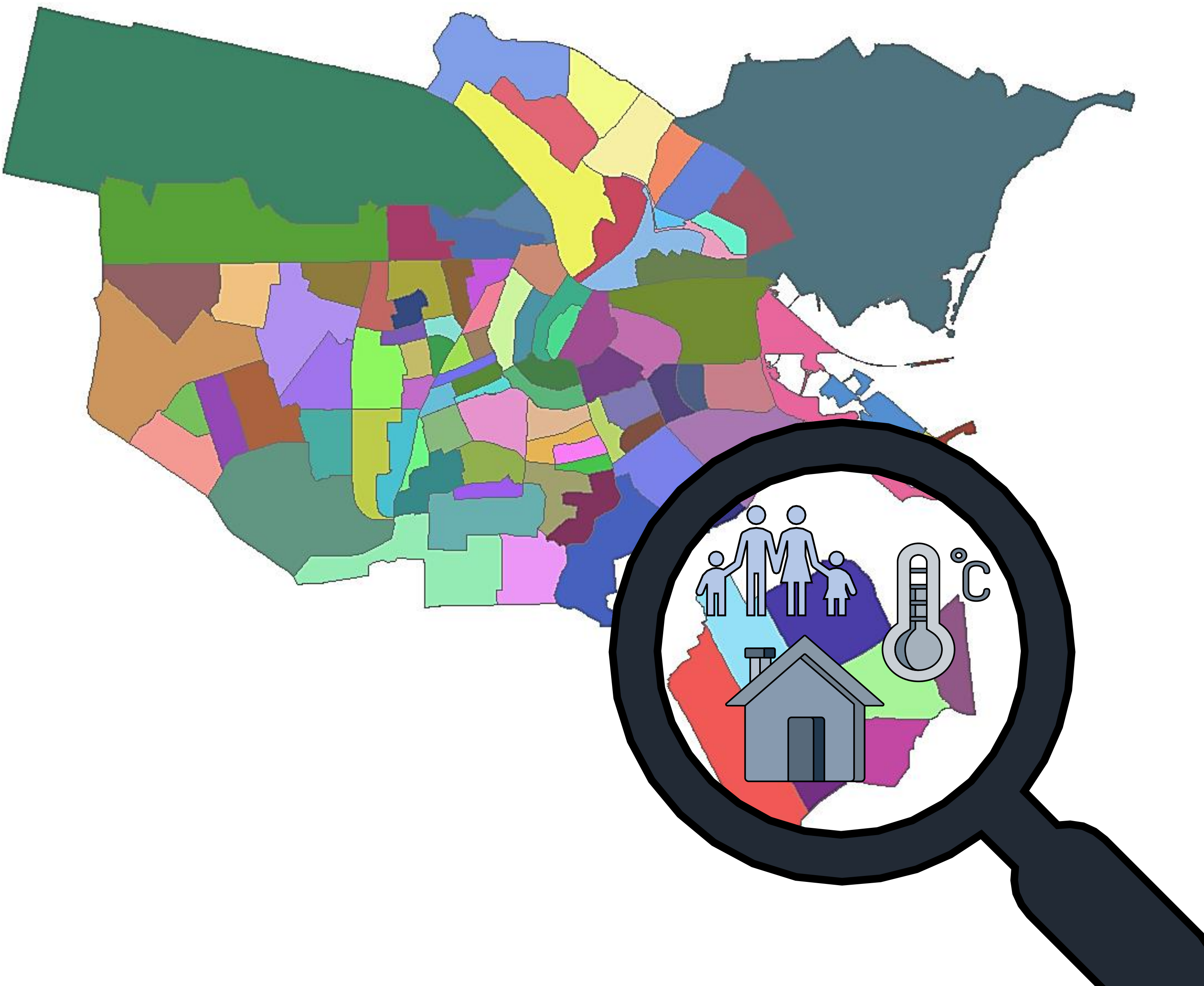
UNIVERSITEIT VAN AMSTERDAM

# ENERGY POVERTY ON THE MAP

## Assessing the suitability of energy poverty indicators for use in local area-based targeting of policies in Amsterdam

MSc Thesis, Rhianne Holdsworth-Morris, 2020



# Summary

Energy poverty is a growing issue in the European Union, although there is currently no commonly accepted definition or measurement. In the Netherlands energy poverty levels are relatively low and as a result the issue has received less attention in national policy. However, the ongoing energy transition to move away from natural gas towards alternative, more sustainable forms of energy is leading to greater concern over the effect this will have on household energy prices. To ensure the energy transition is successful and fair it must benefit all of society and not leave behind those living in energy poverty or worsen the problem. Improving the efficiency of buildings is recognised as an effective way to save energy and lower the number affected by energy poverty, but it is a solution which requires long-term action and funding. Households worst affected by energy poverty are often living in the most inefficient homes and these should be prioritised to receive financial support and targeted funding for renovations. In order to do this, energy poverty needs a clear definition to be able to effectively identify these households and target them to receive extra support.

The most common methods used by EU member states to measure energy poverty are so called ‘energy expenditure-based metrics’ that compare ratios of income to energy expenditure. This research assesses the suitability of quantifiable indicators for identifying energy poverty on the neighbourhood level for Amsterdam. By comparing the spatial distribution of energy poverty under two different energy expenditure-based metrics, the 2M and the LIHC indicators. Other methods that are being increasingly used to target households is with the use of multiple indicators combined into one spatial model. This enables users to measure the vulnerability to energy poverty based on the data that is available at the local scale, such as in different neighbourhoods. To test this method a machine learning (ML) model is developed based on both the 2M and LIHC definitions to predict energy poverty occurrence in neighbourhoods dependent on the socio-economic and built environment factors that influence energy poverty vulnerability. The results show that low income, private-rented, single parent households and those over the age of 65 are main factors which increase the likelihood of energy poverty. The predictive models demonstrate that they can bridge the gap between the numbers and the underlying factors relating to the causes of energy poverty. A local spatial model has the advantage of providing a clear and easy to monitor spatial representation of the issue for policy making, and to target renovations and other measures for energy poverty alleviation to the appropriate areas. The outcomes of this research could be applied to other areas within the Netherlands and be useful for municipalities that are considering implementing energy poverty strategies. Furthermore, it highlights some limitations of the current measurements and encourages further research into the potential methods for mapping energy poverty and a better monitoring of the situation.

## Acknowledgements

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# 1. Introduction

In the Netherlands, energy poverty is a term which receives comparatively less attention compared with the rest of the EU. However, in recent years concerns are growing over rising energy prices related to the ongoing energy transition. Consequently, energy poverty, or *energiearmoede* in Dutch, is a term which is becoming increasingly common. The European Commission defines energy poverty as the situation where "individuals or households are not able to provide required energy services in their homes at an affordable cost" (Pye & Dobbins, 2015). The main energy services in the home include heating of space and water, cooking, lighting and the use of other household appliances. In the Netherlands, natural gas accounts for around 90% of building heating demand (Beckman & van den Beukel, 2019). Household appliances and lighting are powered by electricity provided through the national grid. In general, the availability and supply of gas and electricity to Dutch households is not a major issue. Therefore, it is mostly the affordability of these energy sources that determines whether a household will be in energy poverty. The demand for energy is determined by a range of factors including building characteristics, spatial aspects and behaviour. The three main factors that are identified as causing energy poverty in Europe are (i) low incomes, (ii) high energy prices and (iii) inefficient building quality (Pye & Dobbins, 2015). Energy poverty has further social consequences. The most prominent of these are physical health issues, such as respiratory illnesses, pneumonia and ultimately death, which are particularly exacerbated in the winter periods (Jessel et al., 2019). The effects also extend to mental health consequences such as depression, alongside the wider impacts of social exclusion (Liddell & Morris, 2010). Estimates suggest that around 665,000 to 750,000 Dutch households are affected by energy poverty, with the number rising to 1.59 million in 2030 (Ecorys, 2019; Straver et al. 2017).

The responsibility of coordinating the transition from gas to more sustainable sources of energy for heat has been given to municipalities (Klimaatakkoord, 2019). The transition involves stopping natural gas production at its Groningen fields by as early as 2022 and introducing houses onto new district heating networks or providing heat pumps. The impacts from the energy transition and rising energy prices will place a greater burden on households, especially those in energy poverty. Action is already taking place at municipality level to understand and address energy poverty. For example, in 2016 the Amsterdam municipality recognised that energy poverty was a growing problem in the city and put forward an initiative involving the use of energy coaches to provide advice on energy savings (Gemeente Amsterdam, 2016). Presently, however, the Netherlands lacks a policy which provides an official definition for energy poverty. In fact, the term 'energy poverty' is rarely used at the ministerial level, instead the problem is more generally referred to as 'energy affordability' and is indirectly addressed by means of broader social policies. The lack of recognition for the problem means that policy, research, monitoring and measurement methods are relatively less developed in the Netherlands than within the rest of the EU. For municipalities to effectively and efficiently target energy poverty, a clear definition and suitable metric of measurement is needed.

The lack of a common method to measure energy poverty in the EU means that some member states have applied inappropriate indicators on a national level that were not suited to reflect the local situation. This can lead to an underestimation or misrepresentation of the number of households and areas that are affected by energy poverty. Common measurements of energy poverty are based energy expenditure to income indicators. For example, the so called '10% measurement' or 'energy ratio', whereby a household is deemed to be energy poor if more than 10% of disposable income is spent on energy. A recent report by PBL (2018) considers using the energy ratio in combination with a poverty gap indicator to measure energy poverty in the Netherlands. This approach is similar to the UK's current method to measure energy poverty, known as the Low Income High Costs (LIHC) indicator. There are many metrics and indicators that can be used to measure energy poverty, each producing different results. Furthermore, the choice of indicator can also impact the spatial occurrence of energy poverty and the profile of those identified as in energy poverty (Rademaekers et al, 2016; Fizaine & Kahouli, 2018; Mashhoodi et al., 2019). To solve the problem of energy poverty, the three primary causes must be targeted using a suitable indicator. Increasing income, providing fuel subsidies or financial support, and improving building efficiency through renovations to the building stock will all help to reduce poverty levels.

Ideally, quantitative measurements of energy poverty using energy expenditure to income methods would use detailed data at the household level. This includes data on building characteristics to calculate the required energy consumption to reach an adequate level of warmth and to be able to match this with data on household income and composition of residents. However, this data is not always available at the local level and alternative methods need to be applied to measure energy poverty. One method which is becoming more popular in recent years makes use of readily available data from census sources on vulnerability factors associated with energy poverty such as low income, resident age, building age, or privately rented households. These social factors are often shared at the neighbourhood level but are sometimes overlooked by energy expenditure to income indicators applied at the national level (Robinson et al., 2018a). Methods that combine vulnerability factors are referred to as composite index approaches. They combine multiple dimensions of energy poverty to produce a proxy measure based on vulnerability at a local level (Walker et al., 2014). Adding in multiple dimensions of vulnerability gives a more detailed picture on the causes and dynamics of energy poverty. This can be informative for policy makers and other actors who are considering putting in place measures to alleviate energy poverty.

This research will compare the use of energy expenditure to income indicators and a composite index approach, built using a machine learning (ML) model based on vulnerability factors. These methods are adapted to measure energy poverty at a neighbourhood level in Amsterdam.

## 1.1. Research aim and research questions

The research aim is to assess which indicators are best suited to define and measure energy poverty at a local scale in the Netherlands to allow for the efficient targeting of solutions. This will be assessed based on the main question:

"Are the current indicators used for measuring and monitoring energy poverty suitable to implement effective policies to target energy poverty alleviation in Amsterdam?"

The main question is supported by the following sub-questions:

- Do different metrics lead to different patterns and/or numbers of households in energy poverty?
- In which neighbourhoods does energy poverty occur in Amsterdam?
- Which factors influence energy poverty in Amsterdam?
- Is data at the neighbourhood level sufficiently detailed to measure and reflect the characteristics of energy poverty?
- Does accounting for multiple socio-economic vulnerabilities improve energy poverty measurement?

## 1.2. Reading guide

Section 2 of this thesis includes the theoretical framework, which contains a literature review of energy poverty indicators in use throughout the EU. An evaluation of the strengths and weaknesses of various indicators in the literature is provided under the sub-headings for different indicators. Sections 2.1 and 2.2 evaluate the single energy expenditure to income indicator approaches in use. In section 2.3 the composite index approaches are evaluated. Section 2.4 evaluates the indicators in relation to the Netherlands. Section 2.5 includes a review of recent ML methods for modelling energy poverty. Section 2.6 outlines the criteria for evaluating an effective energy poverty indicator from the literature review. The criteria can be found in Table 1.

Section 3 is the methodology section. The study area and data collection methods are given in section 3.1. The research design of the thesis is given is section 3.2. Section 3.3 details the calculations for the energy expenditure to income approaches. Finally, the ML method to construct a composite index approach is explained in section 3.4.

The results in section 4 map energy poverty in Amsterdam at the neighbourhood level. Four different maps are presented for the different indicators. Firstly, for two different energy expenditure to income approaches using the 2M indicator in section 4.1 and the LIHC indicator in section 4.2 The results of two modelled composite index approaches trained on the 2M in section 4.3 and LIHC in section 4.4. A comparison of all the indicators is given in section 4.5. To conclude the results, section 4.6 provides a comparison of the local numbers in energy poverty for Amsterdam to the national situation.

