment using spatial joins. The process resulted in a shapefile containing the 4806 small areas that make up the study area as well as the data of the 14 attributes.

3.7.2. RECLASSIFY THE ATTRIBUTES

The attributes were scored according to the procedure outlined in the scoring section. This was done by first calculating the percentile cut-off values. Using the example of unemployment again (Table 3.5.), the cut off for the 10th percentile in the unemployment data distribution is 4%, hence all small areas with unemployment lower than 4% are scored 0. The next cut off for the 30th percentile in the unemployment data range is 6.51%. Hence all small areas with an unemployment rate of 4% - 6.51% are scored 20. Table 3.10. exhibits the calculated scoring intervals.

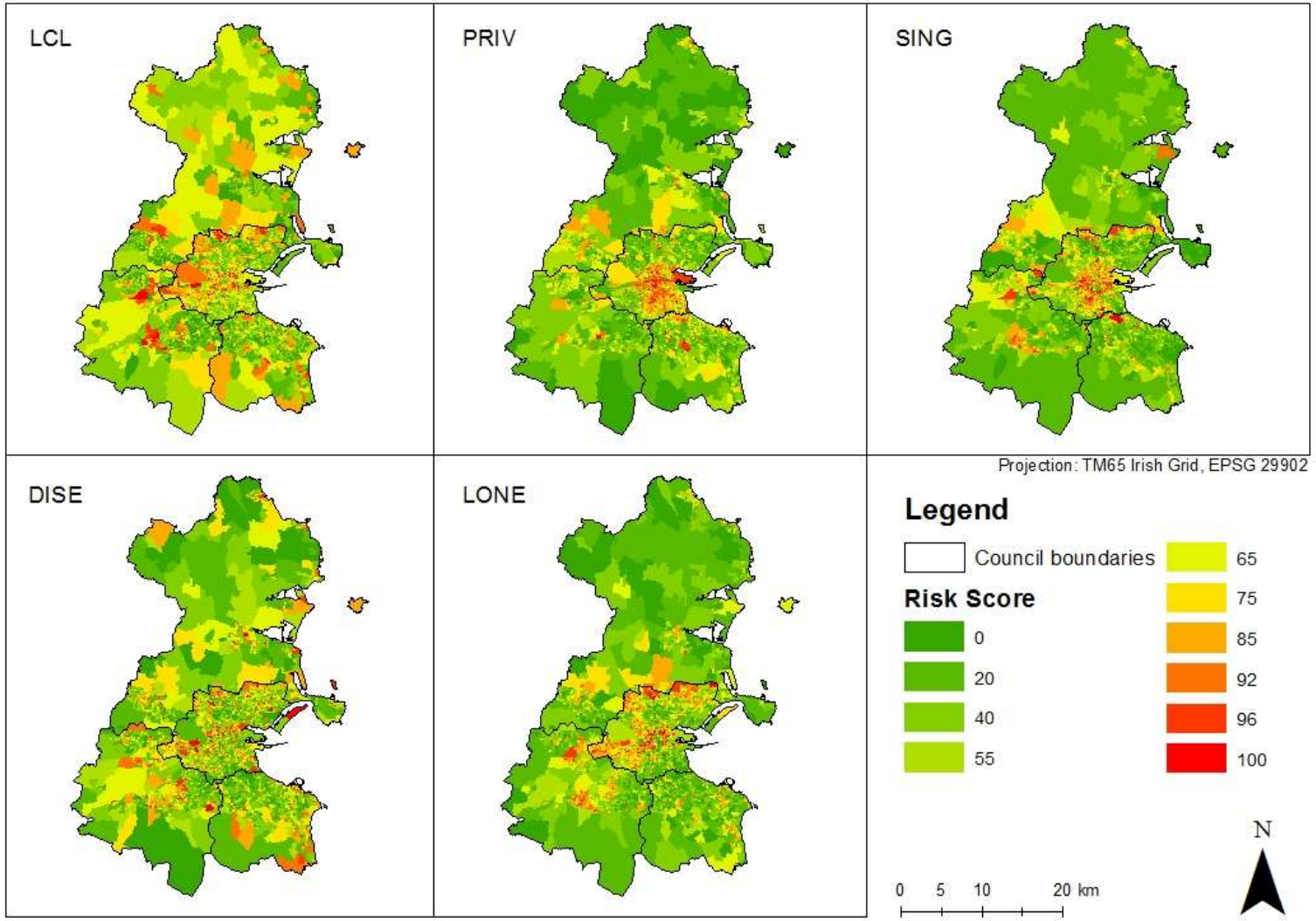
Table 3.10. Intervals created based on percentiles for each of the 14 attributes.
The table outlines percentages, percentile intervals and the risk scores for each attribute. The attribute THED (third level education completed) is scored inversely, the highest percentage equals the lowest risk score. The BER (building energy efficiency) attribute is scored according to the small area BER values.

Risk score	**Percentile**	**LCL**	**PRIV**	**SING**	**DISE**	**LONE**	**CHLD**	**RET**
0	10th	0.00%	4.72%	43.85%	2.23%	11.76%	0.00%	1.27%
20	30th	1.32%	9.71%	51.54%	3.41%	19.61%	1.25%	5.16%
40	50th	2.80%	17.55%	57.14%	4.42%	26.67%	2.50%	10.70%
55	60th	3.95%	24.09%	59.92%	4.94%	31.25%	3.75%	13.62%
65	70th	6.02%	33.33%	63.26%	5.56%	37.21%	5.00%	16.67%
75	80th	12.99%	47.37%	67.02%	6.29%	44.44%	6.25%	20.00%
85	90th	33.73%	65.24%	72.36%	7.59%	54.19%	8.75%	24.69%
92	94th	48.92%	74.74%	75.52%	8.48%	60.00%	10.00%	27.98%
96	98th	72.79%	86.59%	81.45%	10.98%	71.39%	12.50%	34.09%
100	100th	98.68%	98.95%	100%	29.11%	100%	25.00%	72.73%

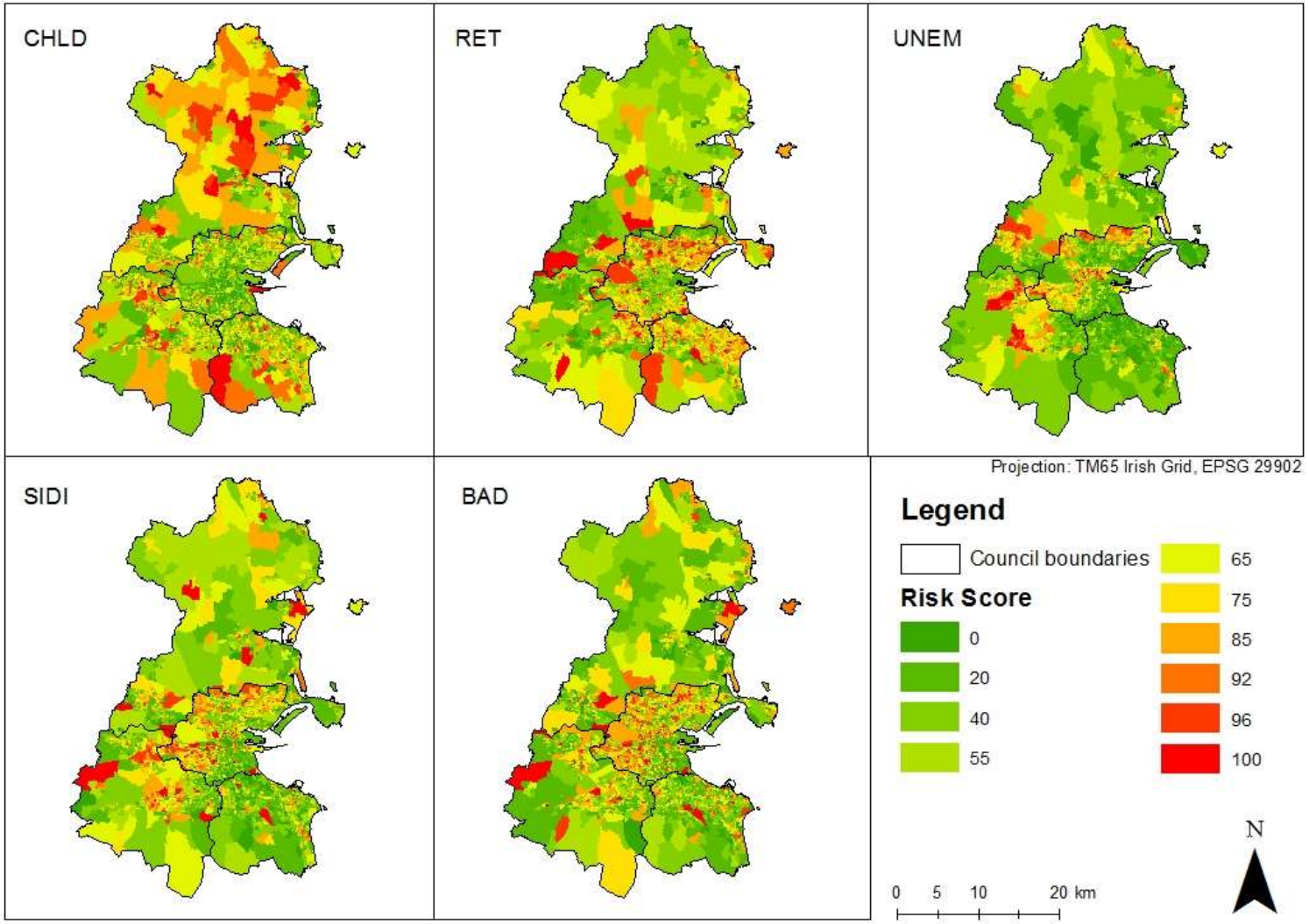
Risk score	**Percentile**	**UNEM**	**SIDI**	**BAD**	**NOED**	**THED**	**AGE**	**BER**
0	10th	3.82%	0.54%	0.00%	9.15%	61.80%	19.63%	212
20	30th	6.51%	1.54%	0.68%	17.24%	44.75%	24.94%	245
40	50th	9.42%	2.68%	1.19%	26.63%	32.33%	29.24%	267
55	60th	11.20%	3.46%	1.50%	33.36%	25.77%	31.94%	279
65	70th	13.20%	4.55%	1.94%	41.18%	18.94%	35.81%	291
75	80th	15.87%	6.01%	2.49%	49.92%	13.37%	43.12%	308
85	90th	20.59%	8.19%	3.40%	61.54%	7.34%	54.34%	333
92	94th	23.58%	9.52%	4.03%	65.99%	3.52%	61.98%	351
96	98th	29.07%	12.42%	5.67%	72.43%	2.22%	72.93%	378
100	100th	62.00%	45.98%	22.56%	88.80%	0.00%	100%	504

With the calculated cut-off points, a python reclassification code (ESRI, 2016) was used to score each attribute in the field calculator tool in ArcMap 10.3. The reclassification code is noted below using the example of the local authority tenant attribute percentile cut-offs (see column LCL in Table 3.10.). The resulting attribute layers are available in maps 3.2 – 3.4.

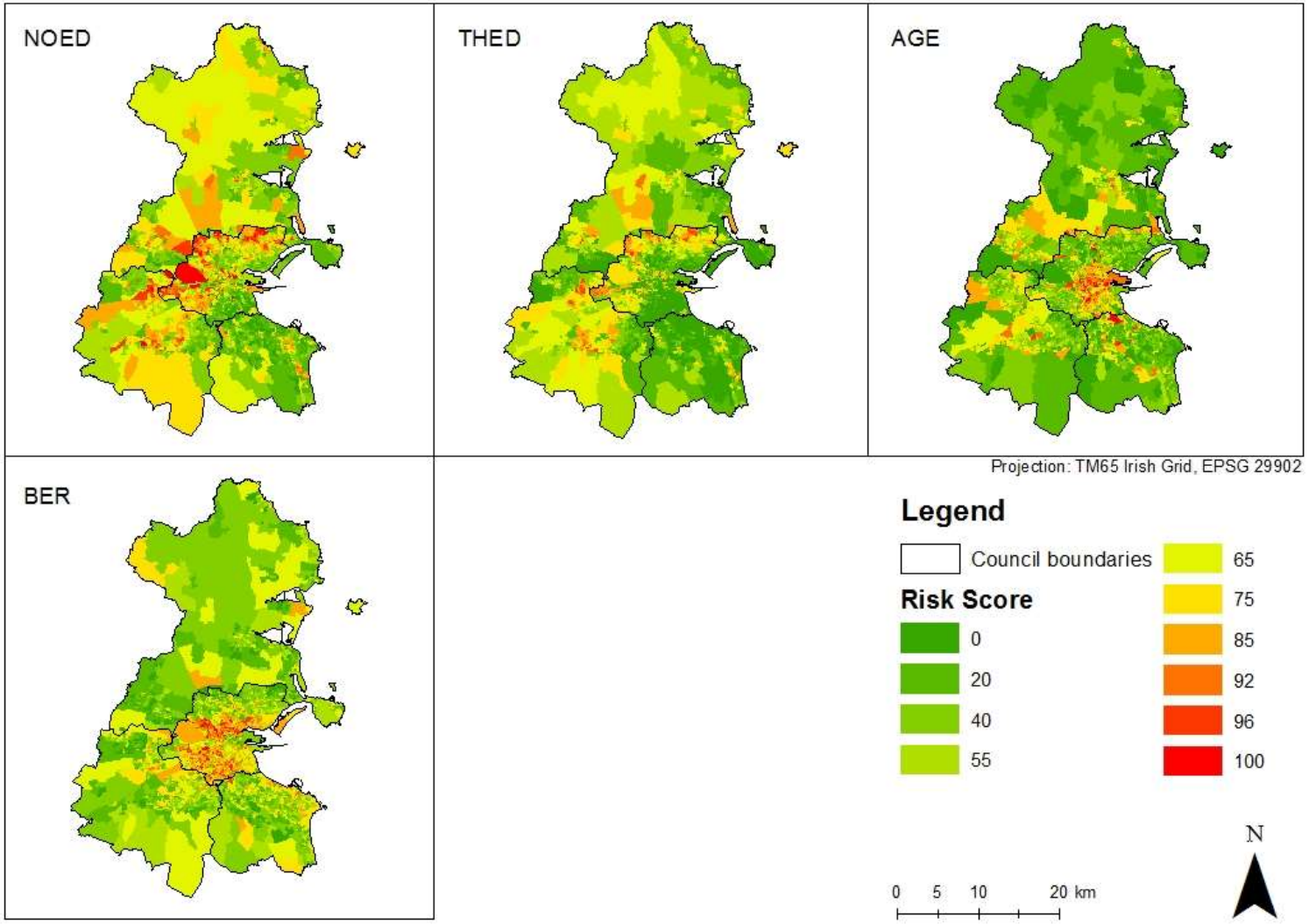
```
Parser:
Python

Expression:
Reclass(!FIELD_NAME!)

Code block:
def Reclass(prcnt):
    if (prcnt <= 0.00):
        return 0
    elif (prcnt > 0.00 and prcnt <= 0.0132):
        return 20
    elif (prcnt > 0.0132 and prcnt <= 0.0280):
        return 40
    elif (prcnt > 0.0280 and prcnt <= 0.0395):
        return 55
    elif (prcnt > 0.0395 and prcnt <= 0.0602):
        return 65
    elif (prcnt > 0.0602 and prcnt <= 0.1299):
        return 75
    elif (prcnt > 0.1299 and prcnt <= 0.3373):
        return 85
    elif (prcnt > 0.3373 and prcnt <= 0.4892):
        return 92
    elif (prcnt > 0.4892 and prcnt <= 0.7279):
        return 96
    elif (prcnt > 0.7279):
        return 100
```



Map 3.2. The spatial distribution of risk of the scored attributes: LCL, PRIV, SING, DISE and LONE



Map 3.3. The spatial distribution of the risk of the scored attributes: CHLD, RET, UNEM, SIDI and BAD



Map 3.4. The spatial distribution of the risk of the scored attributes: NOED, THED, AGE and BER

3.7.3. CALCULATE THE ENERGY POVERTY RISK

The models A – C were calculated using the scored attribute layers (maps 3.2 – 3.4) together with the calculated weights (Table 3.8.). The ArcMap 10.3 field calculator tool was used for this as well and the calculations used in the GIS are outlined below. These are the same algorithms as those diagrammatically depicted in figures 3.4 – 3.6.

Model A

This model gives the physical and social dimension equal weights.

```
Social dimension risk calculation:
([LCL_Prctl] * 0.062) + ([PRIV_Prctl] * 0.052) + ([SING_Prctl] * 0.020) +
([DISE_Prctl] * 0.101) + ([LONE_Prctl] * 0.019) + ([CHLD_Prctl] * 0.011) +
([RET_Prctl] * 0.028) + ([UNEM_Prctl] * 0.265) + ([SIDI_Prctl] * 0.074) +
([BAD_SD] * 0.171) + ([NOED_Prctl] * 0.132) + ([THED_Prctl] * 0.011) +
([AGE_Prctl] * 0.053)

Combining the social and physical dimension risk scores:
([Social_dim] * 0.5) + ([BER_Prctl] * 0.5)
```

Model B

The attributes are weighted without being categorised into physical and social dimensions.

```
Calculating Model B risk scores:
([LCL_Prctl] * 0.050) + ([PRIV_Prctl] * 0.043) + ([SING_Prctl] * 0.017) +
([DISE_Prctl] * 0.083) + ([LONE_Prctl] * 0.017) + ([CHLD_Prctl] * 0.01) +
([RET_Prctl] * 0.024) + ([UNEM_Prctl] * 0.230) + ([SIDI_Prctl] * 0.061) +
([BAD_SD] * 0.146) + ([NOED_Prctl] * 0.109) + ([THED_Prctl] * 0.010) +
([AGE_Prctl] * 0.045) + ([BER_Prctl] * 0.154)
```

Model C

Model C, a test model, applies equal weighs to all 14 attributes.

```
Calculating Model C risk scores:
 ([LCL Prctl] * 0.071) + ([PRIV Prctl] * 0.071) + ([SING Prctl] * 0. 071) +
([DISE_Prctl] * 0. 071) + ([LONE_Prctl] * 0. 071) + ([CHLD_Prctl] * 0. 071) +
([RET_Prctl] * 0. 071) + ([UNEM_Prctl] * 0. 071) + ([SIDI_Prctl] * 0. 071) +
([BAD_SD] * 0. 071) + ([NOED_Prctl] * 0. 071) + ([THED_Prctl] * 0. 071) +
([AGE_Prctl] * 0. 071) + ([BER_Prctl] * 0. 071)
```

3.8. MODEL EVALUATION

To assess the model of best fit, structured interviews with 80 households in seven locations were carried out between 13/12/2016 and 19/12/2016. The households were accessed by knocking on doors in selected areas and each respondent was asked to answer for the whole household.

The study aimed to survey a minimum of 10 households in each area but the number of respondents reached varied between 6 – 18 per area (Table 3.11.). I accessed the households by walking through the area on one side of each street at the time and knock/call on all doors/apartments until a sufficient number of respondents were reached, or until there were no further households to try.

Map 3.5 depicts the seven surveyed locales.

Table 3.11. Surveyed areas, number of households and number of respondents.
* The Cabra Park area consists of three small areas made up of 81, 91 and 92 households respectively. As few respondents (four and five respectively) were reached in two of the areas and as the areas are part of the same estate (Map 3.7), the answers from all three areas have been treated as being part of the same area.