Section 5 includes a discussion over the strengths and weaknesses of the indicators in relation to the outlined criteria in section 2.6 and their effectiveness at the local level. In section 5.4 Table 19 provides an evaluation of the different indicators next to the outlined criteria.

In section 6 the limitations of the research are given in detail. Section 7 gives conclusions from the research. Section 8 suggests some recommendations for further research on energy poverty.

# 2. Theoretical Framework: Overview of indicators

This section will provide a more detailed look at the different dimensions of energy poverty and an overview of the various indicators that are being used within the EU for measuring and monitoring the situation. The strengths and weaknesses of various indicators in the UK, France, Northern Ireland and Belgium are discussed and a list of criteria for a suitable indicator to measure poverty in Amsterdam is then defined. Measurement can be based on quantitative data such as an energy expenditure to income ratio, or qualitative data collected from surveys that measure perceived levels of energy poverty. Both methods have advantages and disadvantages that have important consequences for energy poverty monitoring. Quantitative measurements are relatively easier and less time consuming to collect as opposed to surveys. These income to energy expenditure methods are often favoured for reporting on national statistics. Collecting data in survey form on energy poverty can be problematic, because households may not be willing to admit that they are in energy bill arrears, or aware that they are unable to keep their home adequately warm (Herrero, 2017). The evaluation of indicators in this study is restricted to quantifiable indicators with the acknowledgement that the potential of qualitative indicators would be useful to evaluate in further research. Today, throughout the EU the most commonly used method to quantify energy poverty is using the energy expenditure to income measurements (Robinson et al., 2018a). An overview of the different indicators is given in the following sections 2.1-2.4.

## 2.1. Boardman's 10% income to expenditure indicator

The first official definition to measure energy poverty was proposed by Boardman in 1991, which stated that a household is in energy poverty if energy expenditure exceeded more than a 10% share of their income (Boardman, 1991). A measurement can be either absolute or relative, whereby absolute measures are based on defined thresholds and relative measurements compare a household/area's situation to that of the average (EnR, 2019). Boardman's indicator can be considered an absolute method because it sets a threshold level of 10% for defining those in energy poverty. The basic calculation for this is:

$$\frac{\boldsymbol{Energy\ expenditure}}{\boldsymbol{Income}} = \boldsymbol{Energy\ poverty\ ratio} \qquad \textbf{(1)}$$

$$\boldsymbol{Energy\ poor\ households} = \{\boldsymbol{households\ where\ Energy\ Poverty\ Ratio} > \mathbf{10}\%\}$$

The 10% method has been criticised because the threshold of 10% no longer reflects the current situation. It was based on median energy expenditure data of the lowest income deciles in 1988, of which was then 5% energy expenditure share in income in England (Herrero, 2017). In response to this, more recently the indicator threshold is calculated as twice the median energy expenditure share ratio depending on the national situation and it can be recalculated each year. The indicator in this form is sometimes referred to as the 2M, or twice the median indicator (Rademaekers et al., 2016). The 2M energy expenditure to income indicator has been adopted by a number of countries within the EU. In 2019 the Netherlands environmental assessment agency PBL considered using it to measure energy poverty in the Netherlands, where it was referred to as the 'payment ratio' (further detail in section 2.4).

Energy expenditure can be calculated in different ways depending on the data available. It can be based on actual energy expenditure or modelled required energy expenditure; the latter has the benefit of including 'hidden energy poverty'. This is where households deliberately restrict energy consumption below reasonable levels in order to ensure energy bills are kept affordable, whereas the former based on actual consumption excludes these households (Hills, 2011). Energy expenditure can also be adjusted by using an equivalisation factor. This is based on household characteristics such as the size of the house and composition of residents to take into account differences in consumption needs (Robinson et al., 2018a). Equivalisation can change composition of the energy poor by either reducing or increasing the numbers in energy poverty depending on the household compositions (DECC, 2012). The more data is available, the more detailed and complex the calculation can become.

The threshold choice has a great impact on whether a household will be defined as in energy poverty. If the threshold is set too high it will exclude those in energy poverty, conversely if it is too high it will include those that are not necessarily in energy poverty. However, there is no standard method to set the threshold level and it is often based on arbitrary decisions (Hills, 2011). The 10% indicator does not give an indication of severity, but rather presents only a binary view of those in energy poverty and those not in energy poverty. Furthermore, the single indicator based on energy expenditure to income does not take into account the household composition and whether there may be vulnerable residents present such as elderly residents, young children, unemployed or disabled who are known to be more exposed to energy poverty (Herrero, 2017). These residents may spend increased amounts of time at home or require higher temperatures. Energy expenditure to income indicators focus largely upon the affordability dimension of energy poverty, however energy poverty is a multi-faceted issue in which social dynamics play an important role (Fizaine & Kaouhli, 2018). Indicators which ignore this can result in inappropriate solutions for some groups of society or lead to policy that neglects certain groups completely (Middlemiss et al., 2018). In 2011, Hills proposed a new indicator known as the Low Income High Costs (LIHC) indicator. One of the main criticisms given in defence of replacing the 10% indicator was that energy prices were too strongly emphasised. This results in increases in energy poverty that closely follows increases in energy prices, despite improvements in energy efficiency and a reduction in energy consumption. To better reflect and monitor the trend of energy poverty the LIHC indicator was adopted and this is now the current method of measurement used in the UK.

## 2.2. The UK's LIHC indicator

The Low Income High Costs (LIHC) indicator defines a household as energy poor based on two thresholds, if energy costs are above the national median and household income is below the 60% median poverty line, or another relevant poverty threshold (see Figure 1). One benefit of the LIHC is that it also allows for a measurement of the depth of energy poverty (Fabbri, 2019). This is known as the 'energy poverty gap', which is the amount needed to reduce the energy bill or increase income to lift a household out of energy poverty (Hills, 2011). The LIHC is a relative measure, because it is based on median thresholds. This makes the measurement less sensitive to energy price fluctuations, resulting in a more stable energy poverty measure in comparison to the 10% indicator. It prevents the numbers in energy poverty from rapidly increasing or decreasing with rises and falls in energy prices, meaning the impact of alleviation measures can become more apparent (Hills, 2011). However, it has been criticised as reducing the number of people in energy poverty by focusing only on those most severely affected and ignoring the important influences arising from energy prices (Robinson et al., 2018a; Thomson et al., 2017; Walker et al., 2014). As the energy costs threshold is relative to the median of the population, an energy price increase for all means that the number in energy poverty will not increase (Heindl & Schuessler, 2015). Moreover, problems caused by energy pricing in the market will be less evident in the indicator (Middlemiss, 2017). Finally, the eradication of energy poverty also becomes impossible as there will always be those in the population that are above the median (Thomson et al., 2017).

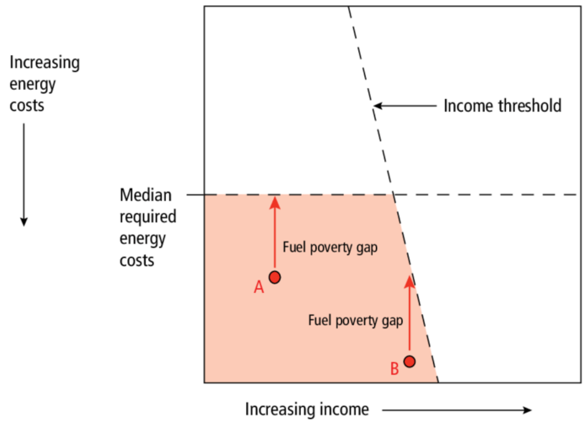


*Figure 1 - The UK's LIHC indicator (Hills, 2011)*

The measurement of income deducts energy costs and housing costs, known as an after-housing cost measurement, whereas the previous 10% indicator used income before housing costs (Thomson et al., 2017). Using income after housing costs is a more appropriate measurement, as energy poverty is affected by the amount of disposable income available to spend on energy and housing costs cannot be spent on energy (Moore, 2012). The decision on which measurement to use can have a large effect on the number of people in poverty (Legendre & Ricci, 2015). The income threshold is set at 60% of median income after housing costs. This is the recommended at-risk-of-poverty line commonly used within the EU (EC, 2019). Equivalising income and energy costs is also important to account for different household size and compositions. For example, if two households with a couple have the same income, but one of these households has a child, the equivalised income would be lower for the latter (Imbert et al., 2016). In the UK's LIHC indicator the income threshold is an angled line because it includes a deduction for modelled energy costs, see Figure 1. This is to reflect the increased risk for energy poverty that comes from high energy costs (DECC, 2012). In this way those households that are just above the income threshold boundary may become low income high cost category after the pressure of high costs is included (DECC, 2012).

A study in the French context by Imbert et al. (2016) considers applying the British LIHC with modifications based on the availability of data. Currently a version of the British 10% indicator is used in France with some differences in methodology, such as the UK approach using modelled energy requirements whilst the French uses actual energy consumption due to a lack of data. Similar to findings of Robinson et al. (2018a), the LIHC indicator reduces the total number of households in energy poverty compared to the 10% indicator. Imbert et al. (2016) finds that only 35% of the same households are classed as energy poor under both indicators. The type of household identified as energy poor also differs between the two indicators, the LIHC is more likely to class couples with children and single parents as energy poor compared to single person households. The inclusion of after housing costs income means that energy poor households are more commonly identified in urban areas with higher housing costs (Robinson et al., 2018a). The LIHC shows greater spatial diversity on smaller scales, reflecting the concentration of household size being denser in urban areas with higher housing costs compared to income. Robinson et al. (2018a) conclude that single indicators can produce widely different results depending on the local situation and that a single indicator should be chosen to reflect the situation or accompanied by other supporting indicators.

## 2.3. Composite index approaches

A number of studies have used spatial techniques to map energy poverty in different countries within the EU. The idea behind these spatial techniques is that energy poverty is often concentrated in specific areas, relating to the spatial characteristics that contribute towards causes of energy poverty (Bouzarovski, 2017). The methods used vary, often reflecting the national approach to defining and measuring energy poverty. These studies construct a composite index for modelling energy poverty vulnerability on local scales, this has the benefit of being specific for characteristics in the area and allowing for flexibility depending on the availability of data. For example, studies by Walker et al. (2014) and März (2018) use a composite index of variables related to the three main causes of energy poverty to identify geographic areas at risk of energy poverty. The variables often relate to the known vulnerabilities of energy poverty. For example, an old building age will often reflect a poorer building energy efficiency, or an older resident age will reflect that this group is more vulnerable to experiencing energy poverty. Individually these variables cannot determine energy poverty, but combined they can give an indication of the level of vulnerability to energy poverty. A brief overview of studies and evaluation measurement methods in countries within Europe is given below.

In Northern Ireland there has been progress in area-based targeting of energy poverty policies based on spatial methods. The study constructs a composite fuel poverty risk index and determines the spatial distribution of risk on small area level of parcels of 125 households (Walker et al., 2014). The index is shown in Figure 2 which includes: the heating burden related to energy prices, the building quality vulnerability using floor space, and the social vulnerability measured by benefit assistance to represent vulnerable households. The heating burden dimension considers the spatial variation in temperature in different regions. For example, colder rural areas will generally require higher energy consumptions to heat homes to an adequate temperature (Walker et al., 2014). The built environment distinctly influences energy poverty, in that larger floor spaces require higher amounts of energy to heat. For two areas which are of similar temperatures the building vulnerability dimension will determine the difference in energy poverty vulnerability.

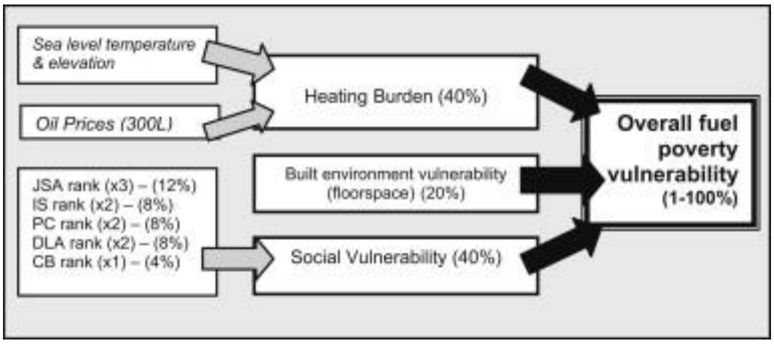


*Figure 2 - Example of a multi-criteria energy poverty vulnerability index (Walker et al., 2014)*

They perform a cluster analysis to identify areas of concentrated energy poverty and highlight the effectiveness of targeting these areas for policy support in the form of building renovations. The availability of data affects the risk index. For example, using a more accurate measure for building energy efficiency such as the EPC or modelled required energy consumption would result in a more refined index (Walker et al., 2014). They conclude that spatial methods allow for easy changes to underlying algorithms and the ability to show varying levels of severity at different spatial levels.