Survey area	Number of households	Respondents
Kiltalown	77	16
DeSelby	76	8
Wood Quay	72	11
Rathmines	116	10
Arran Quay	81	11
Cabra Park	264*	18
Belmayne	115	6

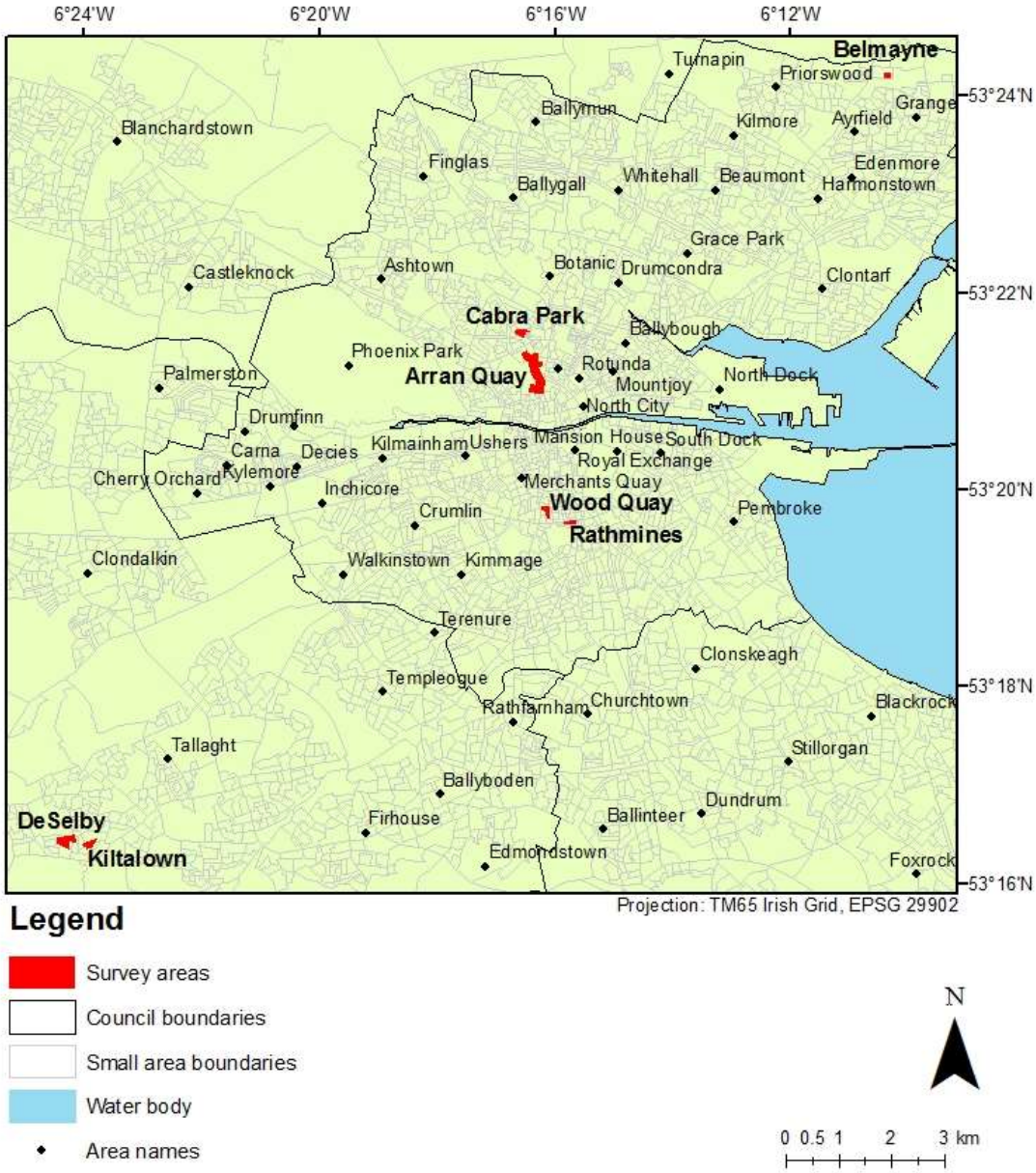
The interview questions are outlined in APPENDIX 4. These capture social characteristics of the households, physical dwelling characteristics, and assess energy poverty prevalence. Incidence of energy poverty was observed using the consensual measure. The consensual measure questions in the survey are the same as those used to assess energy poverty prevalence in Ireland in the four national studies informing this thesis (Healy, 2003a; Healy and Clinch, 2004; Scott et al., 2008; Watson and Maitre, 2015). The risk factors identified to build the models A – C, are therefore identified against the same energy poverty measure as is used in the evaluation survey. These four questions are:

- In your opinion, is your home kept adequately warm?
- Have you had to go without heating during the last 12 months through a lack of money?
- Is there damp and rot in your home? For example, rot in the window frames, damp marks on the walls/ceiling and likewise.
- Have you missed paying a utility bill in the last 12 months through a lack of money?

By assessing the degree of energy poverty in the selected locales with a survey, observations of energy poverty can be compared to the predicted energy poverty risk in each model. This makes it possible to assess if an area which is predicted as a high-risk area also is an area where we find high portions of energy poor households. The assumption is that an area with high predicted risk according to a model should also in the survey results display higher prevalence of energy poverty, if the model has a good fit.

Since the models are calibrated differently the risk in each area is not the same for each model. An area that is high-risk according to Model A, and low-risk according to Model C, can for example be surveyed and compared to an area that is high-risk in Model C and low-risk in Model A. If the survey results find that the former area has a higher potion of households in energy poverty, it is an indication that Model A has a better fit than Model C for that area.

Survey areas were selected using this logic. Five of the areas surveyed are as different as possible from each other in terms of the predicted risk according to the three models (Kiltalown, Wood Quay, Rathmines, Cabra Park and Belmayne). Additionally, one area which is a low-risk area in all models (DeSelby), and one area which is a high-risk area in all models (Arran Quay), were surveyed to assess if the models accurately identify high- and low-risk areas.



Map 3.5. Areas surveyed using structured interviews.

4. ANALYSIS AND RESULTS

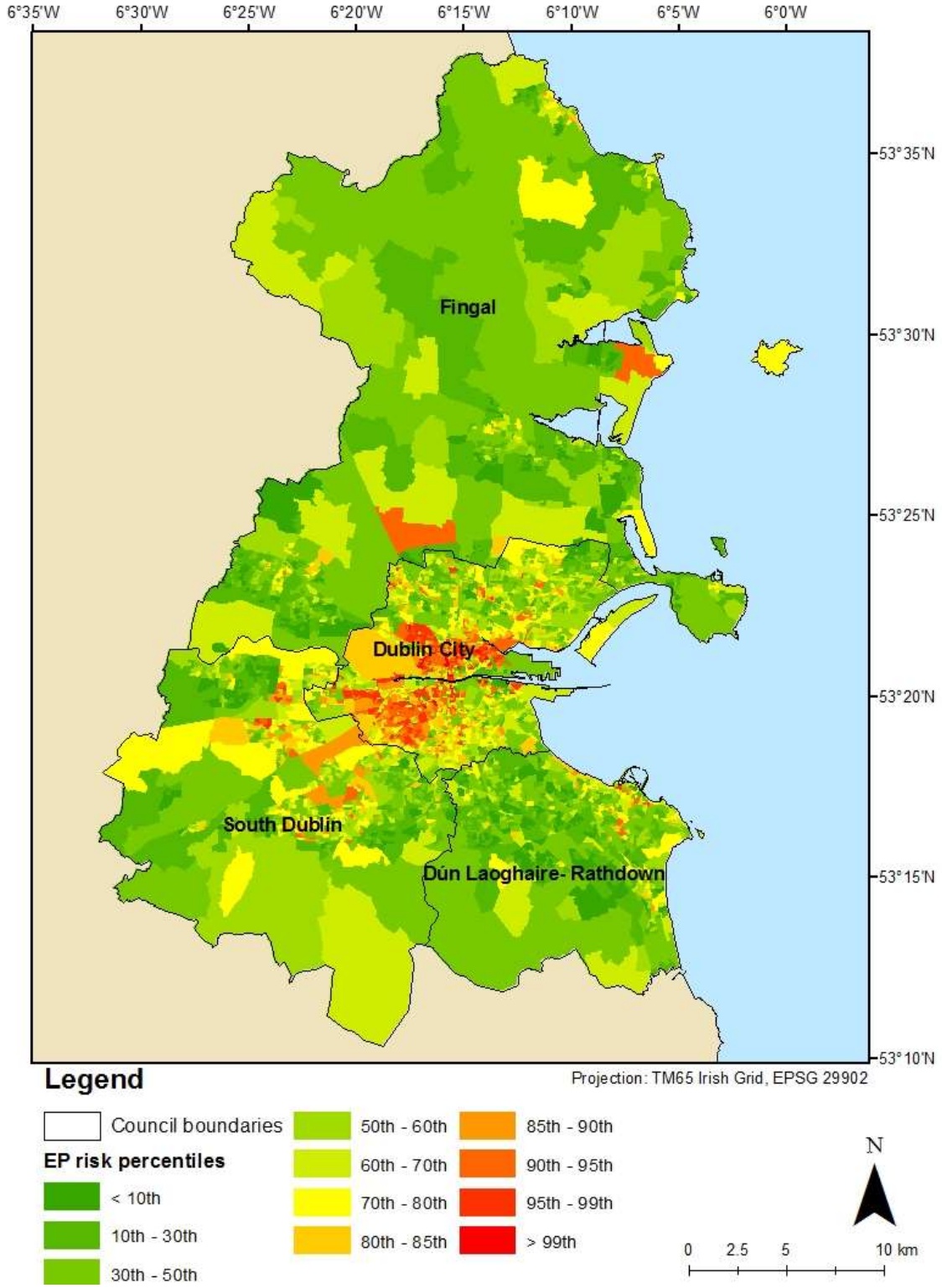
4.1. MODEL RESULTS

The three models produced similar results but with some important differences. An overview is presented in maps 4.1 – 4.3. The classification of the risk scores is done according to percentiles of the data distribution to make comparisons across the models possible.

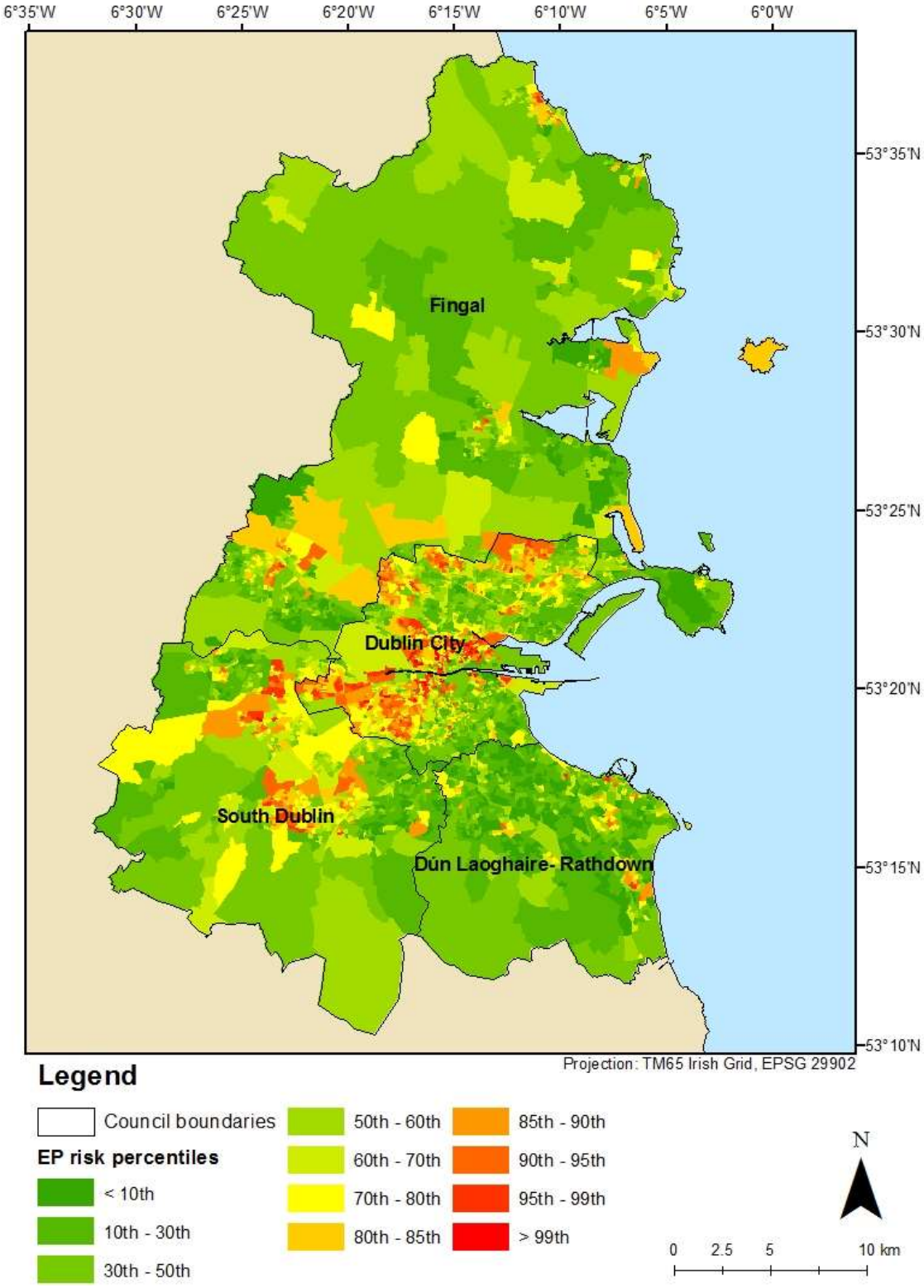
It is clear from these maps that the highest risk is predominantly concentrated in Dublin city council for all three models. In Model B and C, the risk is slightly more dispersed. Naturally as Model A gives the physical and social dimension equal weights (and therefore gives the BER attribute a high weight) the Model A results follows the distribution of the BER attribute more closely (compare BER Map 3.4 and Model A results Map 4.1.).

Model B, which gives a lower weight to the BER attribute, identifies a greater number of areas with high risk in the South Dublin council area which in Model A are not identified as high-risk. Lastly Model C that gives all 14 attributes equal weights, identifies the highest risk predominantly in the Dublin city council area but also in the South Dublin and Fingal council areas.

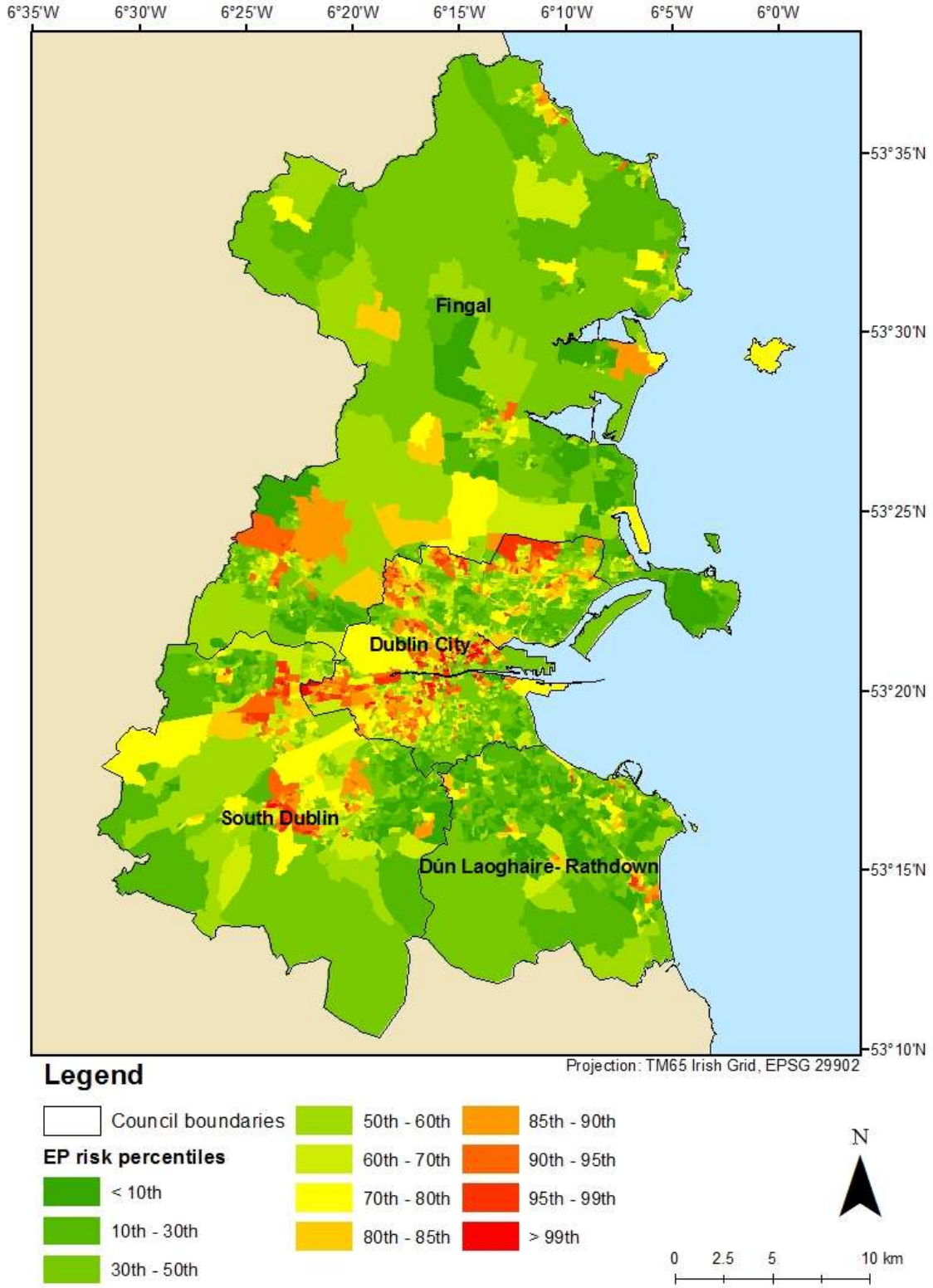
Next section outlines the survey results and contrast these with the predicted risk according to models A, B and C.



Map 4.1. Model A results. The physical and social dimension risk is equally weighted in this model. The results show that the top 5th percentile of risk according to this model is nearly exclusively located centrally and south-west in Dublin city council.



Map 4.2. Model B results. The social dimension risk is emphasised in this model. The results show that the top 5th percentile of risk is mostly located centrally, south west and in the north of Dublin city council. Some high-risk areas are also found in South Dublin council.



Map 4.3. Model C results. All risk factors are equally weighted in this model. The results have a similar spread as Model B but with greater risk in the north and south west Dublin city council.

4.2. SURVEY RESULTS

4.2.1. GENERAL SURVEY RESULTS

A total of 80 households were interviewed. In some areas, it was more difficult to get a sufficient number of respondents which resulted in the number of surveys collected in each area varying significantly from 4 to 16. However, where few households were reached, small areas bordering the selected unit were included to produce a better picture of the experienced degree of energy poverty in the area.

Figures 4.1 – 4.7 presents the general survey data of the respondents in terms of: dwelling type (4.1.); number of adults (4.2.); age group of respondents (4.3.); household composition (4.4.); employment level (4.5.); tenure status (4.6.); and marital status (4.7.).

Adult children (16 and older) are counted as adults if the children are not studying. This is done to match how the social welfare system in Ireland assesses if a parent can receive child benefits for a child aged over 16 (Citizens Information, 2016a). The same method is used when calculating the number of adults in a household (Figure 4.2).

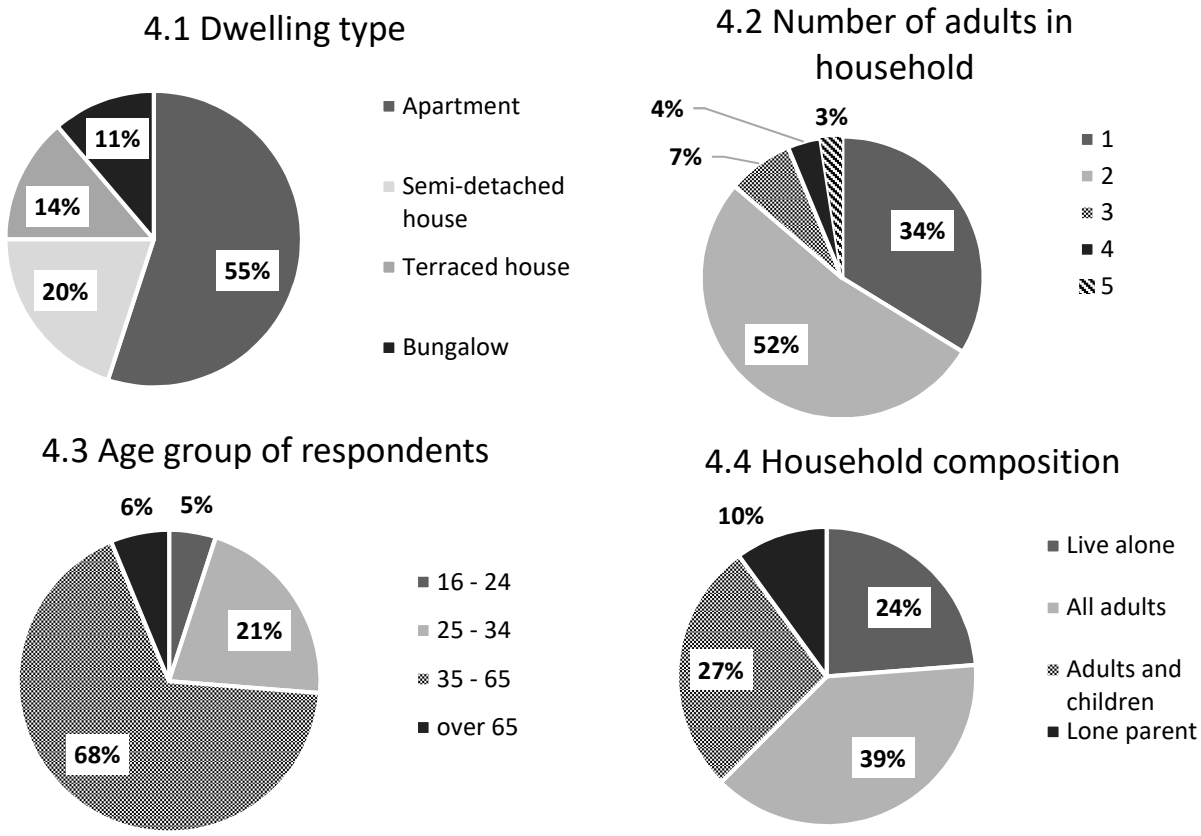


Figure 4.1. – 4.4. General survey data relating to dwelling type, household composition, age group of respondents and number of adults in the household.

The age variable and the marital status variable were only collected for the respondent and not for all adults in the household.

The employment level categories are created based on the proportion of adults in the household with employment and on the job type (part time/full time) of each adult. For example, a household of two adults where one adult is working full time and one is working part time is classified as 'about three quarters' employed. Households with only one adult working part time is classified as 'about half time employed'.

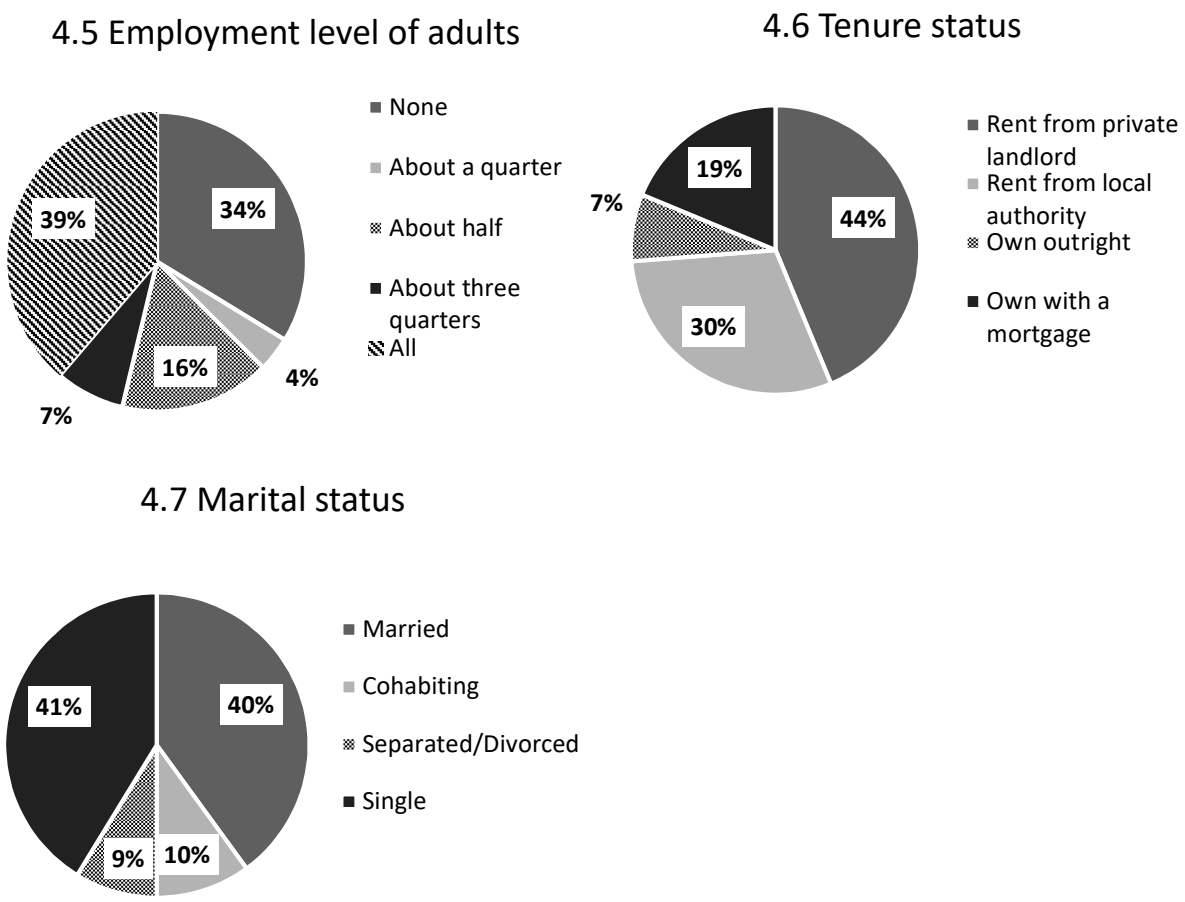


Figure 4.5 – 4.7. General survey data relating to the employment level of the adults in the household, the tenure status and the marital status.

It should be noted that 16% (13) of the surveyed households reported at least one adult in the home who could not work due to sickness/disability. In terms of benefits, a noticeable 44% of respondents reported having a medical card. Furthermore, 28% of the surveyed households reported being in receipt of a fuel allowance.

Only 13% (10) of households stated that they have benefitted of free of charge renovations to make the dwelling warmer. These were nearly exclusively households renting from local authority.

The variables capturing physical characteristics of the households are not included in the analysis due to the portion of households who were unable to answer these questions. Surprisingly, only a handful of respondents knew what a BER rating was, and only one respondent knew what the BER rating of their home was.

In terms of awareness of energy poverty, 24% (19) of the respondents had heard of the concept. Only one respondent had heard of the BEC scheme, but without knowing what it was. From the energy poverty indicators captured, the most commonly reported problem was to keep the home adequately warm (39%) (Table 4.1.).

Table 4.1. Portion of surveyed households reporting each of the four energy poverty indicators.

Energy poverty indicator	% of surveyed households	Number of households
Home not adequately warm	39%	31
Having to go without heat	23%	18
Damp/Rot in dwelling	29%	23
Miss paying a bill	9%	7

Households reporting more than one of the four indicators of energy poverty (e.g. unable to heat home adequately and having missed a utility bill in the last 12 months) are categorized as 'in severe energy poverty'. This builds on the approach used by Healy and Clinch (2004) who differentiate between households in intermittent and chronic energy poverty. Their study classifies households reporting that they have *some difficulties* to adequately heat their home as 'intermittent fuel poor', and households reporting that they *usually* or *never* are able to heat their home adequately as 'chronic fuel poor'.

Here a household is considered in severe energy poverty when it reports two or more energy poverty indicators. More than half of the surveyed households reported at least one indicator of energy poverty (53%) while a lower (31%) reported two or more indicators. Households reporting one or more indicators are referred to as 1+ EPI (Energy Poverty Indicator) and households reporting two or more indicators are referred to as 2+ EPI hereafter.

4.2.2. ENERGY POOR HOUSEHOLDS

A big portion, of the single adult households (42%) and of the lone parent households (38%) in the survey report 2+ EPI (Table 4.2.). Comparing this to the survey sample (Figure 4.4), these groups are overrepresented among households in severe energy poverty.

Table 4.2. Households reporting 2+ EPI by household composition.

Household composition type	Number of households in survey (N = 80)	% reporting 2+ EPI
Live alone	19	42%
All adults	31	26%
Adults and children	22	27%
Lone parent	8	38%

Continuing the same comparisons, 46% of the households renting from local authority and 33% of households owning their house with a mortgage, are in severe energy poverty. None of the surveyed households owning their house outright report severe energy poverty (Table 4.3.).

Table 4.3. Households reporting 2+ EPI by tenure status.

Tenure status	Number of households in survey (N = 80)	% reporting 2+ EPI
Rent from private landlord	35	26%
Rent from local authority	24	46%
Own with a mortgage	15	33%
Own outright	6	0%

Unemployment is the risk factor that is assigned the greatest weight out of the social dimension risk factors in Model A and out of all risk factors in Model B. A noteworthy 54% of the surveyed households reported low employment levels (half or less than half of adults in employment). Interestingly, it is not among the fully unemployed households that the greatest portion of severe energy poverty is found (Table 4.4.). Instead a greater percentage of households with half or a quarter employment level, reported 2+ EPI. There are however only 3 households in the category reporting 'about a quarter', and 13 households in the category reporting 'about half' of the adults in employment.

Table 4.4. Households reporting 2+ EPI by tenure status.

Employment level	Number of households in survey (N = 80)	% reporting 2+ EPI
None	27	33%
About ¼	3	100%
About ½	13	54%
About ¾	6	17%
All	31	16%

This shows that it is not just unemployed households experiencing the issue. The following section looks at differences between the households found in severe energy poverty, this is done by grouping the households that report 2+EPI by their household level of employment.

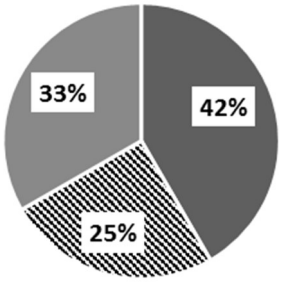
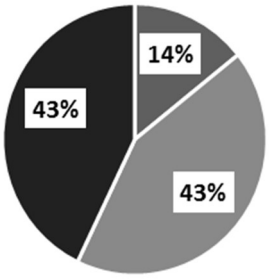
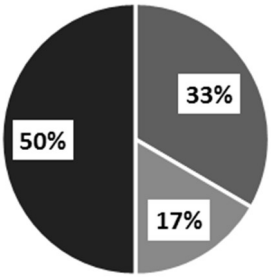
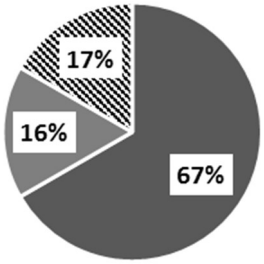
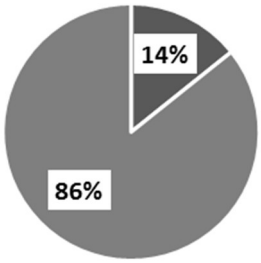
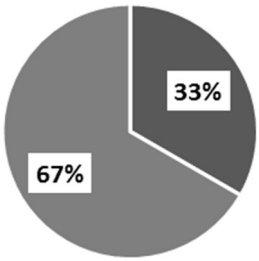
4.3. ENERGY POOR HOUSEHOLD TYPES

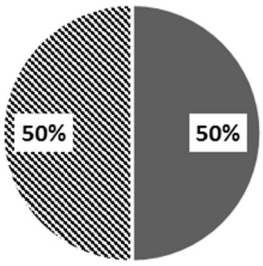
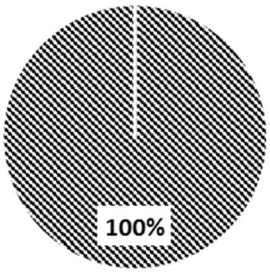
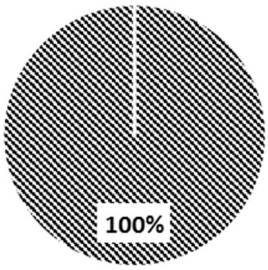
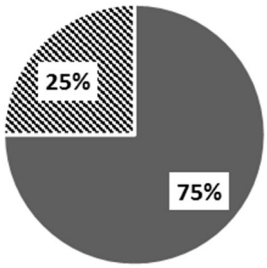
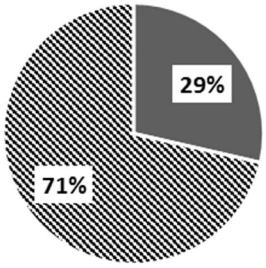
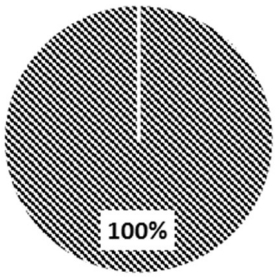
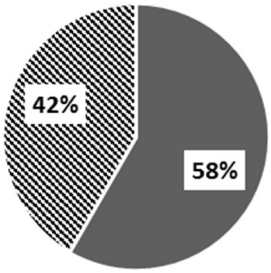
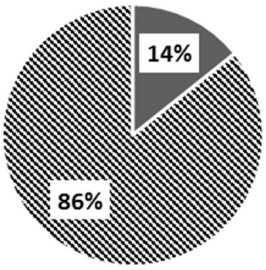
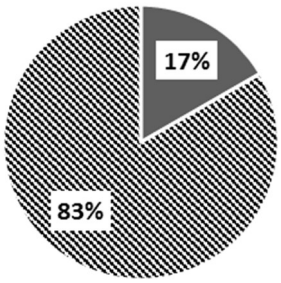
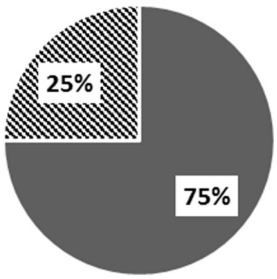
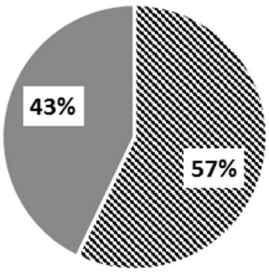
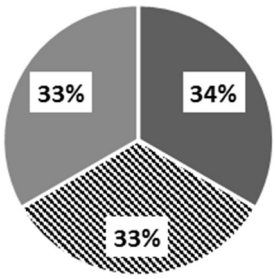
Table 4.5. summaries the characteristics of the households that reported 2+ EPI. The survey results are placed into three groups: low employment level (unemployed and

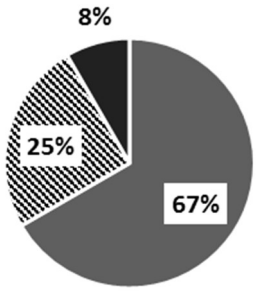
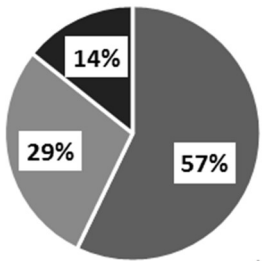
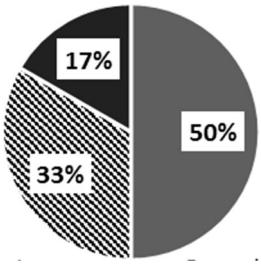
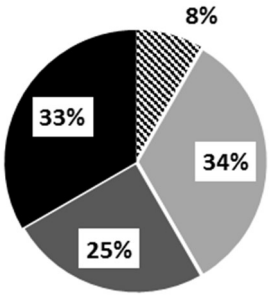
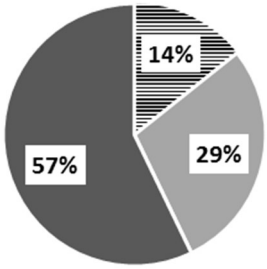
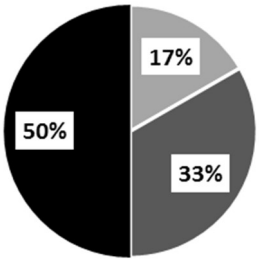
working about ¼), medium employment level (households reporting employment level of about ½), and households of full or nearly full employment level (full time and about ¾ employment level).

The employment status was found to be the attribute with the highest probability to influence household's experience of energy poverty in Ireland (hence obtaining the highest weight in Model B). For this reason, it is used in this study as a grouping variable for energy poor households. By grouping the energy poor households based on the employment level it is possible to reveal how other key characteristics from the survey vary between the households depending on their employment level. The characteristics included in Table 4.5. are: household composition; number of adults; person with sickness/disability; medical card holders; fuel allowance recipient; tenure status and dwelling type. Adding to these, the average energy efficiency (BER) risk score of the survey area is included.

Table 4.5. Households in severe energy poverty by level of employment
The total number of respondents reporting severe energy poverty was 25 (of 80). In each of the groups there were 12 (low employment), 7 (medium employment) and 6 (high employment) households respectively.

Variable and legend	**Households not working or working about 1/4 (N: 12)**	**Households working about half (N: 7)**	**Households working full time or about ¾ (N: 6)**
Household composition ■ Lone adult ■ Lone parent ■ All adults ■ Adults and children			
Number of adults ■ One ■ Two ■ Three			

Variable and legend	Households not working or working about 1/4 (N: 12)	Households working about half (N: 7)	Households working full time or about ¾ (N: 6)
If there is an adult who cannot work due to sickness/disability in the household ■ Yes ▨ No			
Household has a medical card ■ Yes ▨ No			
Household is in receipt of the fuel allowance ■ Yes ▨ No			
Tenure status ■ Local authority renter ▨ Pivate renter ■ Own with mortgage ■ Own outright			

Variable and legend	Households not working or working about 1/4 (N: 12)	Households working about half (N: 7)	Households working full time or about ¾ (N: 6)
Dwelling type Apartment Bungalow Terraced house (Semi) detached house			
BER risk score BER 0 BER 20 BER 40 BER 92 BER 100			

This break-down of the survey results displays three types of energy poor households. A first group (left hand column) with LOw employment level and MEdium to poor housing (LOME); a second group (middle column) with MEdium employment levels and MEdium to poor housing (MEME); and a last group (right hand column) with HIgh employment and predominantly POor housing (HIPO).

The LOME type is distinctly different from the medium and high employment types in terms of characteristics. It is dominated by households renting from the local authority (75%) with one adult (67%) which is either on their own (42%) or a lone parent (25%). The household is often a medical card holder (75%) and fuel allowance recipient (58%). This is the only household type in severe energy poverty where we find households reporting an adult or more who cannot work due to sickness or disability (50%). The energy efficiency risk scores (BER) found in the areas where these surveys were gathered are mixed. The range found goes from extremely poor housing (risk scores of 92-100/100) to medium and no risk (risk scores 40/100 and 0/100).

The MEME and HIPO types display a lot of similarities. It is predominantly two adult households (86% and 67% respectively), often with children (43% and 50% respectively). These households are rarely recipients of fuel allowance (14% and 17% respectively) or a medical card (29% and 0% respectively). The households are often home owners with a mortgage (43% and 33% respectively) or renting privately (57% and 33% respectively). In terms of energy efficiency of the housing the types diverge.

The MEME type display a mixture of BER risk scores ranging from low risk scores (20/100) to high risk scores (92/100). The HIPO type however is clearly dominated by the high BER risk scores of 92/100 and 100/100.

The next section integrates the survey results with the modelled risk in each of the surveyed areas. This highlight what the predicted risk according to each of the three models is compared to the observed level of energy poverty.

4.4. SMALL AREA FINDINGS

4.4.1. TALLAGHT-JOBSTOWN

Two areas in Tallaght-Jobstown were surveyed. One area, referred to as Kiltalown displays high risk in Model B and Model C (in the top 10th percentile) but lower risk in Model A (in the bottom 80th percentile). The other area, referred to as DeSelby, displays low risk (bottom 60th percentile) in all three models. Map 4.4 details these varying risk ratings for the two locations. The underlying risk factor scores for the individual attributes are illustrated in Map A5.1. in APPENDIX 5.

The most notable attributes with high risk scores in Kiltalown are: local authority renter (LCL), divorced/ separated (DISE), cannot work due to sickness/disability (SIDI), bad health (BAD) and unemployment (UNEM). Meanwhile it has a relatively low BER score which indicates that on average in this area, the energy efficiency of the houses is quite good. This explains why the predicted risk of the area is lower in Model A, where the physical dimension has a higher weighting.

The other small area DeSelby has low risk in 12 of the 14 attributes. We can however see that a large portion of the people living there at the time of the Census 2011 were young (age 16 – 34) (AGE), and the unemployment level was in the upper 15th percentile (UNEM).

In both Kiltalown and DeSelby, the most commonly reported energy poverty indicator was issues to keep the home adequately warm (Figure 4.8.). This was reported by a big portion of households in both areas 38% (DeSelby) and 44% (Kiltalown). The portion of households in severe energy poverty (2+ EPI) was however different between the two areas: 13% (DeSelby) and 44% (Kiltalown).

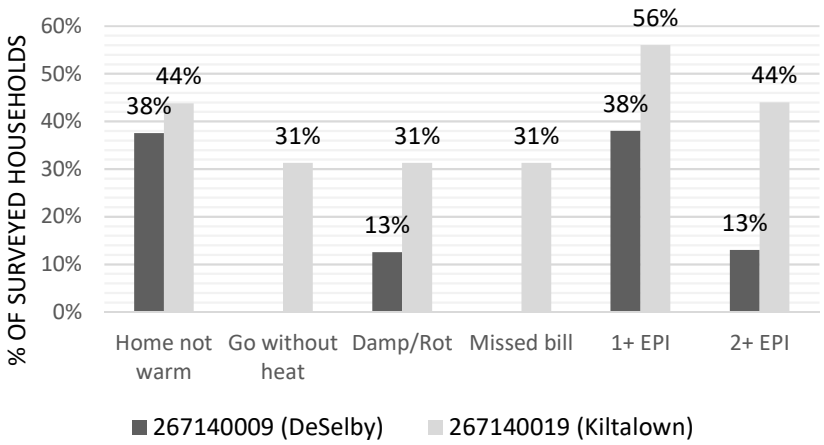
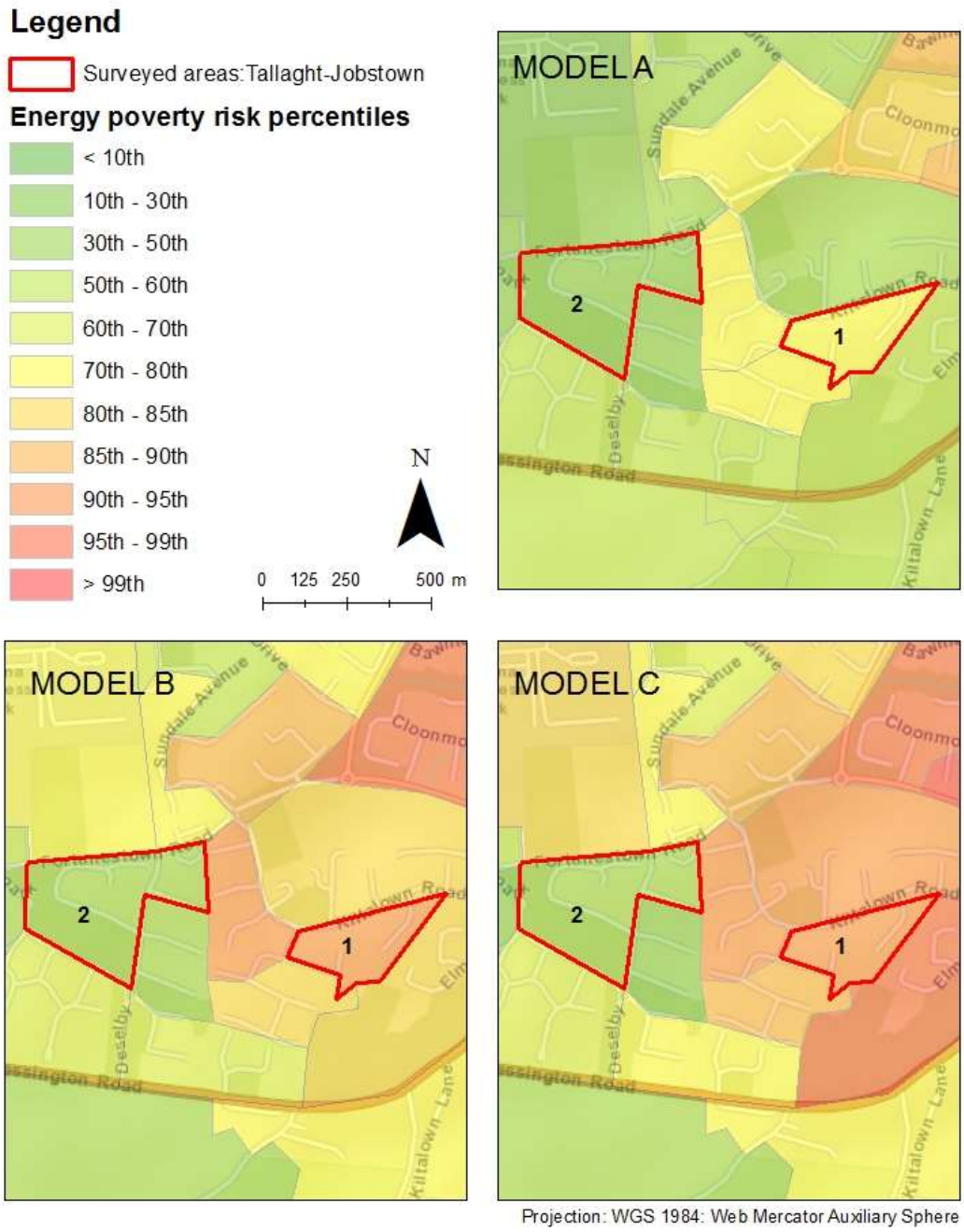


Figure 4.8. Households reporting energy poverty indicators in Kiltalown and DeSelby



Map 4.4. Surveyed areas in Tallaght-Jobstown.
Kiltalown (marked 1) is high risk in models B and C but lower in A. DeSelby (marked 2) is low risk in all three models. Basemap layer: ESRI, World Streeet Map.