März (2018) uses a multi-spatial criteria index with weighted averages that is similar to Walker et al. (2014). The study makes use of expert opinions to weight the criteria based on a decision problem, in this case the contribution of certain factors to energy poverty. This method is often referred to as the analytical hierarchy problem (AHP). The model is then validated by comparing the weighting to that of other expert judgements. Criteria weighting is important as it can influence the results and therefore distribution of energy poverty on the map (März, 2018). The study also highlights the issues that current methods for measuring energy poverty fail to translate into effective tools to target policy solutions towards energy poor households. The research promotes the measurement of energy poverty into the three different dimensions seen in Figure 2: social vulnerability, built environment vulnerability and heating burden or energy prices.

In the Netherlands, Veenstra (2012) conducted a thesis study on the effect of energy prices on the ability for households to pay their energy bills. Various predictor variables are analysed with a binary logistic regression against the 10% definition to determine which have more influence on a household being in energy poverty. The study finds that variables such as minimum income and building age have a positive influence on the occurrence of energy poverty in households (Veenstra, 2012). The study maps payment arrears to show the geographical distribution, however households in hidden energy poverty will not be included in this measurement.

## 2.4. Energy poverty in the Netherlands

Since 2012, research has been conducted on energy poverty in the Netherlands by PBL, ECN, Amsterdam Municipality as well as private consultancies, for example Ecorys (2019) and RIGO (2013). There are also a number of studies by Veenstra (2012), Roelfsema (2015) and Mashhoodi (2019). The growing interest is related to the ongoing energy transition, rising energy prices and taxes, and the fact that household incomes are not rising at the same rate. The Amsterdam municipality issued a proposal in 2016, stating that around an estimated 6000 households were in energy poverty in 2012, that this number was too large a share and it was time to tackle the problem (Gemeente Amsterdam, 2016).

Within Dutch national energy policy, energy poverty is not specifically addressed. Rather the approach is to deal with the affordability of energy through broader social policies. These include subsidies, benefits, and general support schemes for vulnerable households such as information and awareness initiatives. A vulnerable household in the Netherlands is defined as someone "for whom ending the transport or the supply of electricity or gas would result in very serious health risks for the domestic consumer or a member of the same household of the household customer" (Pye & Dobbins, 2015). These households are offered protection through exemption to energy disconnections. This offers some support to those in energy poverty, but it does not prevent or alleviate the problem.

A study by Rademaekers et al. (2016) evaluated the choice of indicator metrics for the Netherlands. In total three expenditure-based metrics are studied on different income deciles:

- above threshold metrics: 10% indicator, 2M
- below threshold metrics: LIHC, a minimum income standard metric
- a hidden poverty metric

They find that using a metric which measures twice the national median share of income spent on energy as the threshold for defining energy poor households most effective in the Netherlands. The current 10% threshold is criticised for being too arbitrary and incorrectly measuring high income households who have more money to spend on energy as in energy poverty (Rademaekers et al., 2016). Also considered as a possible metric for the Netherlands in this study is the LIHC indicator, where findings show that high income households are excluded, and the lowest income groups are in the highest energy poverty (Rademaekers et al., 2016).

Finally, the hidden energy poverty metric measures household energy expenditure that is abnormally low (Rademaekers et al., 2016). Some energy expenditure metrics can exclude these households from measurement when the actual energy consumption is used. They find that this metric is useful when absolute energy expenditure is measured rather than a share of income spent on energy due to the spending habits of higher income households. The measure most effective is found to be that which measures energy expenditure half below the median absolute energy expenditure.

## 2.5. Machine learning in energy poverty modelling

Machine learning (ML) is a tool which is becoming increasingly popular in the field of energy prediction and poverty modelling (Hassani et al., 2019; Jean et al., 2016). The UK's department for Business, Energy and Industrial Strategy (BEIS) conducted a study into the potential of ML to identify energy poor areas and recognises ML as a powerful, predictive modelling tool with the potential to identify households and areas in energy poverty (BEIS, 2017). ML develops an algorithm to predict values based on a training set of data. The method is explained in detail in section 3.4. One of the benefits of ML in terms of energy poverty modelling is that readily available data for factors relating to energy poverty such as income, building age and resident age can be used. This acts as an alternative method for measuring energy poverty, meaning that intensive data collection to model required household energy consumption is not needed. However, a sizeable sample is required to train the algorithm ML models. In local contexts, municipalities often have extensive data available on citizen and housing demographics, which makes this an interesting tool to apply spatially at this level. The machine learning model method once constructed can be relevant for use in other municipalities, reducing the need for intensive data analysis. Ahmed (2013) applies a logistic regression modelling technique to identify which factors contribute to energy poverty under the LIHC indicator in the UK. A common critique of ML models is that it is hard to understand their construction, making them difficult to reproduce and evaluate. Therefore, it is important that the underlying assumptions used to construct the model are made to be transparent. ML offers a resolution to the criticisms and restraints of more traditional energy poverty approaches because it can incorporate multiple dimensions of vulnerability by utilising alternative sources of data.

## 2.6. Criteria for a suitable energy poverty metric

It becomes apparent from the review of indicators and measurement methods used in the EU that an energy poverty metric should include multiple factors pertaining to the characteristics of the problem, it also must be flexible to adapt to changes in energy expenditure over time and be relevant to the specific situation in the area of measurement. These multiple requirements mean that often methods have limitations in their design and hence their ability to accurately measure and monitor energy poverty. A composite metric based on multiple indicators reduces the risk of exclusion from measurement, but it also has the risk of increasing the amount of data required and increasing the complexity of the method. Data readily available from census collections combined with proxy indicators may be a viable option for an energy poverty metric. Research in the Netherlands into mapping energy poverty is sparse. Whilst Ecorys (2019), Mashhoodi (2019) and Veenstra (2012) have used mapping techniques to represent energy poverty, there is a still a gap in research on the effectiveness of a composite index approach within the Netherlands on a local scale.

In this study the aim is to find a metric to measure energy poverty that allows for the effective targeting of policy initiatives at the local level to alleviate energy poverty. With the responsibility given to municipalities to coordinate the energy transition, there is a need for working tools at this level. Therefore, a suitable indicator of energy poverty should accurately reflect the severity and needs of energy poor households at local scales and represent the different dimensions. From a review of literature there a number of criteria that are recommended for a suitable metric of energy poverty, these are given in Table 1.

*Table 1 - Criteria for a suitable energy poverty metric*

| Criteria | Description |
|---|---|
| **Severity** | To represent the different levels of energy poverty (Rademaekers et al., 2016; Pye & Dobbins, 2015; Walker et al., 2014) |
| **Flexible** | To be able to adapt to work in different local areas and monitor over time to reflect changes in energy prices and incomes (Rademaekers et al., 2016; Hills, 2011) |
| **Inclusive** | Include all households, even those households in hidden energy poverty who may restrict their energy use below required levels (Rademaekers et al., 2016) |
| **Representative** | Can differentiate the different types of energy poverty, for example higher income households who have related high energy consumption, but not a payment risk (Pye & Dobbins, 2015; Hills, 2011) |
| **Effective** | Captures and communicates the key features of energy poverty. Indicators that reflect the characteristics of the area to be able to identify appropriate solutions (Pye & Dobbins, 2015; Walker et al., 2014) |
| **Operational** | Constructed with data that is easily available and accessible for use by municipalities, housing associations and researchers (Walker et al., 2014) |

# 3. Methodology

In the methodology section the study area and a description of the data is given. In section 3.2. the experimental design is presented to outline structure of the research process. The indicators and methods with which these are constructed to measure energy poverty are given in sections 3.3 and 3.4.

## 3.1. Study area and data collection

The study area is the city of Amsterdam, located in the province of North-Holland in the Netherlands. The population in 2018 was 854,047 residents and number of households was 467,606 (CBS, 2018). Amsterdam is split into 8 districts: Centrum, Noord, West, Nieuw-West, Zuid, Oost, Zuidoost and Westpoort. These districts can be further divided up into 99 neighbourhoods that are shown in Figure 3 (for reference to the maps presented in the results, the codes and names of the neighbourhoods can be found in Appendix 1. Neighbourhood codes).

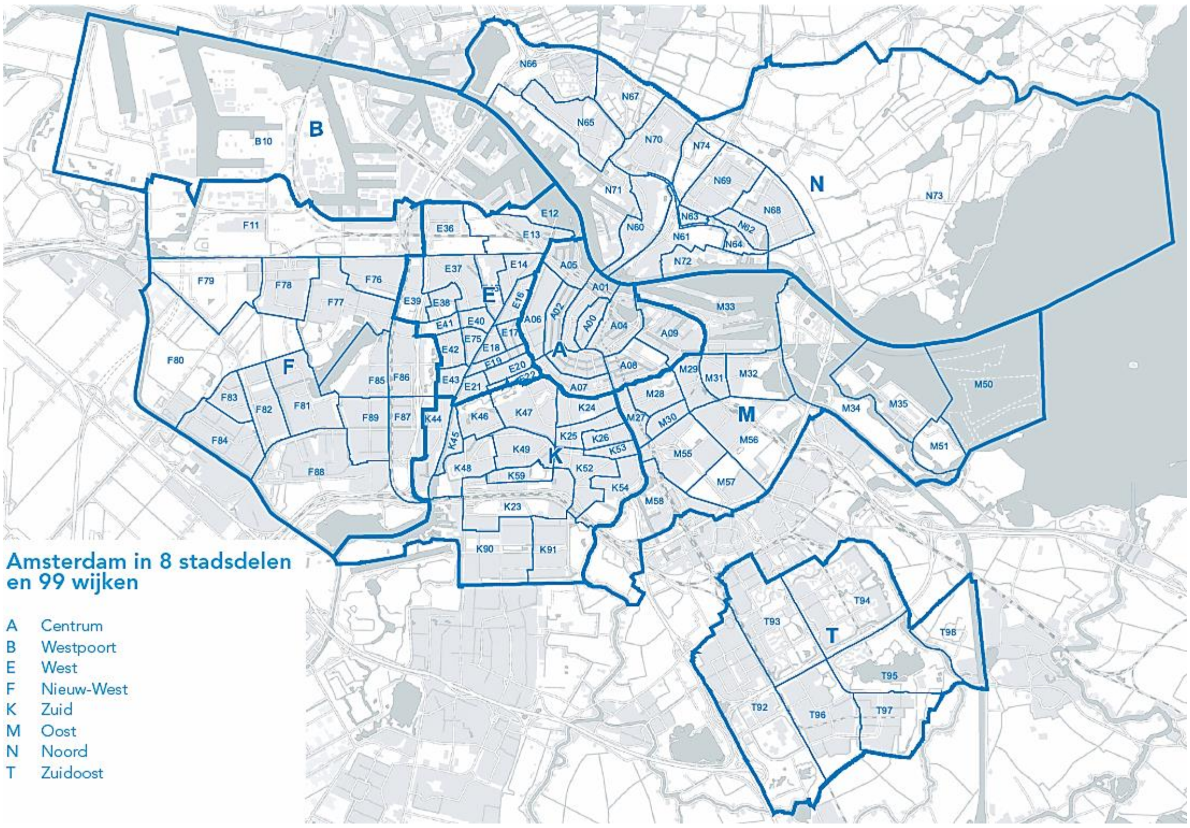


*Figure 3 - Study area of Amsterdam's 8 districts and 99 neighbourhoods (OIS, 2019)*

The districts in Amsterdam have diverse incomes, building characteristics and household compositions which provide a good representation of the different dimensions of energy poverty. Furthermore, data is available from the municipality at the smaller neighbourhood level. This scale will present a more accurate representation of energy poverty vulnerability as these neighbourhoods are likely to exhibit similar income levels and building characteristics (Robinson et al., 2018b). It may be that there are some individual households that have characteristics outside the norm, however a household level analysis requires the availability of detailed data and confidential information. Monitoring at this level is time consuming and expensive as it often requires home visits and assessments, therefore data is rarely available at the individual household level (Walker et al., 2014). With these limitations in mind, the best available data and level of a neighbourhood analysis will be used as this is shown in previous studies to be effective for the purpose of identifying relative risk to energy poverty to target policy initiatives (März, 2018). Working with readily available data, such as that collected in censuses, has the advantage of ease of access and transferability to other regions which have similar data collections (Baker, Starling & Gordon, 2003).

The Amsterdam municipality offers a public data service provided by the research, information and statistics department (OIS). Information is given for the 99 neighbourhoods on household incomes, composition, residents age and other socio-economic factors, as well as building age and floor area. The variables used within the Amsterdam dataset in this study are given in Table 2, note that data for some neighbourhoods is missing. These missing neighbourhoods are Westelijk Havensgebeid, Bedrijventerrein Sloterdijk, Geuzenbuurt, IJburg Oost and Amstel III/Bullewijk. Reasons for the majority of missing data are a small housing stock or relatively new build neighbourhoods.

In addition to the municipality, CBS also offers a public data service known as 'Statline'. This provides some additional informational at the neighbourhood level that is not available on the OIS service. For example, on gas and electricity consumption. In some cases, there are differences in the names of neighbourhoods between datasets, which requires matching before analysis can proceed. In the Statline database energy consumption data after 2015 does not contain matching neighbourhoods for Amsterdam. For this reason, energy consumption data from 2015 is used. As energy consumptions are similar in 2015 and 2018, this causes no major impact on the results.