4.4.2. WOOD QUAY & RATHMINES

Two areas in Wood Quay and Rathmines were surveyed. In contrast to Kiltalown, these two areas obtain higher risk scores in Model A compared to B and C. Wood Quay displays risk in the 90th – 95th percentile in Model A, while in Model B it is in the bottom 80th percentile and in Model C the bottom 60th percentile. The risk in Rathmines is in the 85th – 90th percentile in Model A, while in Model B it is in the bottom 70th and in the bottom 60th percentile in Model C (Map 4.5.).

The underlying risk factor scores for the individual attributes are found in APPENDIX 5 (Map A5.2.). The attribute scores explain why the areas get a higher risk profile in Model A than in B and C. The BER risk score is very high for both areas, particularly in Wood Quay. In Wood Quay we also see high degrees of private rental households but otherwise the risk factors for the social dimension remain low in this area. In Rathmines, other than the high BER risk, social dimension risk factors which score high are: private renters (PRIV), single marital status (SING), divorced/separated marital status (DISE) and people 16 – 34 years of age (AGE).

The survey results for these areas show considerable portions of households that have issues with the home not being adequately warm, as well as issues with damp and rot (Figure 4.9.). However, when it comes to the ability to afford energy, only one household in Rathmines reports having gone without heat in the last 12 months. No household reports issues with not being able to pay utility bills in either of the two areas.

The portion of households reporting any of the four energy poverty indicators is high in both areas, 40% in Rathmines and 55% in Wood Quay. But when we look at the portion of households reporting 2+ EPI, the results are halved (20% and 18% respectively) (Figure 4.9.).

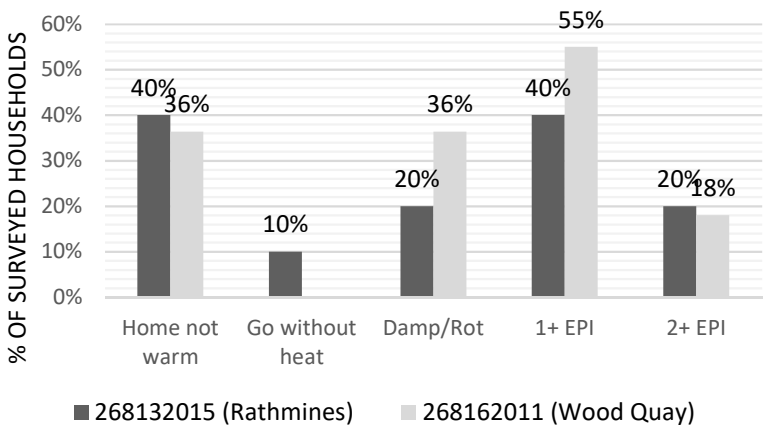
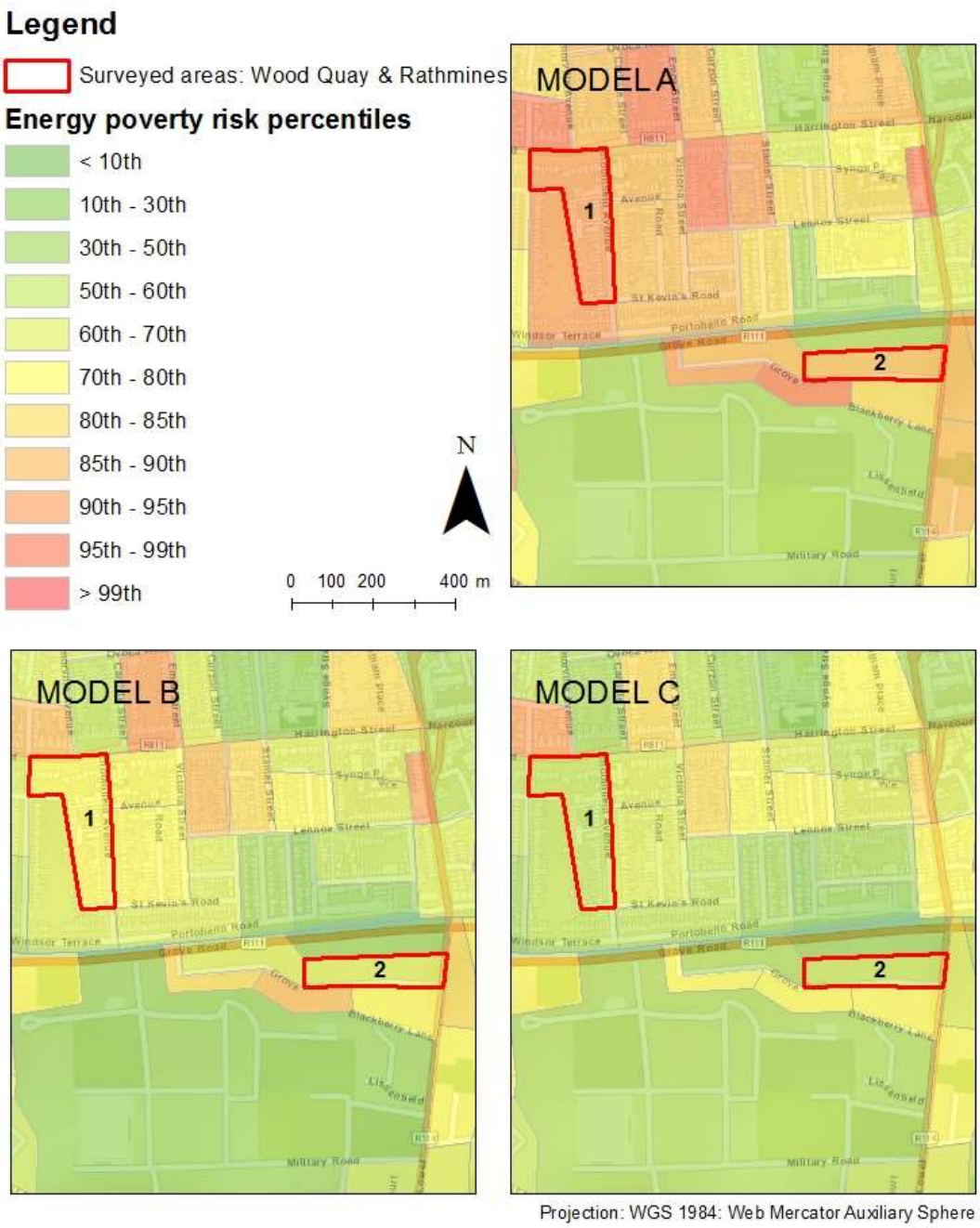


Figure 4.9. Households reporting energy poverty indicators in Rathmines and Wood Quay.



Map 4.5. Surveyed areas Wood Quay and Rathmines.
Both Wood Quay (marked with 1) and Rathmines (marked 2) display high risk in Model A but lower risk in Model B and C. Basemap layer: ESRI, World Streeet Map.

4.4.3. ARRAN QUAY

The area surveyed in Arran Quay is the area with the highest predicted energy poverty risk in both Model A and B. In Model C it is the 9th highest risk area out of the 4806 small areas assessed. The majority of the area consists of industrial land and hence has no residential housing. However, in the south-east corner, there are three blocks of apartments owned by the Dublin city council (81 households according to the Census 2011). These are all local authority housing (Map 4.6.).

The underlying attribute risk scores are available in APPENDIX 5 (Map A5.3.). This shows that Arran Quay scores extremely high in 7 of the 14 attributes. The extreme risk attributes are local authority renters (LCL); lone parent families (LONE); divorced/separated marital status (DISE); people who cannot work due to sickness/ disability (SIDI); bad/very bad health (BAD); unemployment (UNEM); as well as low educational qualifications (NOED).

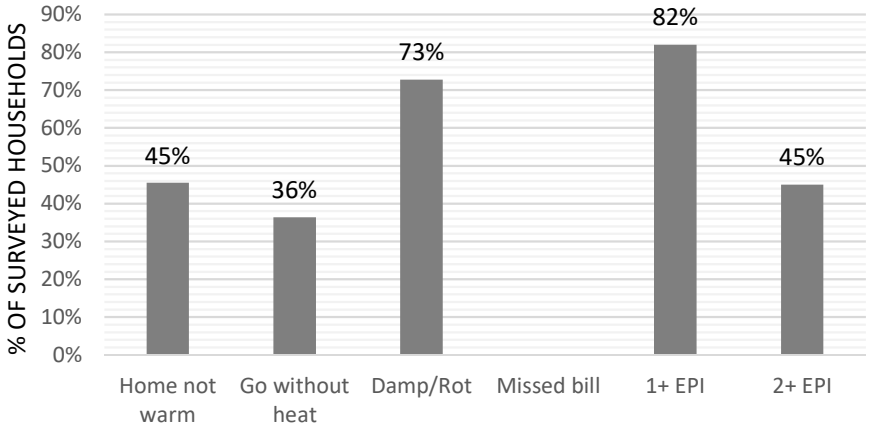
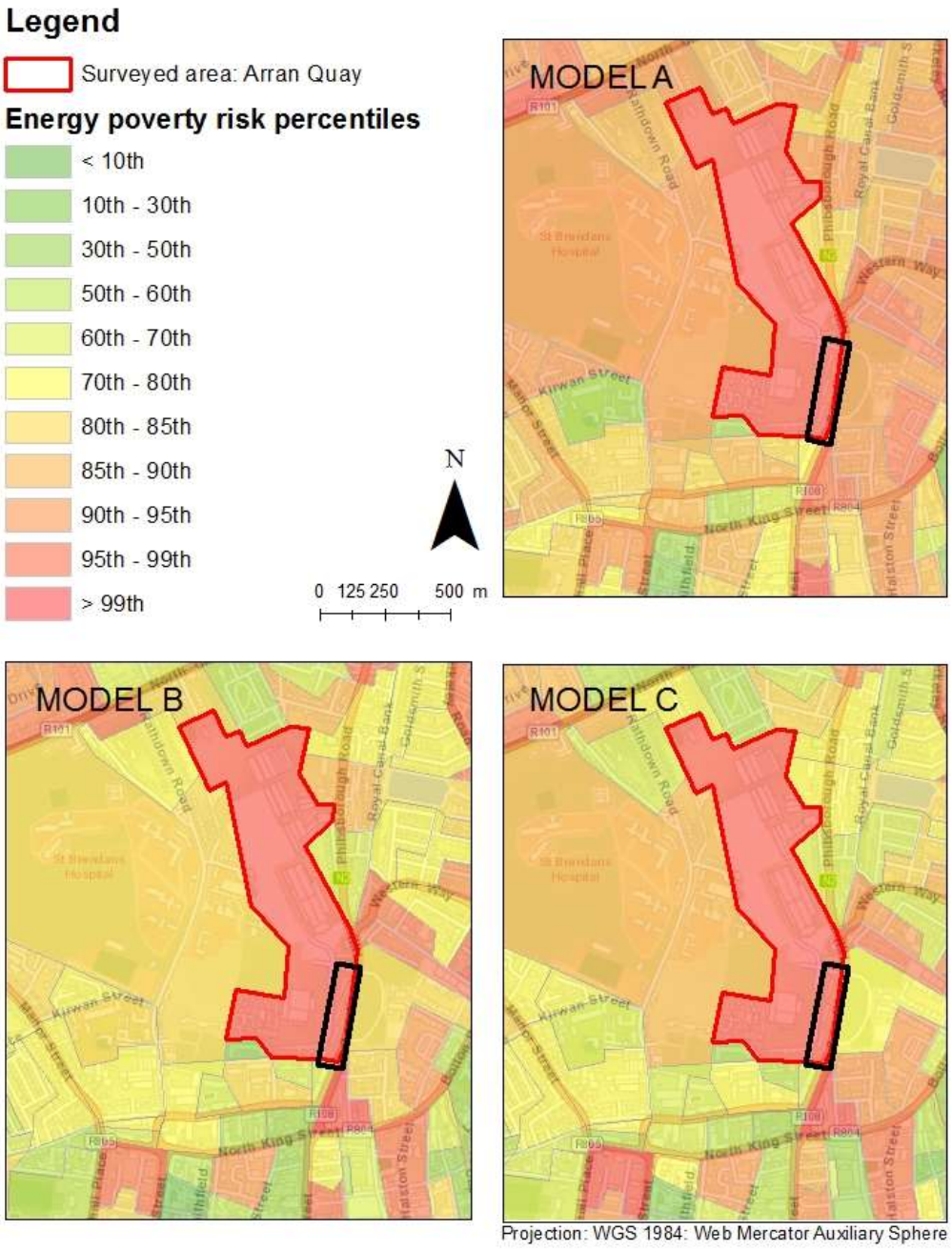


Figure 4.10. Households reporting energy poverty indicators in Arran Quay.

The survey results (Figure 4.10.) show that the most commonly experienced problem in this area is issues with damp and rot (72%). Furthermore, 46% report not being able to keep their home sufficiently warm, and 36% report that they had to go without heating in the last 12 months due to a lack of money. No households report issues with utility bill payments but a striking 82% report at least one of the four energy poverty indicators. The portion of households in severe energy poverty is 45%.



Map 4.6. Surveyed area Arran Quay.
The area displays extremely high risk in all three models. Basemap layer: ESRI, World Streeet Map.

4.4.4. CABRA EAST A

Three small areas, referred to as Cabra Park were surveyed. Due to the low number of respondents in two of the areas, and since the three areas are part of the same estate, they are treated as one in terms of survey answers. All three areas display very high risk in models A and B. Model C assigns extremely high risk for one of the three areas but lower risk for the other two areas (Map 4.7.).

The underlying attribute risk scores are in APPENDIX 5 (Map A5.4.). The areas are dominated by private rental households (PRIV), with poor energy efficiency ratings (BER). Other attribute risk scores which are high include the portion of divorced/separated (DISE), bad/very bad health (BAD) and unemployed (UNEM).

The observations in Cabra Park (Figure 4.11.) show 44% of surveyed households reporting 1+ EPI and 33% of households reporting severe energy poverty (2+ EPI).

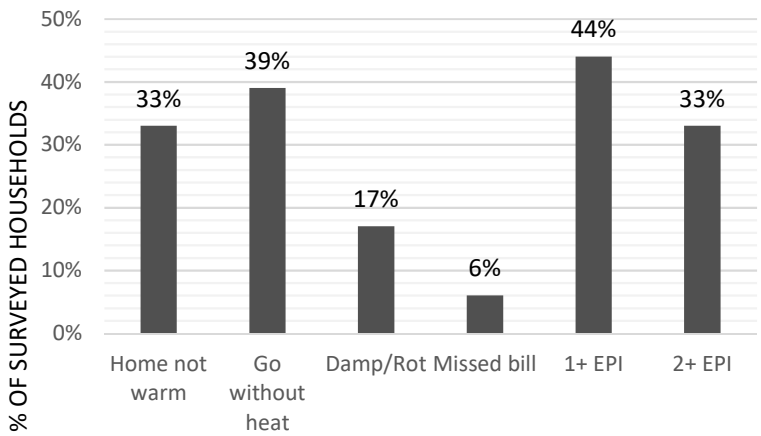
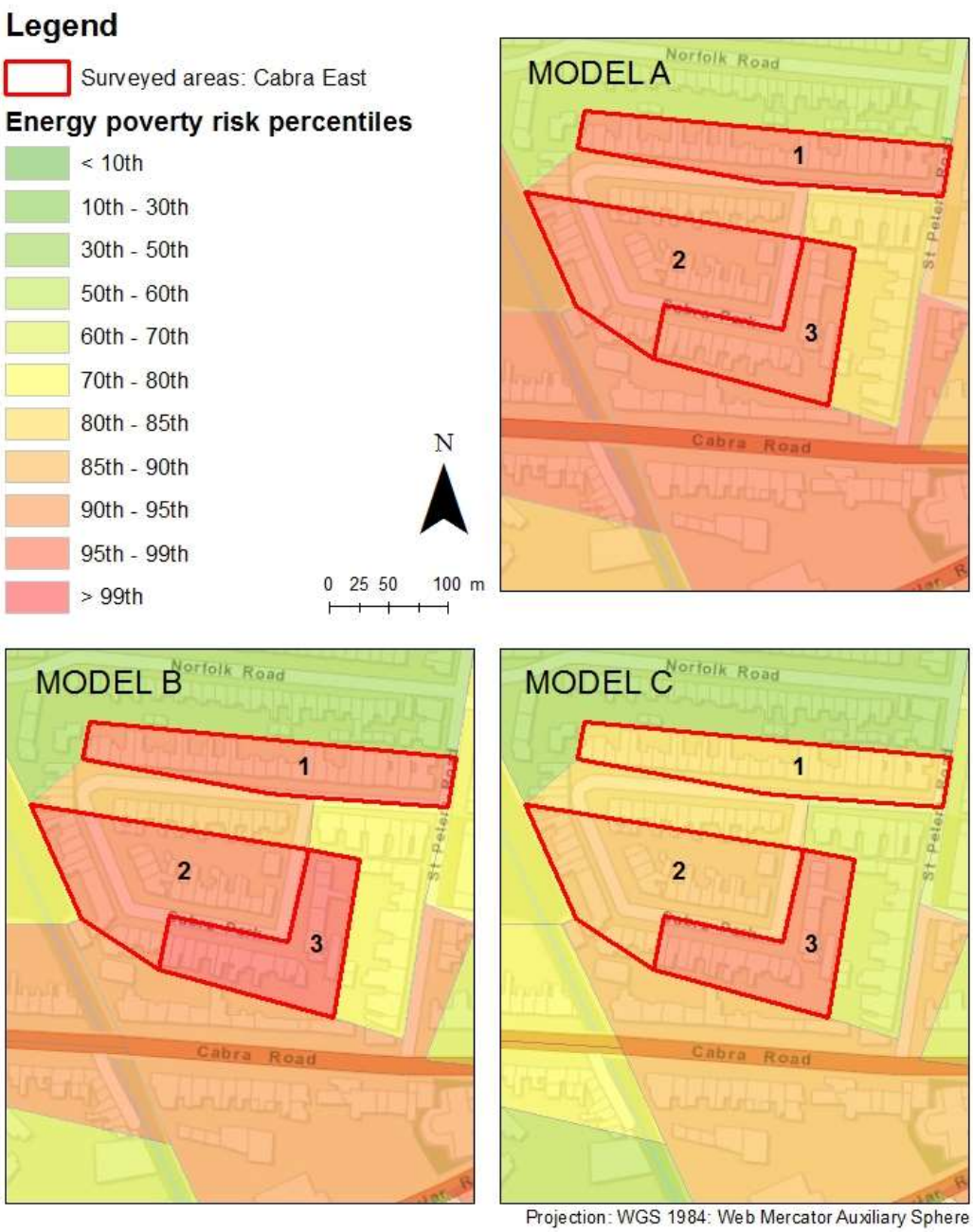


Figure 4.11. Households reporting energy poverty indicators in Cabra Park.



Map 4.7. Surveyed areas in Cabra Park.
All three areas display very high and extremely high risk in models A and B. Model C assigns extremely high risk for one area (marked 3) but lower risk for the other two areas (marked 1 and 2). Basemap layer: ESRI, World Streeet Map.