*Table 2 - Variables and sources in the Amsterdam dataset*

| Variable | Data source | Date |
|---|---|---|
| **Gas and electricity prices** | CBS | 2018 |
| **Average gas and electricity consumption** | CBS | 2015 |
| **Average disposable household income** | OIS | 2017 |
| **Average rental costs per district** | OIS | 2018 |
| **Household composition** | OIS | 2019 |
| **Households below 120% WSM*** | OIS | 2017 |
| **Average unemployment** | OIS | 2018 |
| **Average resident age** | OIS | 2019 |
| **Share in private rent and social rent** | CBS | 2015 |
| **Average floor area** | OIS | 2018 |
| **Average building age** | OIS | 2018 |
| **Average number of rooms** | OIS | 2019 |
| **Average housing value** | CBS | 2015 |

**WSM is the minimum income threshold for low income households to receive support*

Previous studies such as PBL (2018), Broeders (2015) and Veenstra (2012) have also made use of the WoON database that is available on request. This is a series of national housing surveys conducted every three years, the most recent being in 2018. The 2018 WoON dataset contains detail on 922 variables on household characteristics, energy consumption, housing value and behaviour for 67,523 households. In the WoON data the income reported is declared which may result in some inconsistencies where the reported income is zero. Incomes reported as 0 or below zero have been removed.

## 3.2. Experimental design

The research design can be split into two parts:

1. Three metrics are tested to measure energy poverty in Amsterdam: two indicators - the 2M, LIHC, and a predictive model based on the factors correlated to national energy poverty occurrence in the household. Firstly, energy poverty is calculated at neighbourhood level for the 2M and LIHC indicators. Then a ML model built using a binary logistic regression analysis trained on the WoON dataset, for both the 2M and LIHC indicators. This is to find which factors such as socio-economic factors or building characteristics are most important in influencing energy poverty occurrence. The model is then tested and used to predict energy poverty occurrence in neighbourhoods in Amsterdam.

2. The application and visualisation of energy poverty metrics by means of GIS mapping and comparison of the outcomes of the indicators in terms of their practicality and suitability to target solutions to alleviate energy poverty at local levels.

The first step in the research design involves a literature review into the issue of energy poverty from studies in Europe, in the Netherlands and more specifically within Amsterdam. This gives an insight into the dynamics of the problem to help identify unique local drivers of energy poverty in the local context and to gauge numbers in energy poverty. The 2M and LIHC are calculated for Amsterdam at the neighbourhood level to determine the distribution of energy poverty. Subsequently, a statistical analysis using binary logistic regression on these variables gives an indication into which variables have the most significant influence on energy poverty occurrence in the Netherlands. The combined results from the literature review and statistical analysis determine the indicators to include in the model. The factors influencing energy poverty will aim to represent the three main drivers of energy poverty: low income or social factors, energy prices and inefficient buildings (further detail on the ML model is given in section 3.4.).

## 3.3. 2M and LIHC

Energy poverty is measured with the energy expenditure to income approach, which is referred to as twice the median approach (2M). Disposable income is calculated after housing and energy costs are subtracted, as these costs are not available to spend on energy bills (Hills, 2011). A household or neighbourhood will be defined as in energy poverty under the 2M if the energy ratio is above twice the median energy ratio of Amsterdam. The calculation for this is shown below:

$$\boldsymbol{2M\ energy\ ratio}\ \% = \frac{\boldsymbol{Energy\ expenditure}\ (\boldsymbol{gas} + \boldsymbol{electricity\ payments})}{\boldsymbol{Household\ disposable\ income}\ - \boldsymbol{energy\ expenditure} - \boldsymbol{housing\ costs}} \qquad \textbf{(2)}$$

The 2M indicator is calculated for the Amsterdam using the data shown in Table 2 and then for the Netherlands using the WoON dataset.

The LIHC indicator is similar to the 2M but includes two new thresholds that define energy poverty. A low-income threshold which is set at 60% of national median household disposable income and a high energy costs threshold which is over the median household energy expenditure. In addition, a measure of severity known as 'the energy poverty gap' can be calculated (see Figure 4). This is the amount needed to reach the nearest threshold for either income or energy costs to shift out of the LIHC group. It can be calculated by subtracting the energy expenditure from the cost threshold value.

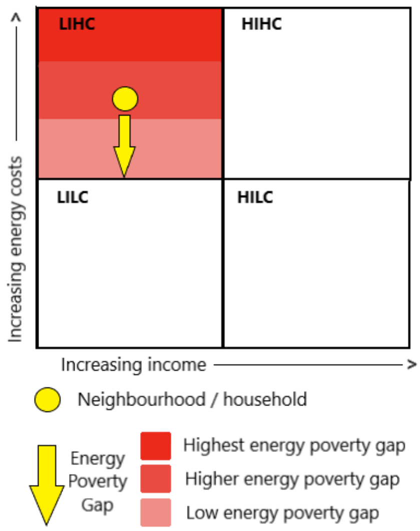


*Figure 4 - The LIHC indicator method (Adapted from Hills, 2011)*

## 3.4. Machine learning logistic regression model

This section explains how the model is built along with an explanation of logistic binary regression. The probability of being energy poor is influenced by a number of factors relating to socio-economic, building characteristics and energy consumption. A binominal logistic regression analysis is used to determine which of these factors are most highly correlated with the occurrence of energy poverty in Amsterdam. The regression curve ranges from 0 to 1 on a logit scale and will produce output coefficients or odds ratio values for each predictor variable. If the output coefficient (on x-axis) is below 0 it decreases the likelihood of energy poverty occurrence and conversely if it is above 0 it increases the likelihood (see Figure 5). For odds ratios a score of above 1 increases the likelihood of being in energy poverty and below 1 decreases the likelihood.

Logistic regression is built using maximum likelihood estimates, which assumes a large sample size. For this reason, the Amsterdam dataset is too small to be able to identify which factors are influencing energy poverty occurrence and instead the larger national WoON dataset is used to build the logistic regression training model. The model is then tested on the Amsterdam neighbourhood level data to predict instances of energy poverty occurrence, depending on the influence of the predictor variables. It is important to note that energy poverty predictors in the Amsterdam dataset are based on average neighbourhood percentage shares, for example the percentage of low-income households in a neighbourhood. However, the WoON dataset used to train the model is at the household level, therefore it attempts to predict energy poverty occurrence for neighbourhoods based on actual occurrence in individual households. Using a training model to predict outcomes on unseen data can lead to misclassifications (Kotu & Deshpande, 2019). For this purpose, the variables included in the model need to be available for both the training and the test datasets. It is assumed that factors influencing energy poverty in the Netherlands and in Amsterdam will be similar. However, there may be some differences which would mean that the WoON is not best suited to represent characteristics in Amsterdam. Ideally, a large enough data sample would be available that is unique to Amsterdam.

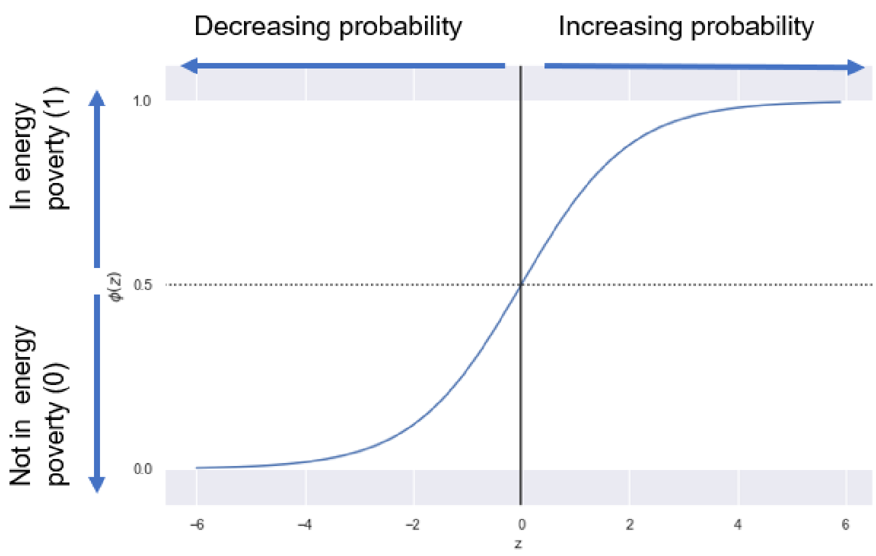


*Figure 5 - The logistic regression curve or sigmoid function*

The analysis is carried out in Python using the Scikit learn library, see

Figure *6*. Firstly, the dataset is split into two classes: households in energy poverty (1) and those not in energy poverty (0) under the 2M and LIHC indicators. As the majority of households fall into the non-energy poverty class, the dataset needs to be balanced to avoid the model being biased towards the larger class. This is carried out in Python through a process known as undersampling. Undersampling removes values from the majority class to match the minority class, which results in a smaller dataset for analysis (BEIS, 2017). The predictor variables in the WoON are categorical and on different scales. It is needed to recode them into binary variables that have a value of 0 or 1, which allows for easy interpretation of the odds ratios (Garavaglia & Sharma, 2016). To transform the Amsterdam dataset a sensitivity analysis is performed using different boundaries to refine the number of correct predictions (see

Figure *6*). For example, only variables with percentage shares in the 3rd quartile are given a binary value of 1. To build the model a stepwise method is used in which the model is trimmed to only include significant variables that are known from the literature to be important in influencing energy poverty (Stoltzfus, 2011). The number and choice of variables included in the model can increase the accuracy and improve the fit of the model. However, for a given training set size, too many variables will weaken the accuracy of the model. The logistic regression model is given below:

$$logit\ (P) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n$$

*P = the binary dependent variable*

*$\beta_0$ = an intercept term*

*$\beta$ = the independent variable coefficients*

*x = the independent variables*

The trained model can be evaluated against an accuracy score, which is produced by comparing the predicted output values against the actual occurrence in the dataset. In addition to accuracy, there are also scores given for precision and recall that give further detail on the performance of the model. These scores are calculated from a confusion matrix, see example in Table 3. The confusion matrix shows the amount of true and false positives (1), and true and false negatives (0). A true positive is when the model correctly predicts actual energy poverty occurrence. False positives, or "false alarms", occur when the model incorrectly predicts a positive value for energy poverty. True negatives are those which are correctly predicted as not in energy poverty by the model. A false negative, or a "miss", in when the model incorrectly predicts a neighbourhood/household as not in energy poverty. The precision score shows the amount of correctly identified true positives, whereas recall shows the amount of positive identifications including false negatives. The method for calculating the model scores in given in Appendix 3. Logistic regression has a standard classification threshold of 0.5 (see Figure 5). Decreasing the model's classification threshold alters both precision and recall scores, resulting in more false positives and less false negatives. In the trade-off between precision and recall, a model which favours recall is preferable in this case, as it results in less false positives, or neighbourhoods in energy poverty being missed out.

*Table 3 - Example of a confusion matrix*

| | **Actual** | |
|---|---|---|
| **Predicted** | **0** | **1** |
| **0** | True negative | False negative |
| **1** | False positive | True positive |

A schematic design of the methodology to build the logistic regression model is shown below.

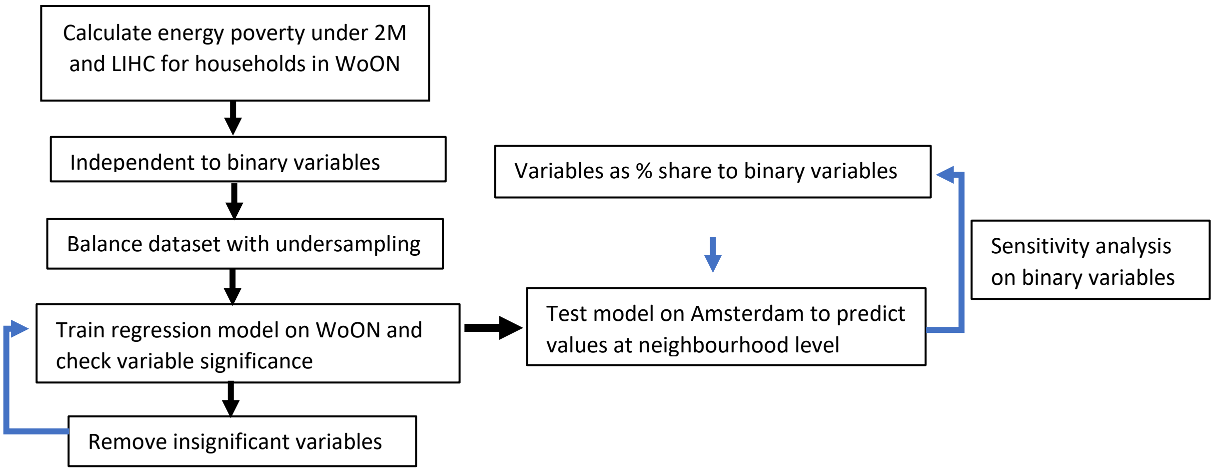


*Figure 6 - Schematic diagram to show process to build the predictive model*

# 4. Results

In this section the results of the single 2M and LIHC indicators for energy poverty in Amsterdam are given in section 4.1 and 4.2. The results of the predictive models and an overview of the parameters based on the LIHC are given in section 4.3., and then similarly for the 2M model in section 4.4. For all indicators there is a corresponding map to show the areas that have the highest levels of energy poverty and a table with the neighbourhood names and other relevant information.

## 4.1. Energy poverty under 2M in Amsterdam

In Figure 7, the distribution of energy expenditure in Amsterdam shows that in general higher income neighbourhoods spend more on energy than lower income neighbourhoods.

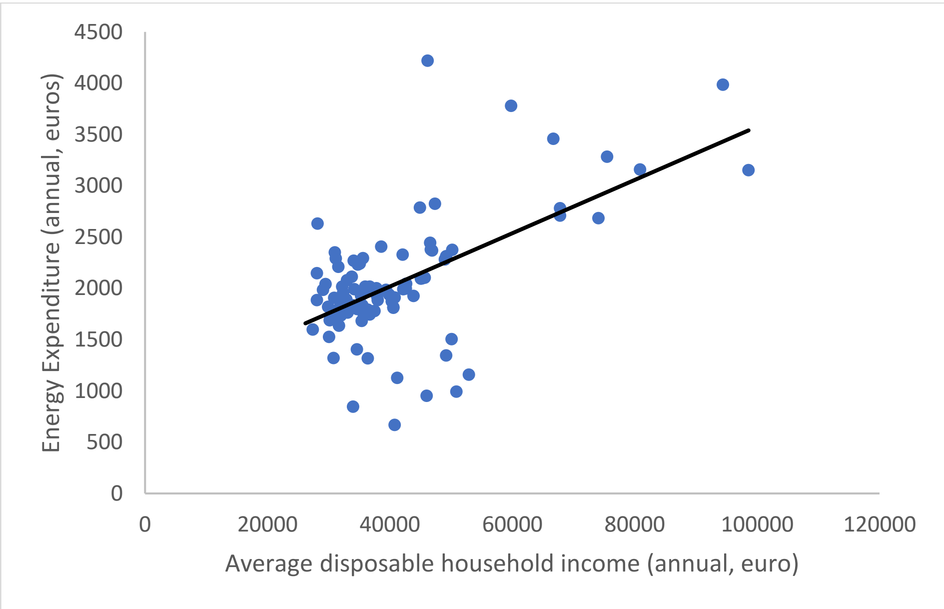


*Figure 7 - Energy expenditure in Amsterdam neighbourhoods by income*

The energy expenditure to income ratio sets the threshold for energy poverty at twice the median of income spent on energy expenditure. The distribution in Figure 8 shows that the lower incomes have overall higher energy ratios, therefore they are spending proportionately more than higher incomes on energy. The median energy ratio in Amsterdam is 5.17%, so twice this would set the energy poverty threshold at 10.34%. The threshold is calculated using income before housing and energy cost deductions.

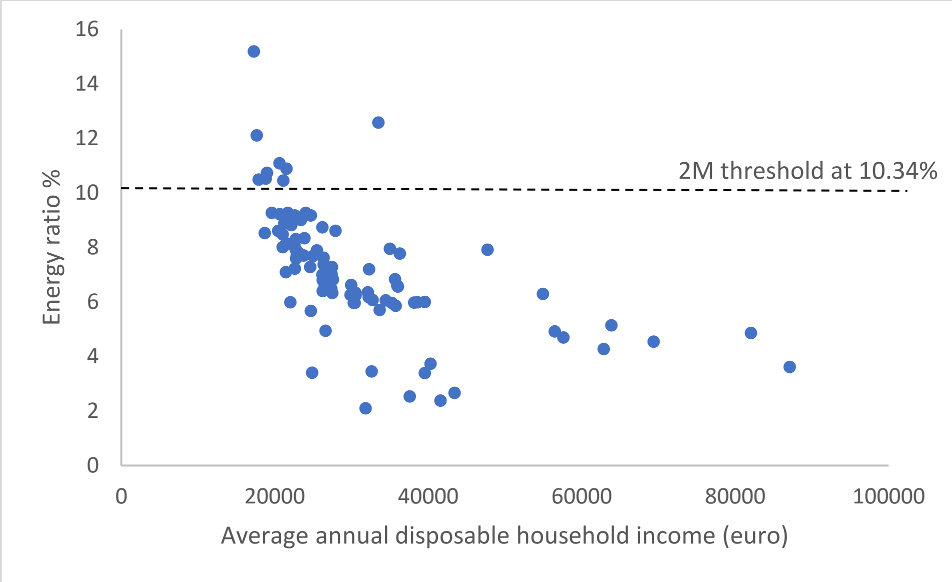


*Figure 8 - Energy ratio by income for Amsterdam neighbourhoods*

The 2M indicator is mapped for neighbourhoods in the city of Amsterdam in Figure 9. The neighbourhoods in yellow are those above the threshold of 10.34%. 5 out of the 9 neighbourhoods are located in the district Noord and are clustered together. A number of neighbourhoods in the districts West, Nieuw-West and Zuid-Oost have higher energy ratios between 7-9%.

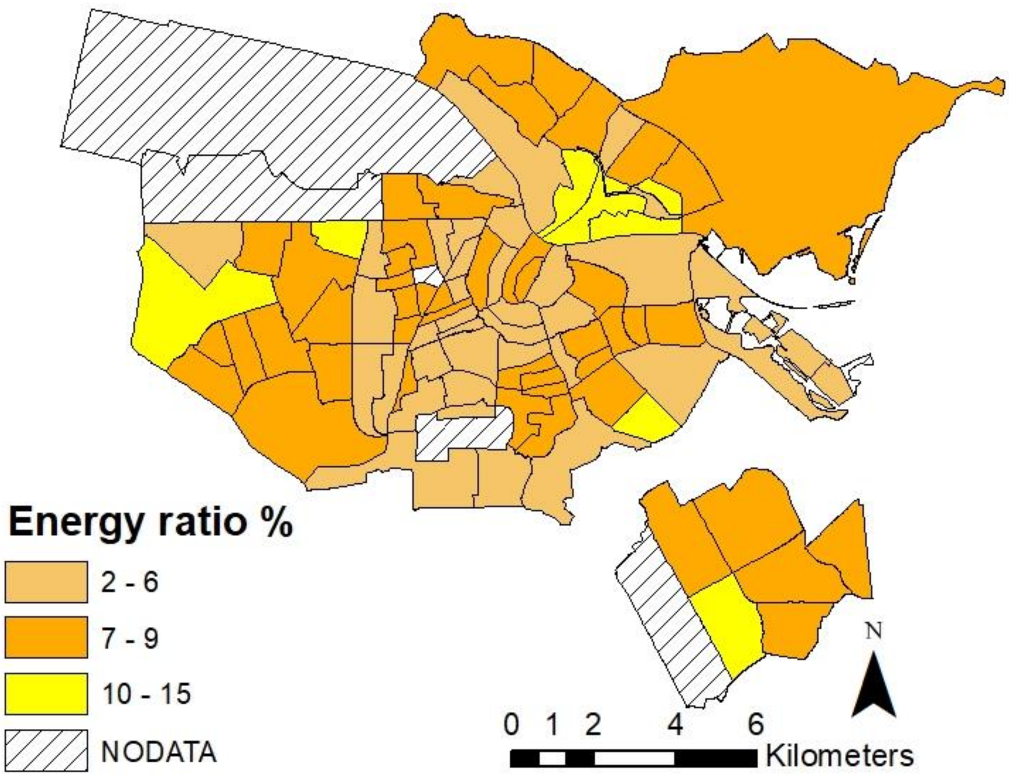


*Figure 9 - Neighbourhoods in Amsterdam in energy poverty under 2M*

The 9 neighbourhoods that cross the 10.34% threshold are given in Table 4, along with the energy ratio and income. The table is sorted in order of highest to lowest energy ratio. It can be seen that the highest energy ratio is in Noordelijke IJ-oevers Oost, which also has the lowest income in the table. However, the next highest ratio is in Lutkemeer/Ookmeer which has an income twice that of Noordelijk IJ-oevers Oost. Aside from income, average energy expenditure is also influencing the energy ratio. In Lutkemeer/Ookmeer energy expenditure is the highest in all of Amsterdam, resulting in the second highest energy ratio despite the relatively high income.

*Table 4 - Neighbourhoods in energy poverty under the 2M indicator*

| Neighbourhood | Energy ratio % | Income (euro/year) |
|---|---|---|
| **Noordelijke IJ-oevers-Oost** | 15 | 17,314 |
| **Lutkemeer/Ookmeer** | 12.6 | 33,527 |
| **Volewijck** | 12.1 | 17,700 |
| **Tuindorp Buiksloot** | 11.1 | 20,654 |
| **Holendrecht/Reigersbos** | 10.9 | 21,560 |
| **Slotermeer-Noordoost** | 10.7 | 19,006 |
| **IJplein/Vogelbuurt** | 10.5 | 18,860 |
| **Tuindorp Nieuwendam** | 10.4 | 21,135 |
| **Betondorp** | 10 | 17,949 |

The percentage of neighbourhoods in energy poverty can be used to estimate the rate of energy poverty. Under the 2M indicator the rate of energy poverty in Amsterdam is 10%. This rate can then be used to estimate the number of households in energy poverty. Given that there were 467,606 households in 2018, this would equate to around 47,000 households in energy poverty in Amsterdam.

In the 2M the threshold is set based on the median ratio which in Amsterdam is 5.17% after housing costs. If the threshold is set based on the median ratio before housing costs, it would be set at 14% and only one neighbourhood would be classed as in energy poverty.

## 4.2. Energy poverty under LIHC in Amsterdam

The LIHC indicator separates each neighbourhood into four groups by means of two thresholds, the annual income threshold of €21,840 and the annual cost threshold of above €1,951 median energy expenditure. On the y-axis the energy ratio is given instead of energy expenditure for purpose of comparison with Figure 8. This means the threshold for energy expenditure is not represented. Under the LIHC there are 8 neighbourhoods which have low incomes and on average higher than the median energy expenditures. Figure 10 shows the distribution of the energy ratio against income, together with the 4 different groups according to the LIHC thresholds. The highest number of neighbourhoods in Amsterdam fall into the HIHC and HILC groups, followed by the LILC and the LIHC group.

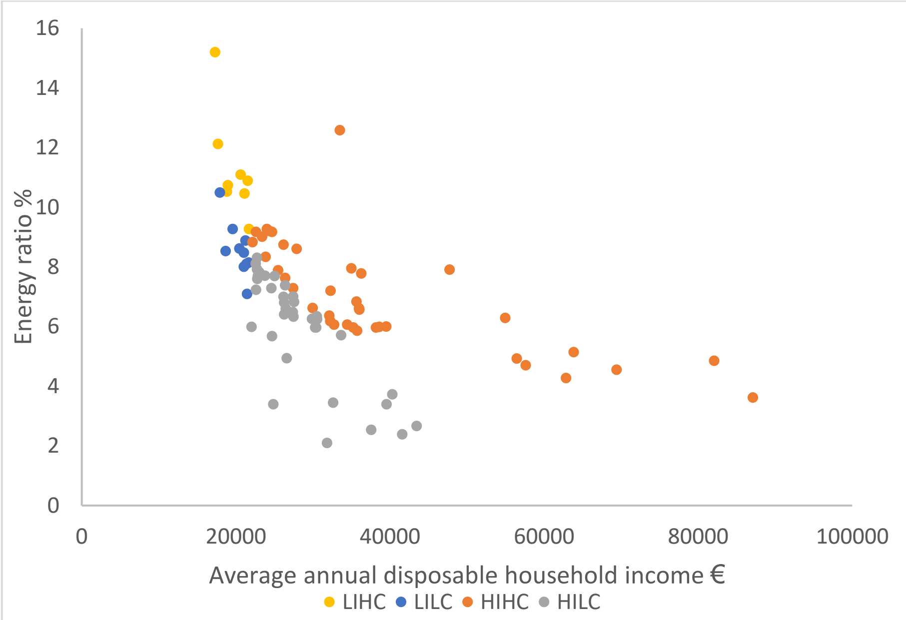


*Figure 10 - The four LIHC groups by energy ratio and income for Amsterdam*

These results are mapped in Figure 11 to show the spatial distribution of these neighbourhoods in Amsterdam. 5 out of the 8 neighbourhoods in energy poverty are found in the district Noord. 2 in Nieuw-West and 1 in Zuid-Oost.