4.4.5. BELMAYNE

Lastly among the surveyed areas is Belmayne where only six respondents were reached. Out of these, only one household reported full time employment, 3 respondents were lone parents, 5 were local authority renters, 5 had a medical card, 3 had fuel allowance, and 5 of the respondents were single adult households.

Belmayne displays high risk in Model C, medium risk in Model B and low risk in Model A. Hence, it performs quite differently depending on which prediction model is used (Map 4.8.). The attribute risk scores for Belmayne are detailed in APPENDIX 5 (Map A5.5). These show that the area has high risk in terms of unemployment (UNEM); people who cannot work due to sickness/disability (SIDI); divorced/separated (DISE); single people (SING); and lone parents (LONE). However, while the social risk is high, Belmayne displays extremely low risk in terms of building energy efficiency (BER).

Among the 6 respondents, 2 report issues with being able to keep the home adequately warm. For the indicators 'go without heat' and 'missed paying a utility bill due to lack of money' a total of one respondent reported issues (Figure 4.12.). Three of the six respondents reported at least one EPI but only one household reported 2+ EPI.

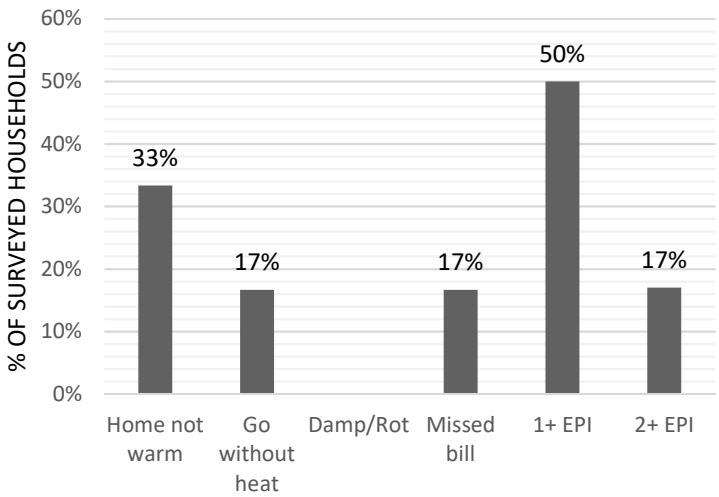
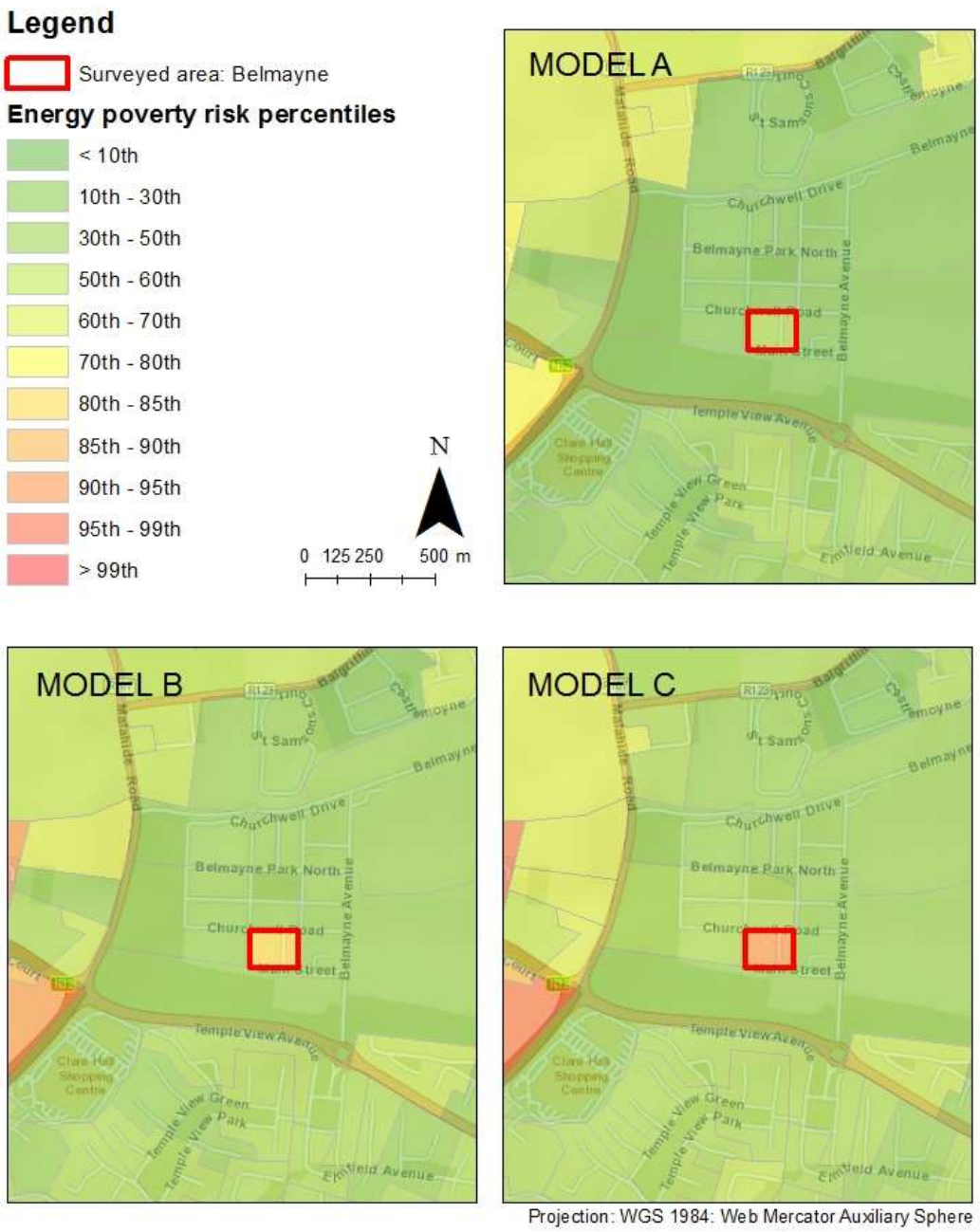


Figure 4.12. Households reporting energy poverty indicators in Belmayne.



Map 4.8. Surveyed area Belmayne.
The area displays very low risk in Model A, quite low risk on Model B and high risk in Model C.
Basemap layer: ESRI, World Streeet Map.

4.5. MODEL OF BEST FIT

Modelled risk scores compared to observed energy poverty help determine the model of best fit (Figure 4.13.).

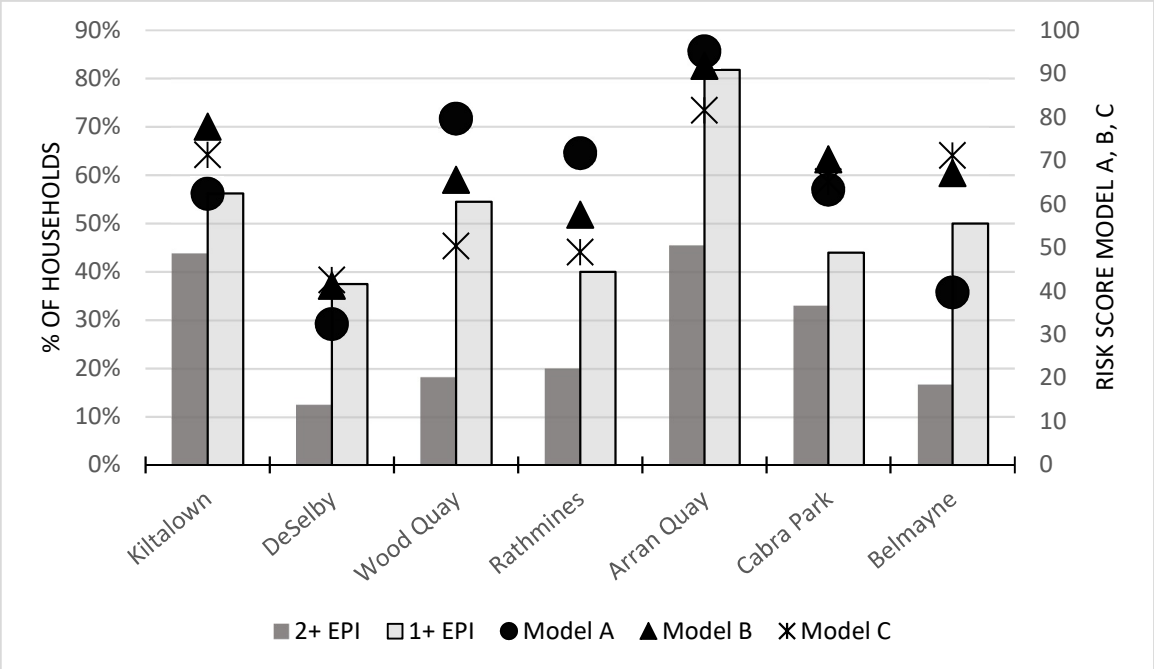


Figure 4.13. The portions of households reporting 1+ EPI and 2+ EPI by area, compared against the modelled risk in models A, B and C.
The figure details the Model A, B and C risk scores (points) against the observed energy poverty among the surveyed households in each survey area (bars).

Based on the figure and the survey results we can establish that the greatest portion of households reporting severe energy poverty (dark grey bars) was found in Arran Quay 5 of 11 (45%) and Kiltalown 7 of 16 (44%). These areas are followed by: Cabra Park, 6 of 18 (33%); Rathmines, 2 of 10 (20%); Wood Quay, 2 of 11 (18%); Belmayne 1 of 6 (17%); and DeSelby 1 of 8 (13%).

The figure shows that all three models rank Arran Quay as the area with highest risk. It also displays that this aligns with the survey results which found that Arran Quay together with Kiltalown are the areas with the greatest portion of households in severe energy poverty (dark grey bars). Furthermore, all three models predict low energy poverty in DeSelby which also matches the observations of the survey.

For the other five areas (Cabra Park, Kiltalown, Wood Quay, Rathmines and Belmayne) the model predictions diverge. Results which do not completely match the survey observations include: Model A and B predict greater risk for Cabra Park than for Kiltalown; Model A predicts greater risk in both Rathmines and Wood Quay than in Cabra Park and Kiltalown; Model C predicts the same risk in Belmayne as in Kiltalown and predicts higher risk in Belmayne compared to Cabra Park.

To summarise, Model B successfully assigns very high risk to the three areas where the highest portions of households reporting severe energy poverty were observed:

Arran Quay, Kiltalown, and Cabra Park. It calculates slightly greater risk for Cabra Park than for Kiltalown, but still places all three areas in the top 10th risk percentile (maps 3.4, 3.6, 3.7).

Less accurately, Model B predicts higher risk in Belmayne than in Wood Quay and Rathmines. This diverges from the survey results which showed approximately the same portion of 2+ EPI households in these three areas. Nevertheless, Model B is good at meeting the objective of predicting high risk areas, based on the observed prevalence of energy poverty in the evaluated areas.

Model A emphasizes the physical dimension and assigns higher risk to Wood Quay and Rathmines than to Kiltalown. Since the survey recorded much higher levels of energy poverty in Kiltalown than in these two areas, Model A appears to place too much weight on the physical dimension and it fails to identify some areas which are vulnerable due to social factors, such as Kiltalown. However, areas which have extreme social and extreme physical risk (e.g. Arran Quay), is still accurately predicted as high risk areas.

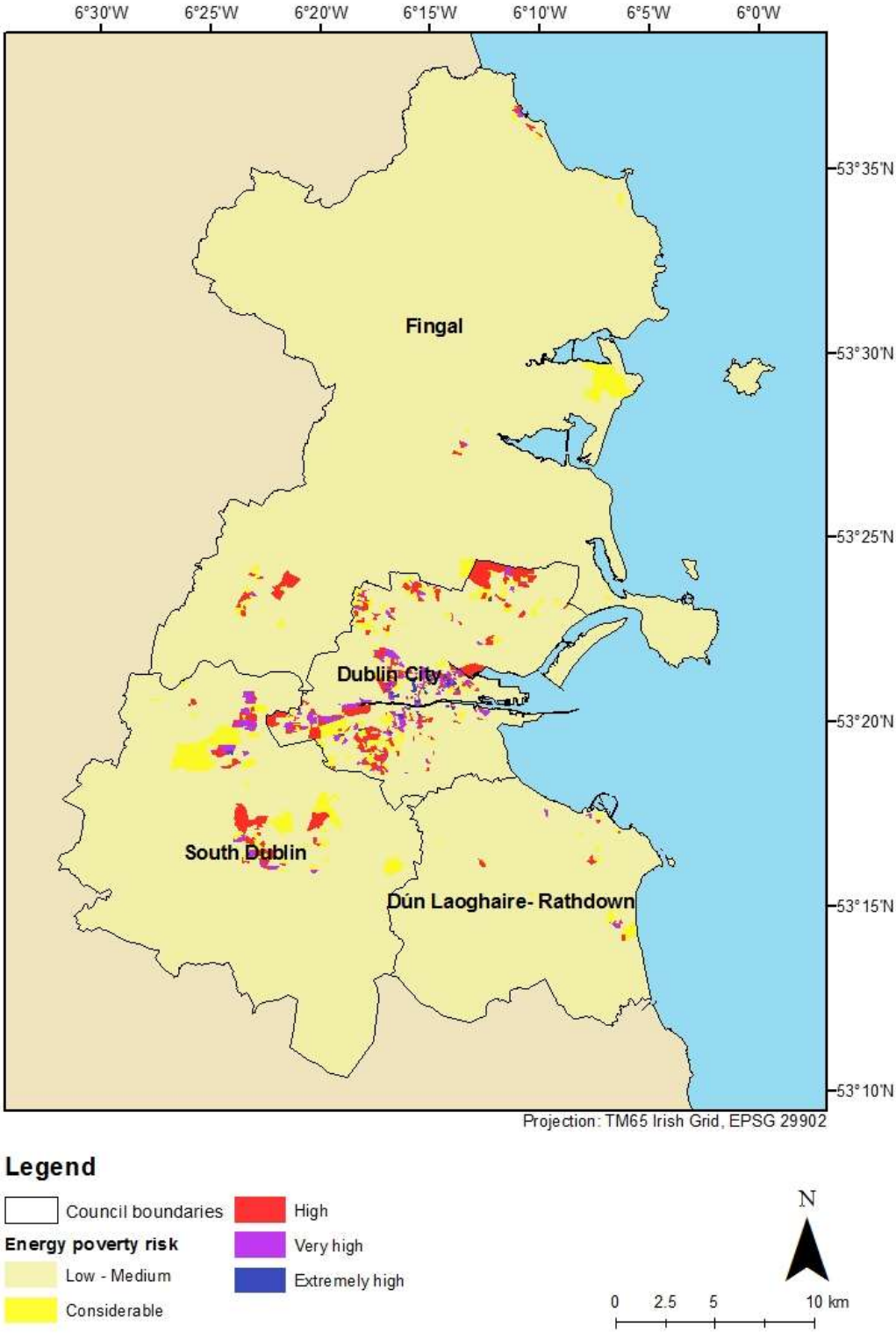
Model C which is uncalibrated, reveals random results. It accurately assigns greater risk to Kiltalown than to Cabra Park but it also predicts greater risk in Belmayne than in Cabra Park. Meanwhile, the observed energy poverty was much higher in Cabra Park compared to Belmayne. Model C is thus not good as a prediction model as it can mask areas that score high on important attributes (e.g. unemployment and energy efficiency), behind low scores on other less important attributes (e.g. single marital status and age).

Model B results are now briefly looked at before a concluding discussion.

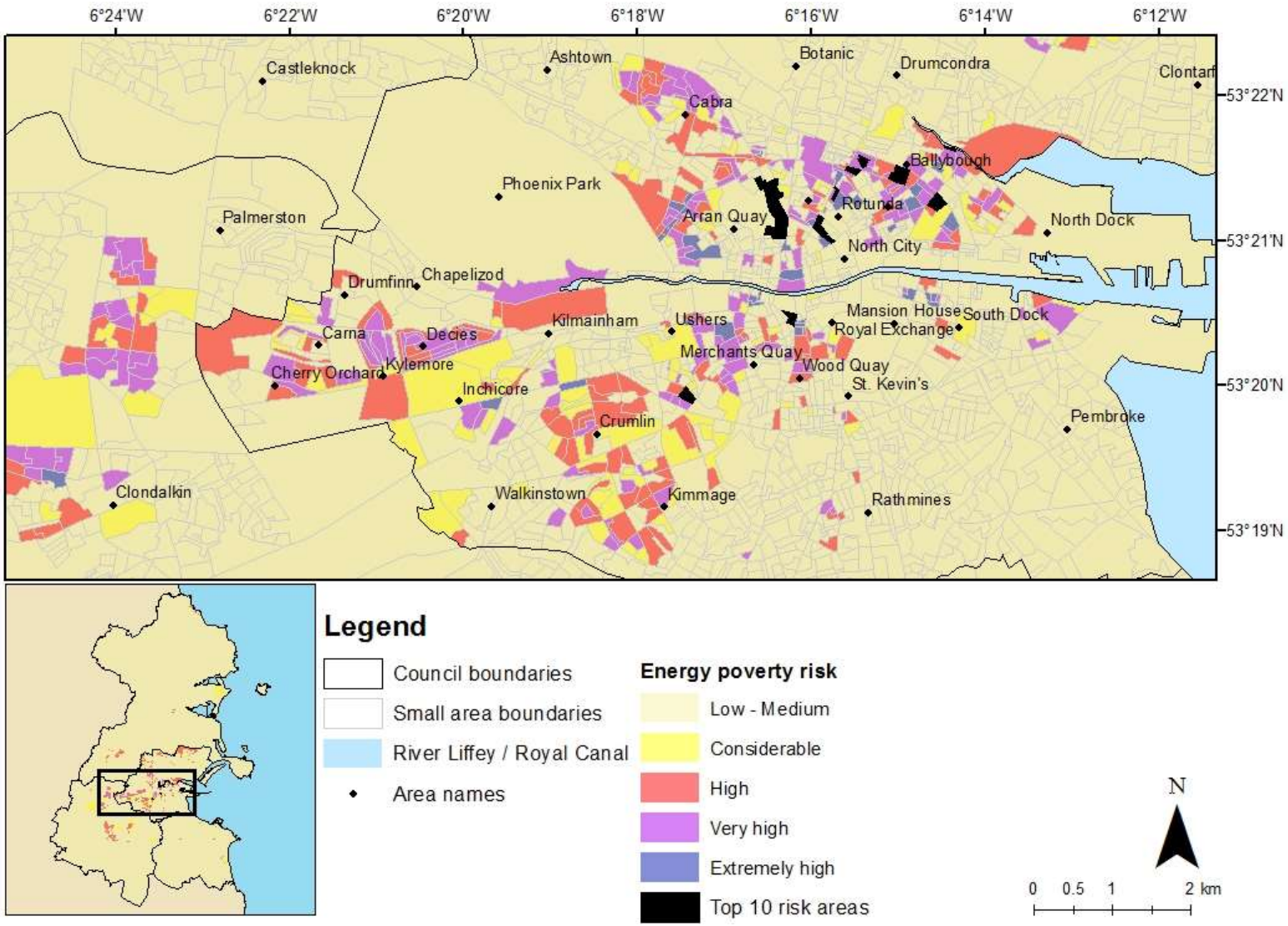
4.5.1. MODEL B RESULTS

This section presents the geography of the areas at highest risk (top 15th percentile of risk) according to Model B. Map 3.9 gives an overview and Map 3.10 zooms in on the highest risk zone as well as displaying the 10 areas that has the highest risk scores in Model B. The areas have been classified into nominal categories of risk along the following classification:

EP risk score percentile	**Level of risk**
< 85th	Low – Medium
85th – 90th	Considerable
90th - 95th	High
95th – 99th	Very high
> 99th	Extremely high



Map 4.9. High risk areas according to Model B.
Only areas in the top 15th risk percentile are shown. The majority of the very high and extreme risk areas are along the 53°20' N latitude. The areas stretch on both sides of the river Liffey, but is primarily found on the north side. It then continues west into South Dublin.



Map 4.10. High-risk areas and the 10 areas that has the highest risk score according to Model B.
The 10 areas with absolute highest risk (black) are mainly found around Ballybough and Rotunda. The considerable and high risk areas are more spread out.

5. DISCUSSION

The following discussion starts off with a review of the findings and how these relate to the core research questions. This is followed by a critical discussion of results and their implications for our understanding of energy poverty risk. Hereafter the limitations of both the model design and the survey are discussed, followed by research and policy recommendations. After the discussion follows a concluding remark.

5.1. ANSWERS TO RESEARCH QUESTIONS

My first research question was, *How should a geographical energy poverty risk prediction model be designed and validated?*

To answer this, three models were created, applied to the Dublin region, and evaluated. The model creation drew on insights from energy poverty studies in Ireland, the UK and GIS-based MCA methods. Through this the study has formulated a new method for GIS-based energy poverty prediction modelling and applied the models to the Dublin Region.

Central to the methodology is the use of risk factors which have been found to increase the risk of a household ending up in energy poverty. Furthermore, the use of the data distribution of the model attributes when assigning the risk scores, made it possible to identify areas with greatest relative risk. This was combined with a weighting technique, in which the risk factor's relative importance in increasing energy poverty risk for a household was considered.

To find the best conceptual approach for the prediction model, three different designs of combining the risk factors were done. The approach which was best at predicting high risk was tested by measuring the energy poverty prevalence in a few sampled areas using a survey. The survey results were then compared to the predicted risk.

The results display that Model B is best at predicting high-risk areas. The model is also good at predicting low-risk areas but requires some calibration improvements for medium-risk areas.

The ability of Model B to identify high-risk areas confirms that the model design methods are suitable for geographical energy poverty prediction modelling. Furthermore, this confirms that the calibration of Model B is suitable for energy poverty prediction modelling in Ireland.

My second main research question was, *What does the application and validation of the model tell us about energy poverty in the study area?*

This was met in two steps: Firstly, by applying the model to the Dublin Region the study identified areas at high risk of energy poverty; secondly, by examining the survey results different types of households in energy poverty were distinguished.

Regarding the first step, the preferred Model B exposes areas of extremely high risk in the Dublin city region, primarily on the north side of the river Liffey around Ballybough and Rotunda. Interestingly, most of the very high and extreme risk areas are found along the 53°20' N latitude, running along the Liffey and then west-ward into the South Dublin area. Zones with considerable and high risk are more widespread, stretching north and south-west in the Dublin City area, as well as in the middle and north of South Dublin.

For the second step, the households identified as in severe energy poverty were grouped according to level of employment. Based on the survey results the analysis then identified further characteristics of these household groups. Additionally, for each respondent the average building energy efficiency in the area was recorded. These various approaches made it possible to ascertain both social and physical dimensions of risk for the households in severe energy poverty.

As a result, the study identifies three types of households in energy poverty. The first type LOME, is characterised by low employment and medium to poor housing. This type is primarily found in the areas identified as at highest risk in prediction Model B, since they mainly are households with high social risk. The type is dominated by lone adult/lone parent households in local authority housing. These are often depending on benefits such as the fuel allowance and the medical card. These households are hence socially vulnerable and often in poor housing but can equally be found in housing of medium energy efficiency.

In the second type MEME, we find households with medium employment level in medium to poor housing. This type is characterised by households with two adults where one is unemployed or where both adults are working part time. Members of this type are often found in privately rented dwellings, or they are home owners with a mortgage. Both tenures are more expensive than renting from the local authority, where rent is based on ability to pay. For this type, the cause of the severe energy poverty is likely related to a financial pressure too high for the degree of employment. This is exacerbated by the fact that few of these households are claiming/qualifying for financial benefits such as the medical card/fuel allowance.

The last type HIPO, is marked by high employment levels but very poor housing. It is similar in character to the MEME type in terms of household size and that it also does not qualify for benefits such as the fuel allowance/medical card. The biggest difference between this type and the MEME type is that we primarily find this type in extremely energy inefficient housing. These would hence be households which despite lower social risk are pushed into severe energy poverty due to extremely poor dwelling standards.

5.2. DISCUSSION OF RESULTS

Since Model B best predicts high risk areas, we can also determine that the social dimension risk factors play an important role for the experience of energy poverty in the study area. This is for example displayed in Kiltalown. This area, together with Arran Quay, display the highest levels of households in severe energy poverty of the surveyed areas. While Arran Quay features very high social and physical dimension risk, Kiltalown exhibits very high social risk but relatively low physical dimension risk. Yet, the observed level of severe energy poverty is about the same in these two areas.

Beyond this, the combined evidence from the preferred Model B and the survey results suggest the following: in areas where the social risk is extremely high, the high risk of energy poverty is significantly reduced if the energy efficiency of the housing is of a very good standard. An example of this is observed in Belmayne. The six interviewed households in this area were low income households. This can be concluded from the fact that five of the respondents were unemployed, five were in local authority housing, three were lone parents and five had a medical card. The medical card in Ireland is given to households below a certain income threshold and is therefore telling of a households income level (Citizens Information, 2016c). Despite this, only one household reported severe energy poverty. The big difference between this area and the Kiltalown and Arran Quay areas, is that the energy efficiency of the apartments in Belmayne is of very good standard.

The opposite relationship is also observed, namely areas with extremely poor building energy efficiency but with low levels of social risk. Examples of this are found in Rathmines and Wood Quay where the observed level of energy poverty is half of that found in Kiltalown and Arran Quay, despite extremely poor housing. It is logical to deduce that the negating factor in these cases is the lower social risk.

This interaction between social and physical risk are important insights for policy makers and researchers alike. Especially considering the recent paper by the ESRI which argued that energy poverty in Ireland is not a distinct form of deprivation but mainly an issue overlapping basic deprivation (Watson and Maitre, 2015). The results of this study also shows that the social dimension is more important than the physical dimension in the experience of energy poverty. However, I would argue like Healy (2003a) that energy poverty is distinct in that it arises in the interplay between social and physical risk.

5.3. LIMITATIONS

5.3.1. MODEL LIMITATIONS

The main methodological building block for the development of all three models was to use the consensual measure of energy poverty. To ensure validity, this was used both in the identification of the risk factors and in the evaluation of the model fit. While this measure differs from the official definition of a household in energy poverty in Ireland the consensual measure was used nonetheless – based on that it

currently is the best way to capture both social and material dimensions of energy poverty.

Related to this problem is the matter of producer bias, which applies to all MCA modelling. Questions of which risk factors to include and exclude are all choices that affect the outcome. For example, a procedure for selecting the attributes for the model through stakeholder interviews would likely result in a different set of risk factors.

This study uses four previous analyses on energy poverty in Ireland to identify risk factors. This step is taken to reduce bias – by relying on risk factors that have already been documented to influence an Irish household's probability of ending up in energy poverty. Still, a degree of producer bias is unavoidable. In this case, a qualitative review of the four studies was conducted to select the model attributes. However, as outlined in APPENDIX 2, the review was selective on which attributes to include and which to exclude. Nevertheless, by clearly outlining the process of these judgements the study has maintained transparency, making it possible to, if needed, change the attribute selection at a later point as our understanding of energy poverty in Ireland keeps evolving.

Another issue of researcher bias relates to the decisions on scoring and weighting. For example, the attributes are scored assuming that they either should be maximized or minimized. That is, the risk did not flatten out at a certain threshold. But of course, there can be attributes which after a certain point do not affect the risk of the area further. I.e. that the total risk of areas with 30% and 40% unemployment respectively, are more influenced by other attributes once the unemployment level is over, for example, 25%. It can then be argued that all areas with 25% unemployment or more, should simply obtain a max risk score for that attribute.

The decision to not apply thresholds to the attributes was made to limit the producer bias since each such threshold set would require a decision which affects the outcome. It was therefore decided that it is better to rely on one assumption that risk increases as risk factors presence intensifies, rather than relying on the ability to accurately set thresholds for all attributes.

Another important methodological choice relevant to all models was to use only one variable for the physical dimension, namely the energy efficiency dataset from Codema. The strength of the dataset is that it is spatially variant. This is an improvement on other physical indicators most of which, are spatially homogenous. However, the BER dataset might also be skewed in terms of the energy efficiency assessments it is based on. While the rating by law has to be applied to all dwellings which are sold or rented out, and is given to all newly built dwellings, some groups may own their homes but not have the resources to sell or rent out – and may therefore not have a BER rating.

Another limitation relevant to the preferred Model B is how it treats medium-risk areas. For example, Belmayne has very high social risk but very low physical risk and ends up in the top 20th percentile of energy poverty risk. Meanwhile, areas such as Wood Quay, which are socially less vulnerable but with very poor dwelling energy efficiency, are predicted to have a lower level of risk than Belmayne. The survey

results on the other hand indicate that the prevalence of energy poverty in Wood Quay is higher than in Belmayne. A possible improvement to overcome this issue is to filter out areas which are above a certain threshold in terms of dwelling energy efficiency. This way socially vulnerable areas with very energy efficient dwellings would not be identified as energy poverty risk areas.

This brings us to the point of the suitability of the models to identify risk in both urban and rural areas. All three models are based on small area data which in urban environments are spatially very fine but which outside the urban environment tend to be quite large. The assumption of spatial autocorrelation means that the closer the households are to each other in distance, the more likely they are to be similar to each other. This suggests that households in the spatially smaller areas are more likely to be similar in their social and physical characteristics than households in spatially larger areas. This in turn implies that risk in the spatially larger areas is more likely diluted by a less homogenous group of households. Based on this, the models are probably more accurate in the urban environment where the areas are spatially small.

5.3.2. INTERVIEW LIMITATIONS

The interviews were based on survey questions that had not first been tested due to insufficient time and resources. Therefore, certain limitations of the questions arose during the fieldwork.

For instance, many low-income households use top-up metering instead of bill pay for their utilities. This is a method where a household buys credit for their gas/electricity and can use the utilities until they run out of credit. This is used to help budget the energy expenditure. Naturally, for these households the issue will never be that they cannot pay a bill, but rather that they run out of credit or simply cannot top-up as much as they would like.

This makes the question on having missed a utility bill redundant for some households. However, households suffering from running out of credit/not being able to top up can still report that they have gone without heating – which is one of the questions in the survey.

Another issue with the survey relates to the subjective question if the home is adequately warm. The response to this question can have very different meanings depending on the household. In a high-income area, a household that states that the house is poorly insulated and difficult to heat might refer to the simple fact that the dwelling is large and that it is difficult to obtain an even temperature throughout the dwelling. On the other hand, a household which reports that the household is not adequately warm and that at night the mother goes to bed with the children to keep them warm, clearly has a very different situation. To get around this issue households were categorised as suffering in severe energy poverty when they reported two or more of the four indicators.

In terms of the sampling of areas and respondents, due to time and resource limitations only a few purposively sampled areas were surveyed and only a limited

number of respondents were reached in each area. This points to a couple of important aspects to consider when interpreting the results:

- The selected areas were not sampled through probability sampling. With greater resources a survey on a greater number of areas and a greater number of respondents in each area could make a statistical analysis of the model fit possible.
- The interviews were mainly held between 9 am and 5 pm on weekdays. It was difficult to obtain answers after 5.30 pm. Naturally, due to the time of the day that most respondents were reached, people working office hours are underrepresented in the sample and unemployed people are likely overrepresented. However, since the respondents answered on behalf of the whole household, adults working office hours were still accounted for where one adult household member was home.

An alternative approach could be to leave questionnaires with the households to be completed independently and then posted. However, this approach was not pursued since it implies greater uncertainty over the response rate. Additionally, the insights gained from direct conversations with respondents would have been lost.

5.4. RESEARCH AND POLICY RECOMMENDATIONS

From completing this study a number of research and policy gaps are identified which would benefit from much stronger attention from scholars and practitioners. This section outlines the recommendations emerging from the results and analysis.

5.4.1. ENERGY EFFICIENCY RISK THRESHOLDS

The observed energy poverty in socially vulnerable Kiltalown is high despite relatively energy efficient housing. But this positive relationship identified between social risk and energy poverty prevalence is not true for the area of Belmayne. This indicates that the total energy poverty risk decreases despite high social risk if the houses are energy efficient enough.

Research into what this BER cut-off point/interval is would help target existing policy measures better. To determine such a cut-off point, locales with a social risk profile similar to Belmayne and Kiltalown, but with varying energy efficiency values, can be identified and surveyed to assess the different levels of energy poverty.

5.4.2. TARGETTING OF AREA-BASED INITIATIVES

The only area-based energy poverty alleviation measure in Ireland is the BEC scheme. This is currently based on self-referral. However, the survey results evidence that this is not a well-known scheme. Only one out of 80 interviewed households had heard of it – and that very household responded that it sounded familiar but that they did not know what it was.

Therefore, the targeting of the BEC initiative is another area which calls for attention. Several routes of enquiry are of interest:

1. What are the locations of BEC projects which have been conducted within the study area in the last few years, compared to the predicted risk in those areas according to the preferred Model B?
2. What are the attribute profiles of areas that successfully have applied for the scheme?
3. Why have the successful applications to date been successful, and how did the applicants behind these know about the scheme?
4. Would information campaigns in high-risk areas (according to Model B), where BEC projects have not been conducted, help raise awareness and motivate the communities to apply to the BEC scheme?

Greater understanding around these questions would help policy makers establish if the scheme should continue on self-referral basis or be converted into proactive targeting.

5.4.3. REDESIGNING THE FUEL ALLOWANCE

The Fuel Allowance appears to reach a large portion of households in energy poverty but is not always sufficient to alleviate the problem. This is indicated by the high portion of households in severe energy poverty who are in receipt of the benefit. This is similarly noted by Healy and Clinch (2004) who finds that the portion of energy poor households is higher among households in receipt of the fuel allowance.

The benefit is currently a set amount of 22.50 Euro per week during the winter months October – March, which the household can spend as they like. It is not paid based on an income assessment but on already being in receipt of other specific benefits such as disability allowance, lone parent benefits and likewise (Citizens Information, 2016b).

While the benefit considers the socio-economic status of the household, the qualifying criteria do not consider the energy efficiency of the home. Thus, a qualifying household in Belmayne where the energy efficiency of the building is very good, compared to one in Arran Quay with extremely poor energy efficiency, will have the same amount paid, despite their energy needs being very different.

There is therefore an argument that the allowance needs to be restructured. Two initial considerations to be investigated are:

1. Can the fuel allowance be tiered so the amount paid to qualifying households considers the energy efficiency of the dwelling?
2. Should the qualifying criteria for households residing in housing of poor energy efficiency be lowered/changed to help assist households in energy inefficient dwellings which currently do not qualify for the benefit?

5.4.4. MODEL IMPROVEMENTS AND GENERALIZABILITY

Since the risk factors have been selected based on the Irish national experience, the preferred model can be applied to all regions in the country. However, currently the building energy efficiency dataset used in the model is only developed for the Dublin Region. If a nationwide building energy efficiency dataset at the small area unit is developed, then the use of the model with its current set of risk factors and weights can be expanded and applied to the rest of the country (adjusting the risk scores to the new datasets).

This said, the methodological framework of the model design is generalizable on a greater scale than Ireland. For instance, my approach can be applied to the UK, which has spatially referenced datasets with a similar resolution to that of Ireland. Applying these concepts to a different context is also a good way to evaluate the reliability of the design.

As a caveat, the applicability of the design in other countries depends on:

- Current knowledge on energy poverty risk factors applicable to that locale
- Available spatial datasets for the needed risk factors
- The spatial resolution of the available datasets

6. CONCLUDING REMARK

The introduction of this thesis stressed that energy poverty is a widespread issue which affects people in all EU member states. This notwithstanding, coordinated policy responses at the EU level are strikingly lacking.

In addition there are unresolved political and scholarly debates about how to measure energy poverty and how to identify exposed groups. This makes energy poverty an urgent, but at the same time under-researched field of enquiry, with multiple gaps to be addressed.

In this web of research needs, my study sought to address a particular issue, namely how to identify geographic areas with high portions of energy poor households. The study specifically looked at how to design an energy poverty prediction model valid for Ireland, and applied this to the case study of the Dublin region.

In accomplishing this, the thesis has contributed to energy poverty prediction modelling research by testing a new method on how to identify and select risk factors. These were identified through a literature review of existing studies on energy poverty in Ireland. The selected risk factors in turn informed the selection of the spatial attribute datasets needed to predict energy poverty risk. Additionally, a unique aspect of this thesis is that it uses the data distribution of the attributes to apply risk scores, which made it possible to ascertain areas at highest relative risk.

Also, adding methodologically to previous work, the thesis tested three different approaches of weighting and combining model attributes. One approach was to give the social and physical dimension equal importance (Model A), drawing on the work of Walker et al. (2013). The other approach focused on each attribute's influence on energy poverty risk without grouping the attributes into dimensions (Model B). This approach partially builds on the work of Morrison and Shortt (2008) and effectively gives socio-economic attributes greater importance. Thirdly, a dummy model without calibrated weights was used as a form of sensitivity testing.

To determine which model best identifies high-risk areas, an empirical evaluation of the models was conducted through structured interviews with households in selected locales within the study area. Certain time and resource constraints meant that the surveyed areas had to be purposively sampled and the results contain a potential skewness in the respondents reached. Nevertheless, the ground truth information collected through the surveys supports that Model B, which emphasises socio-economic risk factors, best identifies areas at high risk of energy poverty.

The application of the preferred model (Model B) reveals a geography of risk in the study region predominantly found in the Dublin City council region, with a concentration of extreme risk around the Ballybough and Rotunda areas.

Furthering our understanding of the issue the study also identifies three types of households in energy poverty. This typology help us understand energy poverty in three ways. Firstly, it confirms that energy poverty is not merely a form of basic deprivation but complex and depending both on physical and social risk. Secondly, by understanding that households ending up in severe energy poverty are not

homogenous, we can better capture the effects macro-economic changes such as rising energy prices can have. Thirdly, it tells us something about what policy responses are suitable for the types.

Take for example a situation of rising energy prices. Households in the LOME type are often dependent on financial benefits. If energy prices increase, these benefits could be adjusted to stop the price rise from affecting these vulnerable households. With adjusted benefits a household already depending on benefits will not necessarily end up notably worse off.

For a household in the HIPO type, increases in the energy price will naturally put a strain on the financial situation. But with full or near full employment, changes in their budgeting might help the household navigate around the negative impacts of the rising prices.

However, the MEME type is financially in a more difficult position than the HIPO type, yet often the type is not in receipt of the benefits available to the LOME type. It could therefore be hypothesised that MEME households are particularly vulnerable to energy price increases.

With these insights, policy responses can be designed in a more targeted manner relative to where on the social and physical dimension risk spectrum the household is situated.

As a starting point for how to move forward I outlined in my policy and research recommendations several gaps which call for attention. These include improving the design of the prediction model and testing its generalizability. Furthermore, several suggestions have been made for enhancing the effectiveness of policies in the Dublin Region. For instance, I propose steps how to identify why the current BEC scheme is not well known in areas of high risk, and how to change this.

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APPENDIX 1

Table A1. The four national studies used to identify factors which increases or decreases risk of experiencing energy poverty in Ireland.

Study	Data source	Description
Healy (2003a)	European Community Household Panel (ECHP) datasets, 1994 - 1997	The study is focused on EU14 but appendix IV of the book contains a multivariate analysis testing the correlation between socio-economic variables and energy poor households in Ireland. The study uses a combination of six consensual measure indicators: *Ability to heat home adequately, ability to pay utility bills, household having adequate heating facilities, household status regarding central heating, presence of damp in the dwelling, and presence of rot in the dwelling*. It further identifies a set of 30 socio economic and dwelling related factors (e.g. 'divorced') from 9 factor groups (e.g. 'marital status') correlated to the issue. The study tests the significance of the correlations against each of the six consensual measure indicators, for four consecutive years (1994 – 1997). Many factors are displaying a significant correlation to some consensual measure indicators but not to all. However, 12 factors display significant correlation to most of the consensual measures for all four years.
Healy and Clinch (2004)	National Household Survey, 2001	The study uses a consensual measure variable *ability to adequately heat the home* to assess energy poverty. It further identifies a set of 18 socio-economic and dwelling related factors (e.g. 'tenant') from 7 factor groups (e.g. 'tenure') correlated to the issue and tests the significance of the correlations. The results display 5 factors of significance.
Scott et al. (2008)	Survey of Income and Living Conditions (SILC), 2005	The study analyses socio-economic variables associated with energy poverty in Ireland both against an expenditure measure and against a consensual measure. The latter is considered here. The consensual measure indicators used are *ability to adequately heat the home* and *having to go without heat.* The authors classify any household answering yes to either of these indicators as energy poor. A set of 43 socio-economic and dwelling related factors (e.g. 'flat/apartment') from 10 factor groups (e.g. 'dwelling') are assessed. The results display 16 risk factors of significance.
Watson and Maitre (2015)	Survey of Income and Living Conditions (SILC), 2004 - 2011	The study identifies energy poverty as households reporting either of the following three indicators: *ability to adequately heat the home; having to go without heat; having arrears on utility bills*. It simultaneously analyses basic deprivation and energy poverty and categorises energy poor into two groups: one reporting only energy poverty; and one reporting energy poverty as well as basic deprivation. Here the two groups have been treated as one for the purpose of extracting risk factors relevant to the model. Out of 39 socio-economic and dwelling related factors (e.g. 'Age 18-34') from 13 factor groups (e.g. 'Age'), 26 risk factors are found significant.

APPENDIX 2

Table A2. The 35 factors identified, details of their importance as risk factors and the reasoning for inclusion/exclusion in the model.