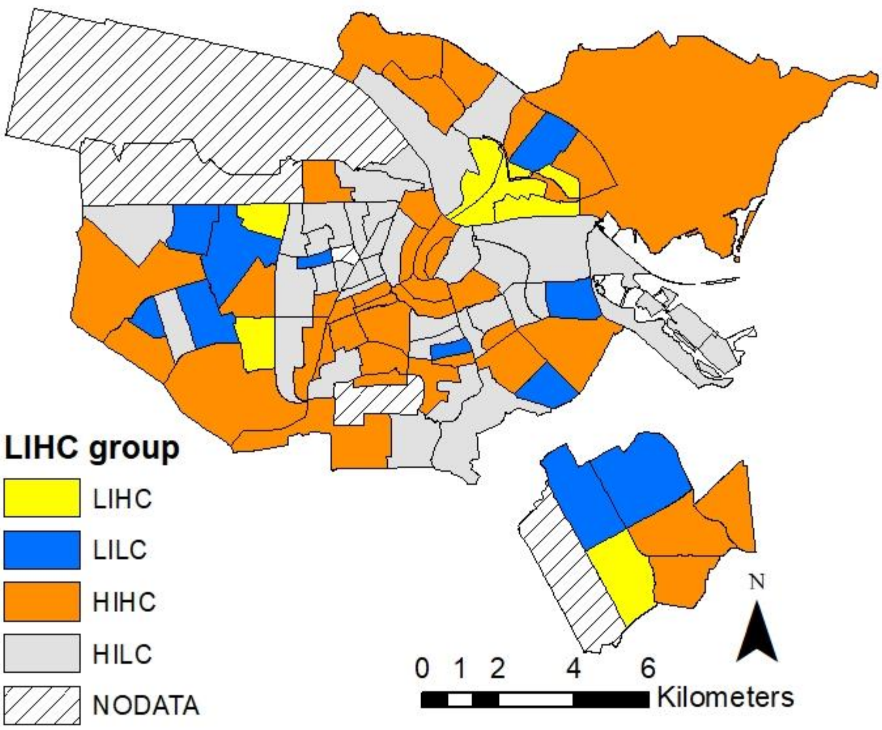


*Figure 11 - Neighbourhoods in energy poverty under LIHC*

Under the LIHC indicator a neighbourhood is considered to be in energy poverty if it has a low income and high energy costs. The eight neighbourhoods in energy poverty are given in Table 5 along with the energy poverty gap. The energy poverty gap is the amount needed to reduce energy expenditure below the high cost threshold. Therefore, the greater the expenditure gap, the greater the severity of energy poverty (BEIS, 2019a). The highest energy expenditure is in Tuindorp Buiksloot, where a reduction of €551 on the energy bill is needed. The lowest energy poverty gap is €40 found in IJplein/Vogelbuurt. The average gap in Amsterdam is €253 to reach the energy cost threshold. All neighbourhoods except Slotervaart-Zuid have an energy ratio above 10%.

*Table 5 - Neighbourhoods in energy poverty under the LIHC indicator*

| Neighbourhood | Energy expenditure gap € | Energy ratio % |
|---|---|---|
| **Tuindorp Buiksloot** | 551 | 11 |
| **Holendrecht/Reigersbos** | 451 | 10.8 |
| **Noordelijke IJ-oevers-Oost** | 430 | 15.1 |
| **Volewijck** | 240 | 12.1 |
| **Tuindorp Nieuwendam** | 160 | 10.4 |
| **Slotermeer-Noordoost** | 90 | 10.7 |
| **Slotervaart-Zuid** | 61 | 9.3 |
| **IJplein/Vogelbuurt** | 40 | 10.5 |

The percentage of neighbourhoods in energy poverty can be used to estimate the rate of energy poverty. Under the LIHC indicator the rate of energy poverty in Amsterdam is around 9%. This rate can then be used to estimate the number of households in energy poverty. Given that there were 467,606 households in 2018, this would equate to around 42,000 households in energy poverty in Amsterdam.

## 4.3. 2M model

The predictive model results for the 2M trained WoON data and the Amsterdam unseen data are presented and evaluated in this section. In Table 6 the factors that influence the occurrence of energy poverty are shown. The extent of influence is indicated by the odds ratio and confidence interval. Those which have the highest influence on the 2M outcome are low incomes, households over 75 years old, and private-rented tenures. Single parent households and households aged over 65 years are decreasing the probability of energy poverty occurrence in this model, as indicated by the odds ratio of less than 1. Buildings that are built after 2010 also have a decreasing effect on the probability of energy poverty occurrence.

*Table 6 - Factors with the greatest influence on energy poverty occurrence in 2M model*

| Predictor | CI 2.5% | CI 97.5% | Odds Ratio |
|---|---|---|---|
| **Low income** | 15.32 | 20.35 | **17.66** |
| **Over 75** | 1.69 | 2.32 | **1.98** |
| **Private-rented** | 1.09 | 1.43 | **1.25** |
| **Built after 2010** | 0.19 | 0.31 | **0.24** |
| **Aged over 65 years** | 0.44 | 0.55 | **0.49** |
| **Single-parent** | 0.65 | 0.88 | **0.75** |

Table 7 shows that the trained model predicts the correct outcome of 2M with 80% accuracy. However, more informative for evaluating the model are the precision and recall scores. The recall is lower at 66% and the precision is higher at 92%, this results in less false positives and more false negatives as shown in Table 7. The confusion matrix shows the total positive values is 37%, identifying a slightly higher proportion of those not in energy poverty compared to those in energy poverty (Table 7). The true positives (those correctly identified as in energy poverty) are higher than the number of false negatives (those incorrectly classed as not in energy poverty). There is a larger proportion of true predictions overall, but the false positive score is still quite high. This results in many neighbourhoods being identified as in energy poverty in the model, whilst they are not actually in energy poverty. The F1 score is a combination of precision and recall.

*Table 7 - Model scores for 2M WoON set*

| 2M model | Score |
|---|---|
| **Accuracy** | 80% |
| **Precision** | 92% |
| **Recall** | 66% |
| **F1 Score** | 77% |

The confusion matrix shows the percentage of true and false negatives, and true and false positives in percentages. The results are shown to evaluate the 2M WoON model.

*Table 8 - Confusion matrix for 2M WoON set*

| | Actual | |
|---|---|---|
| **Predicted** | **0** | **1** |
| **0** | True negative 46% | False negative 17% |
| **1** | False positive 3% | True positive 34% |

This model is then used to predict energy poverty on the unseen data in the Amsterdam dataset. This predicts that 25 neighbourhoods are identified as being at risk under 2M (Figure 12). However, 2 neighbourhoods which are identified in the LIHC group are now incorrectly classified as not in energy poverty, IJplein/Vogelbuurt and Noordelijke IJ-oevers-Oost. In Noordelijke IJ-oevers Oost the amount of privately rented households falls just below the binary boundary for this predictor variable, this highlights the importance and influence of different threshold values and the sensitivity of the model. The thresholds for all factors and their binary transformations are given in Table 22 in Appendix 5.

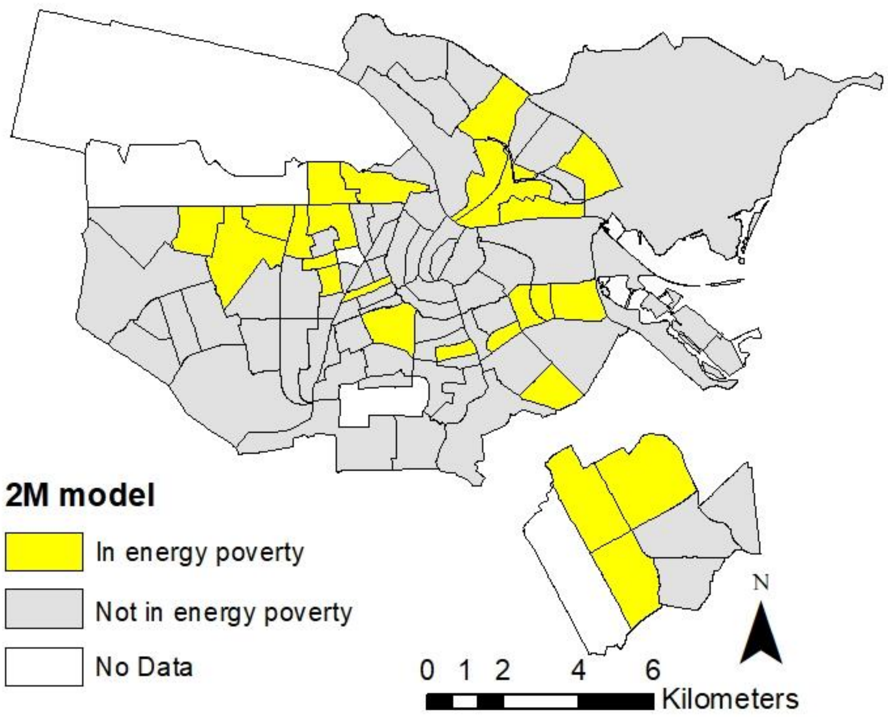


*Figure 12- Predicted neighbourhoods in energy poverty in 2M model*

Table 9 lists the 25 neighbourhoods predicted as being in energy poverty in the 2M model alongside annual household disposable income and annual energy expenditure.

*Table 9 - Predicted neighbourhoods in energy poverty in 2M model*

| 2M predicted neighbourhoods | Income | Energy expenditure |
|---|---|---|
| **Banne Buiksloot** | 22754 | 1890 |
| **Betondorp** | 17950 | 1882 |
| **Bijlmer Centrum (D,F,H)** | 18713 | 1595 |
| **Bijlmer Oost (E,G,K)** | 21485 | 1523 |
| **Dapperbuurt** | 23800 | 1832 |
| **De Kolenkit** | 22047 | 1319 |
| **Geuzenveld** | 21682 | 1764 |
| **Holendrecht/Reigersbos** | 21561 | 2347 |
| **Hoofdweg e.o.** | 22832 | 1734 |
| **IJplein/Vogelbuurt** | 18861 | 1983 |
| **Indische Buurt Oost** | 21400 | 1732 |
| **Indische Buurt West** | 22600 | 1832 |
| **Landlust** | 23062 | 1804 |
| **Museumkwartier** | 69429 | 3155 |
| **Noordelijke IJ-oevers Oost** | 17314 | 2630 |
| **Slotermeer-Noordoost** | 19006 | 2040 |
| **Slotermeer-Zuidwest** | 19627 | 1819 |
| **Spaarndammer- en Zeeheldenbuurt** | 22766 | 1800 |
| **Transvaalbuurt** | 22176 | 1956 |
| **Tuindorp Buiksloot** | 20655 | 2289 |
| **Van Galenbuurt** | 21079 | 1687 |
| **Van Lennepbuurt** | 22631 | 1635 |
| **Volewijck** | 17700 | 2144 |
| **Waterlandpleinbuurt** | 22666 | 2078 |
| **Zuid Pijp** | 20679 | 1905 |

The model evaluation scores given in Table 10 and Table 11 are for the Amsterdam unseen set. By comparing these to the calculated 2M results in section 5.1, a confusion matrix and model scores for the test results can be calculated using the equations in Appendix 3. The results differ from that of the model training set, because the model is trained on the WoON dataset and then tested on unseen data. Table 11 shows that the majority of neighbourhoods identified as in energy poverty in the test set are false positives rather than true positives. The number of false negatives is low, meaning that neighbourhoods in energy poverty are unlikely to be missed by the model. However, the overall model performance has decreased. This can be seen in the decrease in both precision and recall, evaluated by the F1 score, which has decreased from 77% to 40%.

*Table 10 - Model scores for 2M Amserdam unseen set*

| Parameter | Score |
|---|---|
| **Accuracy** | 77% |
| **Precision** | 27% |
| **Recall** | 78% |
| **F1 Score** | 40% |

The confusion matrix shows the values in percentages from which the model scores in Table 11 are calculated. The equations used are given in Appendix 3.

*Table 11 - Confusion matrix for 2M Amsterdam unseen set*

| | Actual | |
|---|---|---|
| **Predicted** | **0** | **1** |
| **0** | True negative 70% | False negative 2% |
| **1** | False positive 20% | True positive 8% |

## 4.4. LIHC model

The model results for the LIHC WoON data set and the Amsterdam unseen data are given in this section. The odds ratios along with confidence intervals (CI) for the predictor variables are given in Table 12. Those which have the highest influence on the LIHC outcome are low incomes and unemployment. Private-rented tenures, single parent households and households aged over 65 years are also increasing the probability of energy poverty occurrence in households. One variable for buildings that are built after 2010 has a decreasing effect on the probability of energy poverty occurrence. This is shown by the odds ratio of less than 1.

*Table 12 - Factors with the greatest influence on energy poverty occurrence in LIHC model*

| Predictor variable | CI 2.5% | CI 97.5% | Odds Ratio |
|---|---|---|---|
| **Low income** | 2.75 | 3.52 | **3.11** |
| **Unemployment** | 1.75 | 4.44 | **2.80** |
| **Private-rented** | 1.52 | 1.97 | **1.73** |
| **Single parent** | 1.31 | 1.73 | **1.50** |
| **Aged over 65 years** | 1.28 | 1.48 | **1.38** |
| **Built after 2010** | 0.19 | 0.31 | **0.24** |

The trained model predicts the correct outcome of LIHC with 70% accuracy (Table 13). However, more informative are the precision and recall scores. The recall is fairly high at 81% and the precision is lower, this results in more false positives and less false negatives. The confusion matrix shows the total positive values is 61%, identifying a slightly higher proportion of those in energy poverty compared to those not in energy poverty (Table 14). The true positives (those correctly identified as in energy poverty) are higher than the number of false negatives (those incorrectly classed as not in energy poverty). There is a larger proportion of true predictions overall, but the false positive score is still quite high. This results in many neighbourhoods not in actual energy poverty being identified as in energy poverty in the model. The F1 score is a combination of precision and recall.

*Table 13 - Model scores for LIHC WoON set*

| Parameter | Score |
|---|---|
| **Accuracy** | 70% |
| **Precision** | 67% |
| **Recall** | 81% |
| **F1 Score** | 73% |

The confusion matrix shows the percentage of true and false negatives, and true and false positives in percentages. The results are shown to evaluate the LIHC training model.

*Table 14 - Confusion matrix for LIHC WoON set*

| | Actual | |
|---|---|---|
| **Predicted** | **0** | **1** |
| **0** | True negative 29% | False negative 9% |
| **1** | False positive 20% | True positive 41% |

Applied to the Amsterdam dataset we see that 19 neighbourhoods are identified as being at risk in the LIHC group (Figure 13). However, 2 neighbourhoods which are identified in the LIHC group are now incorrectly classified as not in energy poverty, IJplein/Vogelbuurt and Noordelijke IJ-oevers-Oost. In Noordelijke IJ-oevers Oost the amount of privately rented households falls just below the binary boundary for this predictor variable, this highlights the importance and influence of different threshold values and the sensitivity of the model.

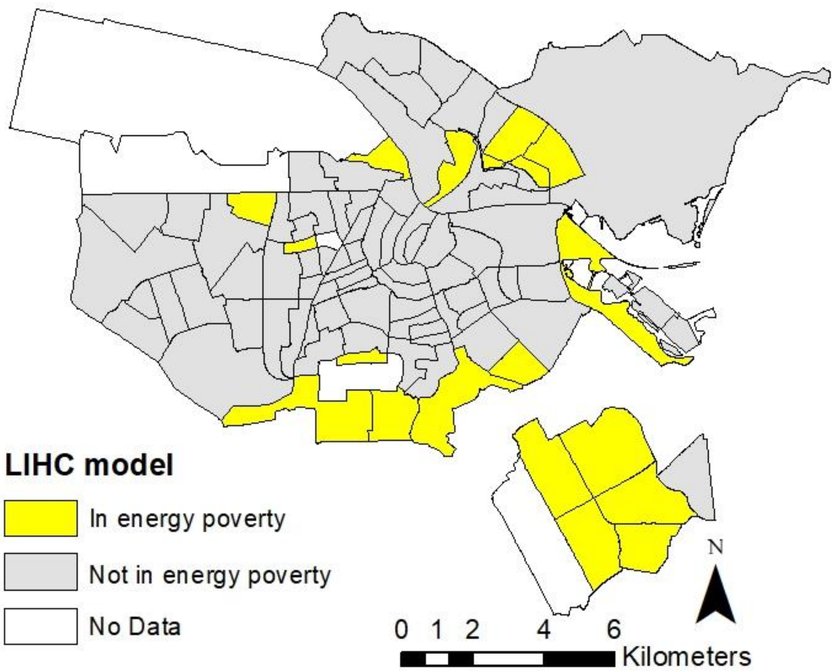


*Figure 13 - Predicted neighbourhoods in energy poverty in LIHC model*

Table 15 lists the neighbourhoods in the LIHC model that are experiencing energy poverty alongside income and energy expenditure. The table is sorted from lowest to highest income. The majority of neighbourhoods are low income, which follows the strong influence of low income in the modelled definition of the LIHC. However, a number of neighbourhoods have high incomes and low energy expenditures. This is likely due to the large number of false positives that are present in the model.

*Table 15 - Predicted neighbourhoods in energy poverty in LIHC model*

| Neighbourhoods | Income € | Energy expenditure € |
|---|---:|---:|
| **Volewijck** | 17700 | 2144 |
| **Betondorp** | 17950 | 1882 |
| **Bijlmer Centrum (D,F,H)** | 18713 | 1595 |
| **Slotermeer-Noordoost** | 19006 | 2040 |
| **Buikslotermeer** | 20481 | 1763 |
| **Tuindorp Buiksloot** | 20655 | 2289 |
| **Tuindorp Nieuwendam** | 21135 | 2209 |
| **Bijlmer Oost (E,G,K)** | 21485 | 1523 |
| **Holendrecht/Reigersbos** | 21561 | 2347 |
| **Waterlandpleinbuurt** | 22666 | 2078 |
| **Nellestein** | 24740 | 2268 |
| **Zeeburgereiland/Nieuwe Diep** | 24887 | 845 |
| **Gein** | 26217 | 2291 |
| **Buitenveldert-Oost** | 30575 | 1909 |
| **Omval/Overamstel** | 31866 | 666 |
| **Buitenveldert-West** | 35281 | 2103 |
| **Houthavens** | 37615 | 951 |
| **Prinses Irenebuurt e.o.** | 63902 | 3282 |

The model evaluation scores given in Table 16 and Table 17 are for the Amsterdam unseen set. By comparing these to the calculated LIHC results in section 5.2, a confusion matrix for the test results can be calculated using the equations in Appendix 3. The results differ from that of the model training set, because the model is trained on the WoON dataset and then tested on unseen data. Table 17 shows that the majority of neighbourhoods identified as in energy poverty in the test set are false positives rather than true positives. The number of false negatives is low, meaning that neighbourhoods in energy poverty are unlikely to be missed by the model. However, the performance of the model has decreased. This is evident in the decrease in both precision and recall, which is evaluated by the F1 score. The F1 score has decreased from 73% on the trained WoON data to 26% when used to make predictions on the Amsterdam data.

*Table 16 - Model scores for LIHC Amsterdam unseen set*

| Parameter | Score |
|---|---|
| **Accuracy** | 82% |
| **Precision** | 18% |
| **Recall** | 50% |
| **F1 Score** | 26% |

The confusion matrix shows the values in percentages from which the model scores are calculated. The equations used are given in Appendix 3.

*Table 17 - Confusion matrix for LIHC Amsterdam unseen set*

| | Actual | |
|---|---|---|
| **Predicted** | 0 | 1 |
| **0** | True negative 78% | False negative 3% |
| **1** | False positive 15% | True positive 3% |

## 4.5. Comparison of indicators

In total there are four different metrics which are based on the 2M and LIHC energy expenditure to income indicators. In Figure 14 the neighbourhoods identified as in energy poverty under each tested metric are shown. In the top two panels the neighbourhoods that are identified as in energy poverty based on the 2M and LIHC are shown. The maps below show the neighbourhoods identified in the predictive models that have been trained using the 2M and LIHC definition of energy poverty along with six accompanying socio-economic vulnerability factors.

It can be seen in the top panels that under the 2M and LIHC indicators the number and areas that are identified are similar. Under these indicators the same five neighbourhoods in Noord are identified and the same neighbourhood in the district Zuid-Oost and Nieuw-West. There are 2 neighbourhoods that are identified as in energy poverty in the 2M but not in the LIHC. Conversely, one neighbourhood is identified in the LIHC but not in the 2M. The list of all neighbourhoods in energy poverty is given for reference in Table 23 in Appendix 6.

Compared to the 2M and LIHC, the predictive models overall show a greater number of neighbourhoods identified as in energy poverty. In the 2M model there are 25 neighbourhoods and in the LIHC predictive model there are 19. Compared to their respective indicators there are 16 more neighbourhoods in the 2M model compared to the 2M indicator. In the LIHC model there are 11 more neighbourhoods than in the LIHC indicator. The smaller number in the LIHC indicator and LIHC model reflects the fact that the LIHC decreases the number identified as being in energy poverty (Robinson et al., 2018a; Thomson et al., 2017; Walker et al., 2014). In both the 2M and LIHC predictive models there are high income neighbourhoods identified as energy-poor, such as Museumkwartier, where average disposable household income is over 69,000 euros a year. This is due to the limited accuracy in the model that leads to a high number of false positives.

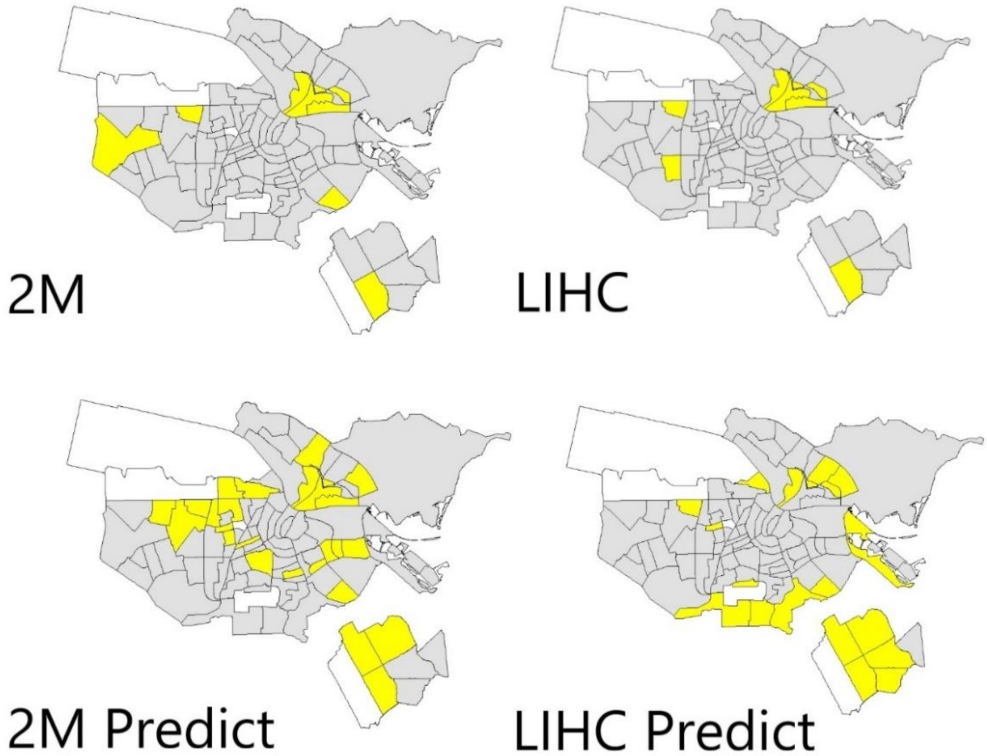


*Figure 14 - Comparison of all neighbourhoods in energy poverty under the four different metrics considered in this study*

In Table 18 the neighbourhoods that have been labelled as energy-poor under at least two metrics are listed. Only 5 of the same neighbourhoods are identified as in energy poverty under the 2M and LIHC indicators. 10 of the same neighbourhoods are identified in both 2M and LIHC predictive models, and 4 of these are not identified by either the 2M or LIHC indicators. The remaining neighbourhoods that are labelled as energy poor under only one indicator can be found in Appendix 6.

*Table 18 - Neighbourhoods most identified as in energy poverty*

| Neighbourhood | 2M indicator | LIHC indicator | LIHC model | 2M model |
|---|---|---|---|---|
| **Holendrecht/Reigersbos** | • | • | • | • |
| **Tuindorp Buiksloot** | • | • | • | • |
| **Tuindorp Nieuwendam** | • | • | • | • |
| **Volewijck** | • | • | • | • |
| **Slotermeer-Noordoost** | • | • | • | • |
| **Betondorp** | • | | • | • |
| **Noordelijke IJ-oevers Oost** | • | • | | • |
| **IJplein/Vogelbuurt** | • | • | | • |
| **Bijlmer-Centrum (D,F,H)** | | | • | • |
| **Bijlmer-Oost (E,G,K)** | | | • | • |
| **Buikslotermeer** | | | • | • |
| **Waterlandpleinbuurt** | | | • | • |

## 4.6. Comparison in numbers of Amsterdam to the national situation

From these results a rate of energy poverty for the Netherlands and for Amsterdam can be obtained, as well as the median energy ratio and an estimate of the number of households affected. In the Netherlands the total number of households is 7,924,000. The number spending more than 10% of their income on energy is calculated from the WoON dataset to be estimated at around 700,000 households. This translates to a rate of 9% energy poverty for the Netherlands. Using the 2M indicator, the median energy ratio is around 4%, therefore the threshold for energy poverty is those spending more than 8% of income on energy. This equates to a rate of 14% and places 1.1m households in energy poverty. The number of households in the Netherlands in energy poverty under the LIHC indicator is reduced to 560,000. This equals a national rate of 7%.

In Amsterdam under the 2M indicator, 9 neighbourhoods are in energy poverty out of a total of 93. This is an estimated rate of 10%, or roughly 45,000 households in 2019. Under the LIHC indicator this is 9% or 40,000 households. The highest number of neighbourhoods is identified under the modelled 2M. This indicator gives an estimated rate of 26% energy poverty, this would be around 126,000 households. Previous estimates from a study of 8,000 households by Gemeente Amsterdam (2013) put the number at 78,000 households. The national median energy expenditure to income ratio share in the WoON dataset is 4%, in Amsterdam, however the median is higher at 7%. This figure agrees with the 2013 study which stated the energy ratio was 7% for all households in Amsterdam (Gemeente Amsterdam, 2013). This suggests that the depth of energy poverty is greater in Amsterdam compared to the national situation. The differences in sample sizes between the WoON and Amsterdam dataset and level of calculations (individual household level vs neighbourhood level) should be kept in consideration, as this could account for the differences in estimates.

According to the four metrics considered in this study, the estimated numbers of households in energy poverty in Amsterdam ranges from 40,000 to 126,000. However, this is a preliminary estimate as it has been shown that the threshold levels to define energy poverty are highly sensitive. Changing the threshold definition and level slightly has great impact on the neighbourhoods identified and therefore the estimated number of households.