Factor Group	Factor Name	Comment	Model inclusion
Tenure	Rented dwelling	Private renting is displayed as a risk factor in all studies with medium to high importance predominantly. The exception is Healy (2003a) which only displays this as an important factor in relation to the consensual measures of rot and damp in the dwelling.	**Include**
	Rent Free/ Local authority	'Local authority renters' and 'rent free' tenure status is a risk factor with high importance in all studies. Scott et al. (2008) does not differentiate between different forms of renters. Watson and Maitre (2015) includes categories 'social renter' but not 'rent free'. Healy (2003a) and Healy and Clinch (2004) both includes the categories 'tenant' and 'rent free'. Clear is that 'social renters' and 'rent free' are at higher risk than other tenants and tenants overall is at higher risk than property owners.	**Include**
	Own with mortgage	Displays as a risk factor with low importance in the study by Watson and Maitre (2015). Healy and Clinch (2004) indicates the variable does not carry significance, while Healy (2003a) and Scott et al. (2008) does not include a factor specifically for households owning with mortgage. The factor is excluded based on inconsistency and weakness.	**Exclude**
Dwelling type	Semidetached/ Terraced	Scott et al. (2008) only distinguishes between houses and apartments and find apartments a greater risk factor. Healy and Clinch (2004) does not include dwelling type in their study. Watson and Maitre (2015) finds that the factor carries medium importance in increasing the risk, while Healy (2003a) finds that the factor brings decrease in risk of experiencing energy poverty when measuring against the consensual indicators of ability to heat home and presence of central heating. The factor is excluded based on inconsistency.	**Exclude**
	Apartment/ Flat	Displays as a risk factor with low importance in the study by Scott et al. (2008) while it is displaying as an inconsistent variable in the study by Healy (2003a). Additionally it appears as a factor reducing risk in relation to experiencing damp and rot in Healy (2003a). In Healy and Clinch (2004) the factor is not included and in Watson and Maitre (2015) it is a medium to low importance factor but the result lacks significance. The factor is excluded based on inconsistency and weakness.	**Exclude**
	Other	The category only exists in the study by Healy (2003a) and here displays as a moderate importance factor that decreases risk of experiencing damp and increases likelihood of a central heating system in place. The factor is excluded based on inconsistency.	**Exclude**

Factor Group	Factor Name	Comment	Model inclusion
Marital status	Single	The factor is displaying importance in all studies except for Healy and Clinch (2004) where the factor is not included. The importance of the factor varies from high to medium to low with the low importance being more prominent.	**Include**
	Widow/ Widower	The factor lacks significance in all studies except for Healy (2003b). In Healy and Clinch (2004) the factor has been grouped together with the categories 'separated' and 'divorced' and displays no significance. The factor is excluded based on inconsistency.	**Exclude**
	Divorced/ Separated	The factor displays high importance in all studies with the exception of Healy and Clinch (2004) which has grouped together the categories of 'widow', 'divorced' and 'separated'. To be noted is that Healy (2003a) treats the categories 'divorced' and 'separated' independently and displays significantly more risk associated for the category 'separated' than the category 'divorced'.	**Include**
Household composition	Lone parents	Healy (2003a) and Healy and Clinch (2004) do not include the category in their analysis. The other two studies display that the factor carry medium to low importance.	**Include**
	Alone adult	Healy (2003a) and Healy and Clinch (2004) do not include the category in their analysis. Scott et al. (2008) displays lone adults as slightly reducing risk but the result is not significant. Watson and Maitre (2015) display that the factor increases risk slightly. The factor is excluded based on inconsistency.	**Exclude**
	Being in a couple reduces risk	Healy and Clinch (2004) finds that being in a couple significantly reduces the risk of experiencing energy poverty. Watson and Maitre (2015) does not look at this particular category but finds that households consisting only of adults reduces risk slightly. Scott et al. (2008) displays that the constellation carries less risk than any household with children but the results are not significant. Finally Healy (2003a) does not include the category. The factor is excluded based on weakness.	**Exclude**
	Number of children/ Households with children	Healy (2003a) and Watson and Maitre (2015) find that an increasing number of children in the household results in higher risk and the factor carries medium to low importance. In the study by Healy and Clinch (2004) the result is not significant but the relationship displayed is the same. Scott et al. (2008) does not include the specific category of number of children but does display that both 'parents with children' and 'other households with children' carries greater risk than households without children and the factors both display medium importance.	**Include**

Factor Group	Factor Name	Comment	Model inclusion
	Multiple adults	The category is included in Healy (2003a) where it displays as a factor with low importance that increases risk (except for the indicator for experience of rot in the dwelling). In Healy and Clinch (2004) the category is included and shows that the number of adults decreases risk but the results are not significant. Watson and Maitre (2015) does not include the category but finds that households with only adults reduces risk. Finally Scott et al. (2008) does not include the category. The factor is excluded based on inconsistency and weakness.	**Exclude**
	Other adult with disability	The factor is only included and looked at in Watson and Maitre (2015) and there displays medium to low importance. The category 'Ill/Disabled' in terms of income status is however significant in two studies and the 'health status' factor is very important in the study by Healy (2003a). On this basis the category will remain included for further evaluation.	**Include**
Income status	Retired	The category has medium importance in both Healy (2003a) (for all indicators except for rot) and Scott et al. (2008). In the latter it is grouped with 'inactive in other way'. Meanwhile in Watson and Maitre (2015), 'jobless households aged 0-59' are shown to be at higher risk. This presumably includes inactive and maybe also retired. Finally Healy and Clinch (2004) do not include the categories related to sources of income in their analysis.	**Include**
	Self employed	Out of the three studies dealing with income source in their analysis, Scott et al. (2008) does not include the specific category of self-employed. Watson and Maitre (2015) includes it and finds a slightly heightened risk for this group but the results are not significant. Finally Healy (2003a) find that the category is increasing the risk of being unable to heat the home, having inadequate heating facilities and lacking central heating. It does not however pose a risk for paying utility bills and it reduces the risk of experiencing rot in the dwelling. The factor is excluded based on inconsistency.	**Exclude**
	Unemployed	For all three studies including income source in their analysis, unemployment is shown as a high importance risk factor. Some inconsistency is found in Healy (2003a) (e.g. medium to low importance factor in relation to the experience of rot in the dwelling). Otherwise across the board, in relation to the ability to heat the home adequately, the factor is consistently very important. Watson and Maitre (2015) simply uses the category 'Jobless household' and does not differentiate between different categories of non-working status.	**Include**

Factor Group	Factor Name	Comment	Model inclusion
	Student	Scott et al. (2008) is the only study including the specific group of 'student' as CES of the household in their analysis. They find that after unemployment, it is the most important risk factor. Watson and Maitre (2015) simply uses the category 'Jobless household' and does not differentiate between different categories of non-working status. Students are likely included in this category.	**Include**
	Other benefit recipient	Healy (2003a) is the only study including categories of benefit recipients and find that this is across the six consensual measures a factor displaying increased risk. The importance degree varies from high (for ability to pay utility bills) to medium and medium-low for the other five measures.	**Include**
	Home duties	Scott et al. (2008) is the only study including this specific category and refers to the CES of the family. They find it has high to medium importance. Watson and Maitre (2015) simply uses the category 'Jobless household' and does not differentiate between different categories of non-working status. Home duties might be included in this category.	**Include**
	Ill/Disabled	Healy and Clinch (2004) has no category for 'health' status or for 'ill/disabled'. In Scott et al. (2008) the factor displays high importance and refers to the CES. Healy (2003a) does not include the factor 'ill/disabled' in terms of income, but includes 'health status' in their study (see below). Watson and Maitre (2015) include a category for people with disabilities which displays as an important factor.	**Include**
	Private income	The factor is only included in Healy (2003a) where it displays high importance for issues with paying utility bills and medium to low importance for not being able to heat the home adequately. Against the indicator of rot in the dwelling, it displays as a factor reducing the risk. The factor is excluded based on inconsistency.	**Exclude**
Health	Bad/Very bad	The category of health is only assessed in Healy (2003a) where it is divided into the categories 'Good', 'Fair', 'Bad' and 'Very bad'. The categories 'Bad' and 'Very bad' displays high importance against all six consensual measures. The exception is the measure on ability to pay utility bills, where 'bad' and 'very bad' health has medium importance as a risk factor.	**Include**
Education	No education/ Primary only/ Secondary not finished/ Education other/Not stated	All studies except for Healy and Clinch (2004) show that lower education level is a risk factor with high to high-medium importance. Healy and Clinch (2004) displays that having a degree is a significant risk reducer. Scott et al. (2008) is the only study including also a category of 'Education other/Not stated' and finds this is a factor with high importance.	**Include**

Factor Group	Factor Name	Comment	Model inclusion
	Secondary finished	Healy and Clinch (2004) do not include education levels lower than secondary school in their analysis, but their results indicate having completed only secondary poses some risk although the results are not significant. Watson and Maitre (2015) similarly finds slightly higher risk for people with completed secondary level compared to those with a third level degree, although these results are also not significant. Scott et al. (2008) uses this level as its base level and sees reduced risk for education levels above this level and heightened risk for education levels below this level. Finally Healy (2003a) finds that depending on which of the six measurements you look at, having secondary education level completed can be both increaser and decrease risk. The factor is excluded based on inconsistency.	**Exclude**
	Education other/Not stated	Scott et al. (2008) is the only study including this category where it displays as a factor with high importance. Since the coding has grouped together 'No education/ Primary only/ Secondary not finished' it seems appropriate to include also 'Not stated' in this group. The factor is grouped on this basis.	**Group**
	Having a degree reduces risk	All studies indicate that having higher education level works as a factor reducing risk. Only Healy and Clinch (2004) specifically displays significant results on that having a degree reduces the risk. Interestingly, Watson and Maitre (2015) displays higher risk for those not completing third level education than those with completed secondary education but the results are not significant. In conclusion, it appears having third level degree is a risk reducer and not having completed secondary and lower levels of education is a risk enhancer. The areas in between are less certain.	**Include**
Personal data	Age	Healy and Clinch (2004) does not have significant results for different age categories. Scott et al. (2008) displays that being under the age of 65 increases risk which is echoed in both Watson and Maitre (2015) and Healy (2003a). The latter studies break down the results by age group which displays that particularly at risk (high to medium importance) are the 18-35 and 16-35 year olds respectively. The risk is then lower for the age group 36 - 65. The age group 16-35 should be kept for analysis.	**Include 16 – 35**
	Sex	Healy (2003a) and Healy and Clinch (2004) does not include sex in their analysis. Scott et al. (2008) find that females are slightly more at risk but the correlation is weak and lacks significance. Watson and Maitre (2015) similarly find femlaes at slightly higher risk but the factor lacks significance. The factor is excluded based on weakness.	**Exclude**

Factor Group	Factor Name	Comment	Model inclusion
Dwelling	Dwelling built year after 1980 reduces risk	Healy (2003a) and Scott et al. (2008) do not include the category. Watson and Maitre (2015) incude 'dwelling built year', but the results have low importance and are not significant. Healy and Clinch (2004) find a general trend that newer buildings mean reduced risk, but the results are lacking significance except for buildings built between 1980 – 1989. The reason for including dwelling age in an analysis on energy poverty in Ireland, is to assess dwelling energy inefficiencies. This in relation to dwelling age is done by determining risk based on the building regulations in place when the dwelling was built. Today there are better ways of estimating energy efficiency of dwellings than using the dwelling built year. The aspect to be included is thus energy efficiency measurements rather than dwelling built year.	**Include**
	Leaks /Too dark	Only included in Watson and Maitre (2015) where it shows high importance. Healy (2003a) treats this differently methodologically where the presence of rot and damp rather is used as a measure of energy poverty, than tested as a factor. As per above factor, this is a factor used to assess the energy efficiency of the building and should be included in some form.	**Include**
	Lack central heating	The factor is used by Watson and Maitre (2015) and shows medium importance. Healy (2003a) uses it as a measurement of energy poverty, not as a risk factor. A recent cross European study (Pye et al., 2015: 15) noted that countries experiencing greater problems of energy poverty (measured using a consensual measure based on SLIC) also report the lowest levels of central heating in Europe. The exception is Denmark where central heating is not widespread and energy poverty rates remain some of the lowest in Europe. Also this factor related to energy efficiencies and should be included.	**Include**
Social Class	Social class unknown	Healy (2003a) and Healy and Clinch (2004) do not include social class factors. Watson and Maitre (2015) find that having social class 'not stated' is a risk factor with medium to high importance. Scott et al. (2008) include social class but not specifically social class 'not stated'. They find all their categories of social class non-significant. The factor is excluded based on inconsistency.	**Excluded**
	Unskilled / Low. Service/ Manual / Intermediate	Healy (2003a) and Healy and Clinch (2004) do not include the category social class. Scott et al. (2008) include the category but do not find the results significant. Watson and Maitre (2015) find that the social classes 'Unskilled' / 'Low. Service'/ 'Manual' as well as 'Intermediate' carried greater risk but the factor has low importance. The factor is excluded based on inconsistency.	**Excluded**

Factor Group	Factor Name	Comment	Model inclusion
Other	Housing allowance recipient	Healy (2003a) is the only study including data on benefit recipients and finds that respondents in receipt of housing allowance, are at higher risk of experiencing energy poverty as might be expected as it indicates low income.	**Include**

APPENDIX 3

Table A3. The 21 risk factors evaluated for data matching against spatial datasets and reason for exclusion where applicable.
The 'Dataset match' indicates the spatial dataset used to form a match (Codema = COD, or the Census 2011 = CEN). The 'Dataset fields & comment' shows the fields from the datasets used and the decision reasoning around this. The 'Attribute name(s)' notes the statistics gathered from the spatial datasets. The 'Abbreviation' is the abbreviation used for the attribute in the model creation. Finally, the status notes if the risk factor was included, grouped or excluded.

Factor group	Factor name	Dataset match	Dataset fields & comment	Attribute name(s)	Abbre-viation	Status
Tenure	Rented dwelling	CEN	Headings from dataset relevant: T6_3_RPLH T6_3_RVBH This includes renters from private landlords and renters from voluntary bodies. Voluntary bodies such as e.g. St Vincent de Paul rents out to people in need and presumably this category would fit better in with social housing and rent free households than private renters. However, my knowledge on the suite of voluntary bodies that rent out to households in Ireland is limited and I can therefore not guarantee that it is always specifically targeting households in need/financial difficulties. On that basis, the factor has been grouped in with normal renters. This is to not run the risk of exaggerating risk as private renters are a lower risk group than social renters.	Private renting households	PRIV	Include
	Rent Free/ Local authority	CEN	Headings from dataset relevant: T6_3_RLAH T6_3_OFRH This include rent free households and renters from social housing.	Local authority and Rent free households	LCL	Include
Marital status	Single	CEN	Relevant headings: T1_2SGLT All people reporting their marital status as 'single'.	Single people	SING	Include
	Divorced/ Separated	CEN	Relevant headings: T1_2SEPT T1_2DIVT All people reporting their marital status as either divorced or separated.	Divorced and Separated people	DISE	Include

Factor group	Factor name	Dataset match	Dataset fields & comment	Attribute name(s)	Abbre-viation	Status
Household composition	Lone parents	CEN	Relevant headings: T4_3FTLF T4_3FTLM Lone fathers and lone mothers with children. Neither of the studies specified if they looked at children under or over a certain age. Therefore, here all lone parents with children (independent of the age of the children) are included.	Lone parent families	LONE	Include
	Number of children	CEN	The studies reviewed found a positive relationship between the number of children and energy poverty risk. Looking at data from CSO we can see that the average number of children per family in Ireland in 2011 was 1.4. At the same time the larger family sizes of 4+ children per family is more commonly seen in the lower social classes (CSO, 2012). To formulate an attribute to measure risk, families of 4 and 5+ children will be combined to determine risk: T4_2_4CT T4_2_GE5T This includes the total number of families with 4 or more children.	4+ children families	CHLD	Include
	Other adult with disability		There is no category in the Census 2011 capturing that there is another adult in the household with a disability. However, the category 'Ill/Disabled' captures all adults of working age not in work due to 'Sickness/Illness' hence 'other adults' too. The risk factor is considered measured through the 'Ill/Disabled' category (Abbreviation SIDI).			Grouped
Income status	Retired/ Inactive in other way	CEN	Relevant headings: T8_1_RT T8_1_OTHT All people reporting their status as retired or as not in labour force for 'other reasons'.	Retired and otherwise inactive people	RET	Include
	Unemployed	CEN	Relevant headings: T8_1_ULGUPJT T8_1_LFFJT All people reporting their principal economic status as unemployed or as looking for first job.	People unemployed or looking for 1st job	UNEM	Include

Factor group	Factor name	Dataset match	Dataset fields & comment	Attribute name(s)	Abbre-viation	Status
	Student		The study by Scott et al. (2008) only noted the risk of energy poverty was increased for households where the CES of the household was a student. The Census 2011 does not collect data on the CES of the household and hence the data of the Census 2011 reflects something very different to the factor Scott et. al. tested. On this basis, the factor has been excluded due to data unavailability.			Exclude
	Other benefit recipient		There is not data on benefit recipients in the Irish census.			Exclude
	Home duties		Scott et al. (2008) only noted the risk of energy poverty was increased for households where the CES of the household reported their principal status as 'home duties'. The Census 2011 does not collect data on the CES of the household and hence the data of the Census 2011 reflects something very different to the factor Scott et. al. tested. On this basis, the factor has been excluded due to data unavailability.			
	Ill/Disabled	CEN	Relevant headings: T8_1_UTWSDT People reporting that they are unable to work due to sickness or disability.	People unable to work due to sickness/disability	SIDI	Include
Health	Bad/Very bad	CEN	Relevant headings: T12_3BT T12_3VBT People reporting their health status as 'Bad' or 'Very bad'.	People reporting bad and very bad health status	BAD	Include
Education	No education/ Primary only/ Secondary not finished/ Education other/Not stated	CEN	Relevant headings: T10_4_NFT T10_4_PT T10_4_LST T10_4_NST People reporting no formal education, primary education only, lower cycle secondary education or 'not stated'.	People with below upper secondary qualifications & those not stated	NOED	Include

Factor group	Factor name	Dataset match	Dataset fields & comment	Attribute name(s)	Abbre-viation	Status
	Having a degree reduces risk	CEN	Relevant headings: T10_4_ODNDT T10_4_HDPQT T10_4_PDT T10_4_DT People reporting having completed a Bachelor degree or higher.	People with completed bachelor degrees and higher	THED	Include
Personal data	Age	CEN	Relevant headings: T1_1AGE16T T1_1AGE17T T1_1AGE18T T1_1AGE19T T1_1AGE20_24T T1_1AGE25_29T T1_1AGE30_34T The age categories in the Census 2011 groups people aged 35-39, hence the grouping used here is 16-34 for the higher risk age group. I use the age group 16-34 according to Healy (2003a). The reason is that in Ireland a household can receive child benefits until the child is aged 16, unless they pursue full time education after this point, in which case the child benefit is payable until the age of 18 (Citizens Information, 2016a). Hence a child (under the age of 18) is no longer considered a child at the age of 16 if they have stopped full time education, and should therefore fall into the age risk group for young adults.	People aged 16-35	AGE	Include
Dwelling	Dwelling built year	COD	The Census 2011 contains information on dwelling built year. However, in the context of energy poverty the age of the dwelling solely matters to estimate energy inefficiencies of the dwelling. The dataset developed by Codema provides average energy efficiency of residential buildings based on actual house assessments and is therefore a superior dataset to assess this.	Average residential building energy efficiency by small area	BER	Include

Factor group	Factor name	Dataset match	Dataset fields & comment	Attribute name(s)	Abbre-viation	Status
	Leaks /Too dark		The Census 2011 does not contain data on dwelling deficiencies. However, house deficiencies such as damp and rot has often been used in energy poverty prevalence assessments as it is an indication households cannot afford to heat their home sufficiently and that the dwelling is energy inefficient. The BER dataset used above accounts for energy inefficiencies and the social dimension attributes accounts for aspects which can cause a household to experience affordability issues. Abbreviation BER.			Grouped
	Lack central heating		The Census 2011 contains information on heating system. However, the BER rating includes consideration of the heating system of dwellings in the assessment. The heating system is therefore already considered in the BER dataset. On this basis the attribute is grouped. Abbreviation BER.			Grouped
Other	Housing allowance recipient		There is not data on benefit recipients in the Irish census.			Exclude

APPENDIX 4

Table A4. Questions used for structured interviews.

UESTION 1

What best describes the people in your home?

1 I live alone
2 All people in my home are adults
3 Both adults and children live in my home
4 I am the only adult and I live with my children
5 Other

QUESTION 2

What best describes your age group (the age group of the respondent)?

1 16 - 24
2 25 - 34
3 35 - 65
4 over 65
5 Other:_____

QUESTION 3

What best describes your marital status? (of the respondant)?

1 I am married
2 I am cohabiting
3 I am separated/divorced
4 I am a widow/widower
5 I am single
6 Other

QUESTION 4

Which best describes your home? (or record without asking)

1 Apartment
2 Semi-detached house
3 Detached house
4 Terraced house
5 Bungalow/terraced Bungalow

QUESTION 5

Do you own or rent your home?

1 Rent (from a private landlord)
2 Rent (from a local authority)
3 Own Outright (not mortgaged)
4 Own with mortgage etc

QUESTION 6 **MULTIPLE**

Which of the following best describes how you heat your home?

1 Electricity (electric central heating storage heating)
2 Electricity (plug in heaters)
3 Gas
4 Oil
5 Solid fuel
6 Renewable (e.g. solar)
7 Other

QUESTION 6.1

Are utilities included in your rent?

1 Yes all
2 Yes heating, not electricity
3 No
4 Don't know

QUESTION 7 **MULTIPLE**

Are you in receipt of fuel allowence? (a welfare payment available in the winter months to qualifying households)

1 Yes
2 No
3 Don't know

QUESTION 8 **MULTIPLE**

In relation to your health. Do you have a Medical Card?

1 Yes
2 No
3 Don't know

QUESTION 9

Further in relation to the heating of your home. In your opinion, is your home kept adequately warm?

1 Yes
2 No

QUESTION 10

Have you had to go without heating during the last 12 months through lack of money?

1 Yes
2 No

QUESTION 11

Is there damp and rot in your home? For example rot in the window frames, damp marks on the walls/ceiling and likewise.

1 Yes
2 No

QUESTION 12

Have you missed paying a utility bill in the last 12 months through a lack of money?

1 Yes
2 No

QUESTION 13

What of the following best describes the adults in this household?
(where different status of different adults record with number after each category)

1 Employed
2 Unemployed
3 Cannot work due to sickness or disability
3 Students
4 Retired
5 Other:_____

QUESTION 14

Does your home have a Building Energy Rating (BER) - a scheme for rating the energy efficiency of your home?

1 Yes
2 No
3 Don't know

QUESTION 14.1

IF [Q9 , 1]

What rating did your home achieve?

1 A
2 B
3 C
4 D
5 E
6 F
7 G

QUESTION 15

Please indicate the approximate proportion of windows in your home which are double glazed?

1 None
2 About a quarter
3 About half
4 About three quarters
5 All

QUESTION 16

Does your hot water tank have outer insulation?

1 Yes
2 No
3 I don't have a hot water tank
4 I don't know

QUESTION 17

Is your attic insulated and if so when was the insulation fitted?

1 Yes, within the last 5 years
2 Yes, more than 5 years ago
3 No
4 I don't have an attic/the house has no attic
5 Don't know

QUESTION 18

Are the external walls of your home insulated?

1 Yes
2 No
3 Don't know

QUESTION 19

I would now like to ask some questions about energy poverty and energy efficiency. Have you ever heard of energy poverty or fuel poverty before?

1 Yes
2 No

QUESTION 20

Have you ever benefitted from free of charge renovations of your home to make it warmer?

1 Yes
2 No

QUESTION 21

Are you aware of a scheme called the better energy communities scheme?

1 Yes
2 No

QUESTION 21.1

IF [Q20 , 1]

On the 7th of December, just last week, the sustainable energy authority of Ireland held an information meeting about the better energy communities scheme for 2017. Which of the following best describes your reaction to this information?

1 I didn't know about the meeting
2 I knew about the meeting but I couldn't go
3 I knew about the meeting but I didn't go as it is not relevant to me
4 I was at the information meeting
5 Other

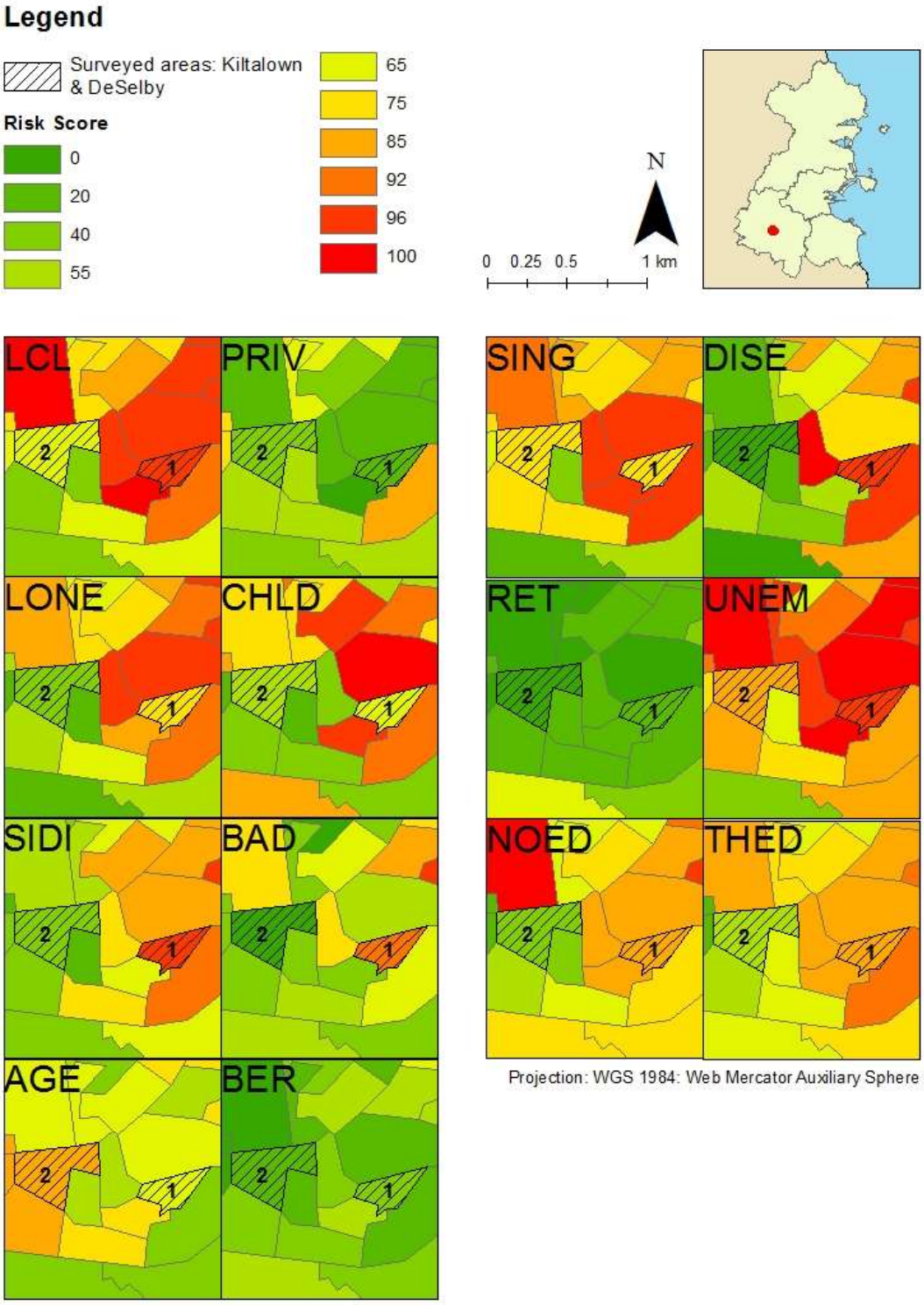
QUESTION 21.2

IF [Q20 , 1]

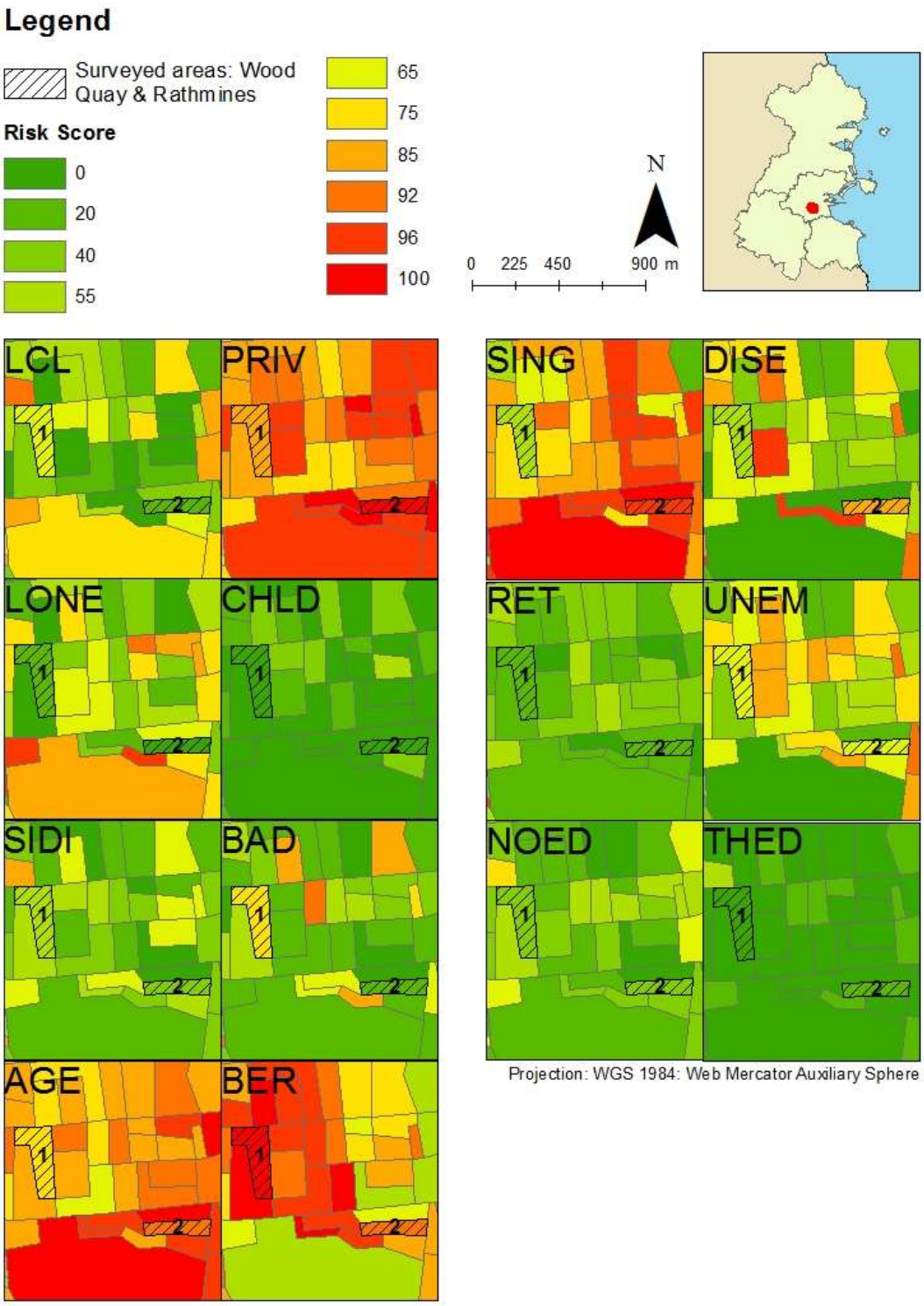
Are you and your community planning to apply for the better energy communities 2017?

1 Yes
2 No

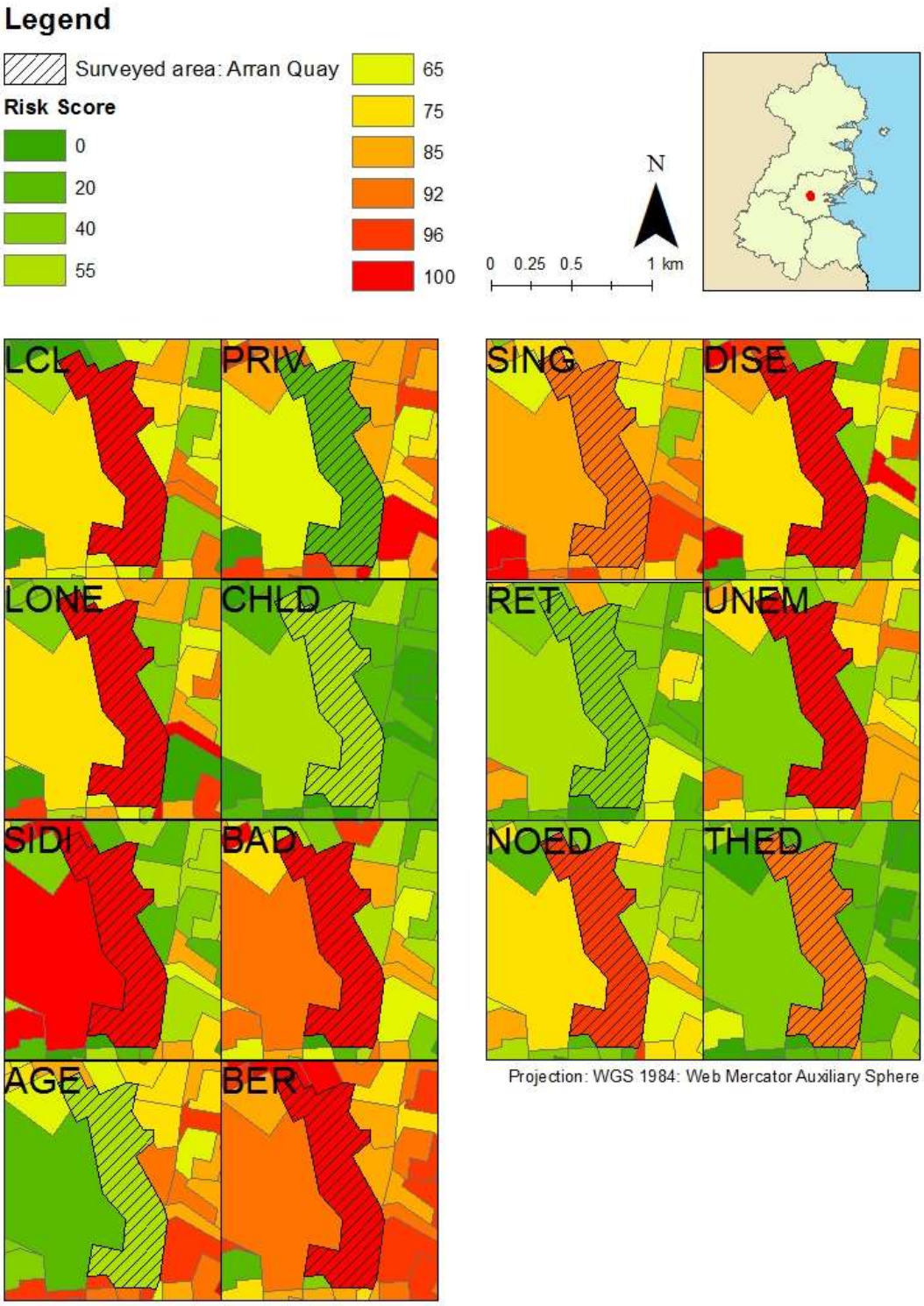
APPENDIX 5



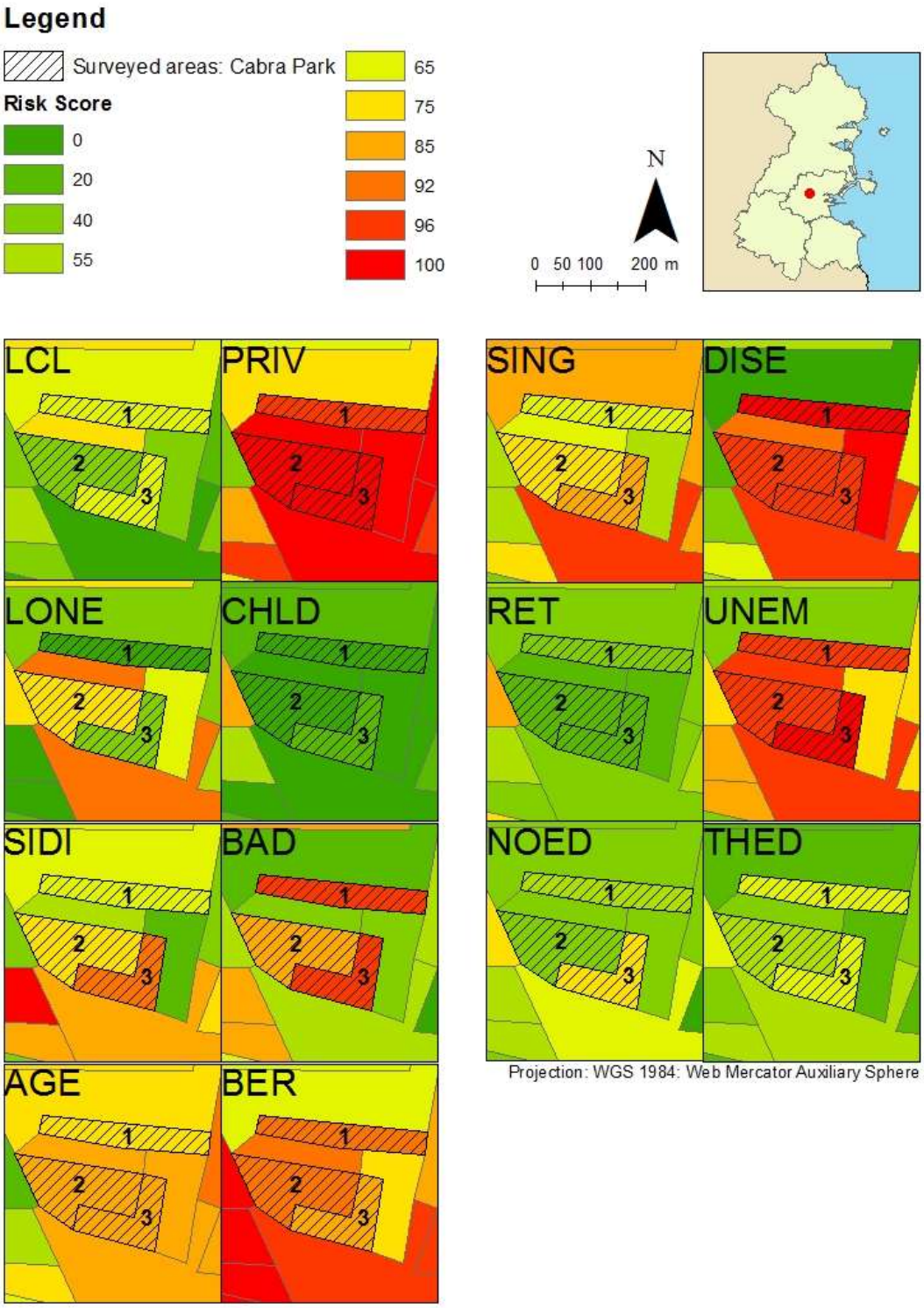
Map A5.1. Attribute risk scores for Kiltalown and DeSelby.
Kiltalown (marked 1) and DeSelby (marked 2).



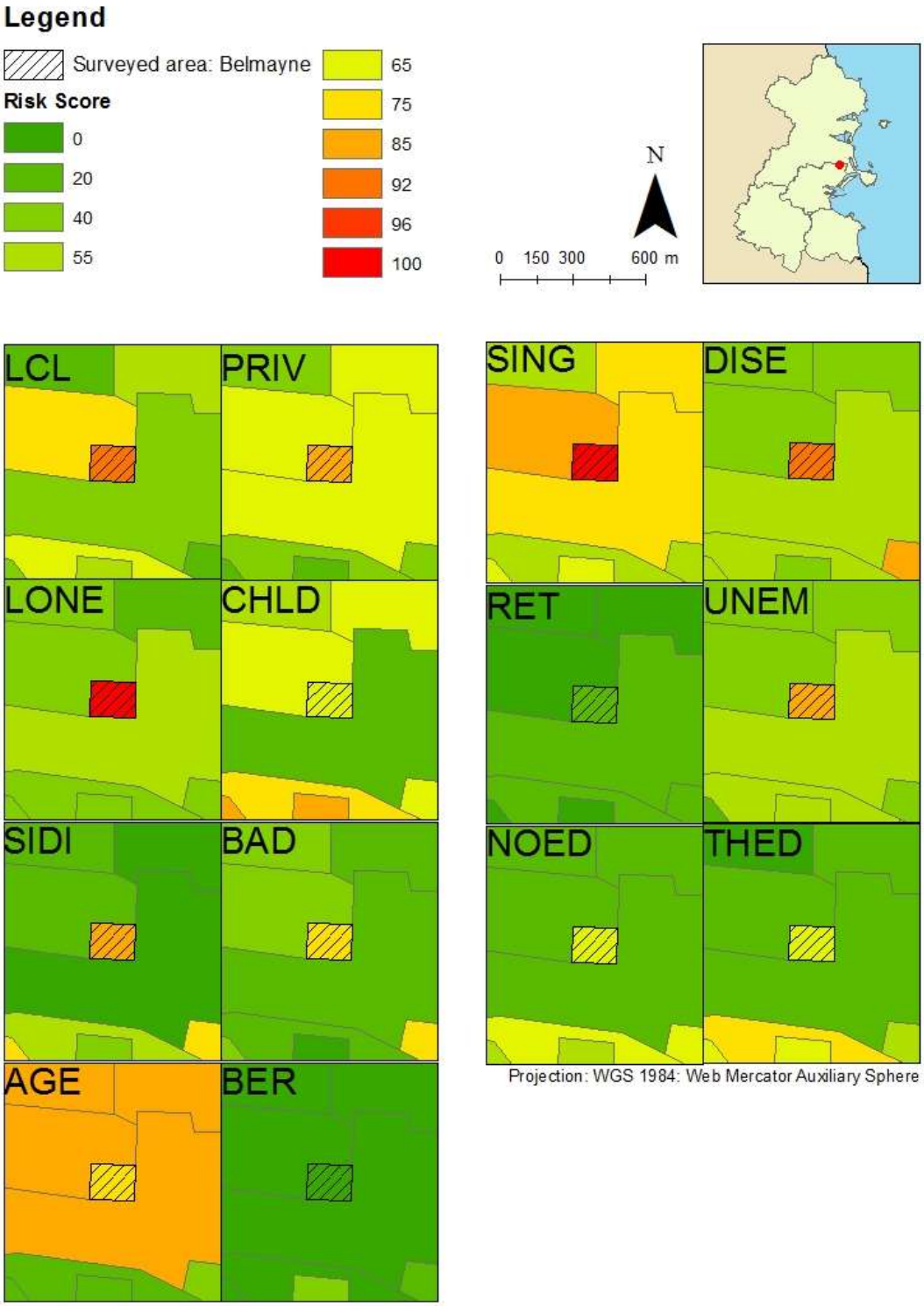
Map A5.2. Attribute risk scores for Wood Quay and Rathmines.
Wood Quay (marked 1) and Rathmines (marked 2).



Map A5.3. Attribute risk scores for Arran Quay



Map A5.4. Attribute risk scores for Cabra Park



Map A5.5. Attribute risk scores for Belmayne

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