# 5. Discussion

This section will provide a discussion over the ability of the tested indicators to identify energy poverty in Amsterdam relating to the suitability criteria outlined in section 2.6. At the end of the discussion section is 5.4 which summarises to what extent the indicators have met the specified criteria. The factors which influence energy poverty in the predictive model are compared to similar results in the literature, these are discussed in section 5.3. The results highlight some strengths and limitations of the evaluated metrics and differences in the neighbourhoods that are defined as energy poor according the thresholds applied. The implications for the targeting of energy poverty alleviation measures are discussed throughout.

For the purposes of this study different indicators are compared on the neighbourhood level. Similar thresholds to those used on the household level are applied to the neighbourhood level to define those neighbourhoods which cross the threshold as “in energy poverty”. In reality it is not the whole neighbourhood, or every household that is in energy poverty, but rather these are the areas which are indicated to have the highest levels and risk of energy poverty.

## 5.1. 2M and LIHC

The 2M energy expenditure to income ratio indicates in which neighbourhoods energy spending is proportionally higher within income. This indicator has the least data requirements and is the simplest to calculate. Overall it gives a clear indication of the different levels of severity in neighbourhoods in Amsterdam, identifying low income neighbourhoods which also have high energy expenditures. There is no method applied in the 2M to distinguish between low and high incomes. Therefore, higher income neighbourhoods such as Luktemeer en Ookmeer can have a higher energy ratio than lower income neighbourhoods. Energy expenditure is higher on average in higher income neighbourhoods as seen in Figure 7. However, it should not be the case that a neighbourhood with a higher energy ratio receives greater attention than a lower income neighbourhood, which has a slightly lower energy ratio but a much higher financial vulnerability. It is a matter of debate whether to include higher income neighbourhoods within energy poverty definitions, the decision should therefore be based on desired outcomes (Raedemakers et al., 2016). An effective indicator should clearly show the different groups in energy poverty and whether they are vulnerable to energy poverty due to high energy costs, low income, or a combination of both, to be able to target the appropriate measures (PBL, 2018). Furthermore, information is given relating to the impact of energy expenditure and income, however there is no indication given of the building quality, or other socio-economic characteristics that may be influencing energy poverty. Section 6.2. discusses further the predictive models which include these factors.

The LIHC uses the same income and energy expenditure data as that used in the 2M with two new income and energy cost thresholds. This is a more dynamic indicator which could prove useful as a tool to help target different alleviation measures and allocate funding towards different groups. Furthermore, there may be different levels of severity between neighbourhoods in a group, which is also important to consider where funding and efforts to alleviate the problem should be targeted. The differences in severity can be seen through calculating the energy poverty gap, that is the difference between the energy expenditure and the energy cost threshold (BEIS, 2019a; PBL, 2018). In comparison the 2M the overall depth of energy poverty can be given by an aggregate average energy poverty gap, this for Amsterdam has been given as

An indicator should be inclusive to show all vulnerable neighbourhoods. However, different neighbourhoods are identified under different indicators. This relates to the restrictive thresholds of each indicator. For example, the 2M indicator does not identify Slotervaart-Zuid as in energy poverty, because even though it has a high an energy ratio of 9.3% it falls below the 10% threshold. Following this rule, a neighbourhood with an energy ratio of 9.99% will not show up as in energy poverty. However, under the LIHC thresholds Slotervaart-Zuid is identified as at risk. There are also neighbourhoods which are identified under the 2M that are excluded from the LIHC such as Betondorp. In this case, Betondorp is below the threshold for high energy costs by 68 euros. This shows that the LIHC has restrictive thresholds that as a result are excluding neighbourhoods. A combination of both indicators would prove more effective, ensuring overall that indicators are more flexible and inclusive through the use of broader and less restrictive thresholds (Kerr et al., 2019). There is currently no method to choose an appropriate threshold and the results highlight the dangers of setting arbitrary boundaries for identifying vulnerable groups (Morrison & Shortt, 2008). Therefore, an appropriate indicator and threshold level should be developed based upon the desired outcomes. In terms of the energy transition and rising energy prices, focus should be directed towards low income areas, and private-rented households, who have less financial space to absorb these changes and ability to invest in energy efficiency measures. Heindl & Schussler (2015) show that using a relative median threshold means that increasing energy prices for all households will raise the median threshold without increasing the number in energy poverty. In some cases, this can even lead to a decrease in energy poverty. Uncertainty is very high amongst both indicators. This impacts their ability to determine the reliable numbers in energy poverty, or which areas are identified as highly vulnerable over time.

The LIHC and 2M indicators are adapted to work with the data available at the neighbourhood level in Amsterdam. Using the neighbourhood aggregated data for income and energy expenditure is less data intensive, however it gives less information and does not allow for individual households living in hidden energy poverty to be identified. Therefore, it may be that energy poverty is being underestimated. This is the greatest restriction of the data, because the required energy expenditure, for example what is needed to be spent to heat the home to an adequate temperature, cannot be calculated. In order for those households restricting energy use to be identified, data is needed on the quality of the building stock and energy poverty should be calculated on an individual household level (Morrison & Shortt, 2008). Under the LIHC indicator there is a group for low income and low energy costs (LILC). It could be that there is hidden energy poverty in this group, whereby a restriction of energy below adequate levels is occurring, however there is no method to ensure whether this is in fact reason for low energy costs. Therefore, the best use for an indicator based on aggregated data is to identify the most at risk neighbourhoods, which then can be targeted in which to carry out further research, surveying and energy advice schemes.

## 5.2. Comparison with modelled 2M and LIHC

In addition to the 2M and LIHC energy expenditure to income indicators, there are two predictive models which use a number of proxy variables to predict energy poverty. Knowledge of the factors behind energy poverty can help to understand the different dynamics of energy poverty and to develop specific measures and forms of advice to alleviate energy poverty (Pye & Dobbins, 2015). The 2M and LIHC indicators give an overview of the neighbourhoods experiencing the highest energy poverty levels, however the underlying causes relating to its occurrence are spatially less clear (DECC, 2015). In this respect the models bridge the gap between the numbers and the factors relating to energy poverty. The evaluation of the models shows that there is potential for identifying areas in energy poverty with a fairly good accuracy of 70-80%, however further work is needed to refine the underlying algorithms to ensure that as many neighbourhoods in energy poverty are correctly identified in the model and a lower number of false positives is returned.

The 2M and LIHC models predict energy poverty occurrence in neighbourhoods based on which factors are influencing the occurrence at national level. For this no specific data is used on energy expenditure or income at the neighbourhood level to predict energy poverty, only the factors correlated to energy poor households at the national level. This method is similar to that used in the UK where at the small area level data is not detailed enough to calculate energy poverty. Therefore, a national dataset is trained based on factors influencing energy poverty at local levels (BEIS, 2019b). These factors give detail on the dynamics of energy poverty and are discussed further in section 5.3. The data on factors influencing energy poverty occurrence is easily available from the municipality, however the model is not trained at the most appropriate level. This is evident in the decrease in the model scores when tested on the Amsterdam data. Ideally, a model would be trained on the Amsterdam household level as research shows that some factors exhibit a spatially heterogenous influence on energy poverty in different cities and neighbourhoods (Mashhoodi, 2019). This would require a large enough sample size for Amsterdam. For example, in this study the final sample size at national level is 6,394 households. There is a bi-annual survey in Amsterdam, “Wonen in Amsterdam” which could act as a potential dataset to train a predictive model. It is interesting for further research to assess whether the model scores can be improved with data at a local level using an adequate sample size for the analysis.

The model is trained on a binary classification of whether the thresholds that define the 2M and LIHC thresholds are crossed or not. Therefore, the predictions only show which factors are increasing the probability of neighbourhoods crossing the 2M threshold or being LIHC. The shortcomings of the binary classification method and its restrictive thresholds have been discussed in section 5.1. These criticisms highlight the need to improve the underlying classification method and explore other more flexible definitions and machine learning methods to define which households are in energy poverty. The results from the predictive model in Figure 12 and Figure 13 show neighbourhoods that are in energy poverty. It is also possible to show the overall distribution of the results to account for the depth of energy poverty in the modelled predictions. One major shortcoming of all the indicators is the exclusion of households that are restricting their energy use below required levels, or those in 'hidden energy poverty'. As previously mentioned, the neighbourhoods in the LILC group could be restricting their energy use, or there could be another factor causing low energy costs such as a higher proportion of energy efficient housing such as zero carbon homes. The most common method to identify hidden energy poverty is by calculating required energy expenditure rather than actual energy expenditure at the household level. Another solution to ensure indicators are more inclusive is to incorporate survey questions that measure perceptions of energy poverty, such as the question "Can your household afford to keep its home adequately warm?" (EU-SILC, 2019).

## 5.3. Factors influencing energy poverty on national and local scales

The factors that are significantly influencing the probability of energy poverty give insight into the dynamics of energy poverty and groups that are at higher risk. In the LIHC model there are six factors included that significantly influence energy poverty (see Table 12). The three main causes of energy poverty are low incomes, high energy prices and energy inefficient buildings (Pye & Dobbins, 2015). Energy expenditure to income indicators have received criticism for not placing enough emphasis on the role of building energy efficiency (Thomson et al., 2017). In the predictive models, the factor 'building age after 2010' is included to incorporate the influence of building quality. Buildings that are newer are more likely to be built to higher standards and therefore have a higher energy efficiency (BPIE, 2014). This corresponds with the odds ratio value of below 1, shown in Table 12, which has the effect of reducing the probability of energy poverty occurrence. Older buildings do not have a significant influence and were excluded from the model. Another factor which indirectly incorporates building quality is 'private-rented tenure'. It is known that these houses are in general of lower standard, as private-rented houses are less likely to receive investments for energy savings measures due to the lower incentive of the landlord to do so (Hills, 2011).

Aside from the building quality, other socio-economic factors such as low-income, unemployment, single-parent households and households aged over 65 are included in the model. Low income and unemployment have the highest odds ratios (see Table 12). If a neighbourhood has a higher low-income share or higher unemployment share, these factors will have the greatest influence on a neighbourhood being identified as in energy poverty. This is understandable as the very definition of energy poor households in the LIHC and 2M is based largely on income. Unemployment is an insignificant factor in the 2M. In the LIHC, the upper and lower confidence levels are separated by more than 1, indicating unemployment has a lower correlation. Research findings from a similar study by the Office for National Statistics (ONS) and the UK's Department for Business, Energy and Industrial Strategy state that confidence levels are important to report as they convey the quality of model estimates (ONS, 2019). Unemployment reduces income, increases the amount of time spent at home and therefore increases the amount of energy used, so a positive correlation between energy poverty occurrence is expected, however it may only be temporary. Single-parent households are vulnerable to energy poverty through lower incomes. Households aged over 65 or 75 years old are more likely to experience energy poverty, have lower incomes, spend an increased amount of time at home and heat living areas to higher temperatures. The factors in the model are identified in the literature and at national level as influencing the probability of energy poverty occurrence. They are acting as proxy measurements and the data is commonly available from the municipality at neighbourhood level. Including factors which are linked to the three main causes, low income, high energy prices and poor building efficiency will improve the model, but more research is needed to understand how they are interacting with the occurrence of energy poverty in complex social situations.

## 5.4. Evaluation of criteria

Table 19 evaluates the four metrics based on the criteria outlined in Table 1. The evaluation scores the metrics based on whether they meet the criteria, do not meet the criteria, or partially meet the criteria.

In this study the 2M partially meets the criteria for representing the severity of energy poverty because it does not include a measure for the energy poverty gap as is in the LIHC. The 2M and LIHC are less flexible than the models as they do not consider local factors. Furthermore, the 2M is shown to inadequately reflect the changes in energy prices due to its relative threshold (Heindl & Schussler, 2015). The models partially meet this criterium as they include local factors in the model. None of the metrics measure required energy expenditure, therefore cannot fully capture those in hidden energy poverty. The LIHC however does include a LILC group showing those who could potentially be at risk from hidden energy poverty. There is no exclusion of high incomes with the 2M metric therefore it does not meet the criteria for representing those in energy poverty. To be effective a metric should be able to capture the characteristics of energy poverty. The 2M fails to communicate the profile of the energy poor as only a high proportion of energy expenditure in income is expressed. Contrary the LIHC provides more detail by the categorisation based on specific risks such as income or energy, or both risks. The models meet the criteria by showing the factors that are related to energy poverty occurrence, allowing for targeted solutions. All metrics are operational in that they are built using accessible data from public sources.

*Table 19 – Evaluation of criteria met by the tested indicators*

| Criteria | Description | 2M | LIHC | 2M model | LIHC model |
|---|---|---|---|---|---|
| **Severity** | To represent different levels of energy poverty | +/- | + | +/- | + |
| **Flexible** | To be able to adapt to work in different local areas and monitor over time as energy prices and incomes change | - | - | +/- | +/- |
| **Inclusive** | Include all households even those households in hidden energy poverty who may restrict their energy use below required levels | - | +/- | - | +/- |
| **Representative** | Can differentiate the different types of energy poverty. For example, higher income households who have related high energy consumption, but not a payment risk | - | + | - | + |
| **Effective** | Captures and communicates the key features of energy poverty. Indicators that reflect the characteristics of the | - | + | +/- | + |

| | | | | | |
|---|---|---|---|---|---|
| | area to be able to identify appropriate solutions | | | | |
| **Operational** | Constructed with data that is easily available and accessible | + | + | + | + |

*+ : meets criteria, - : does not meet criteria, +/- : partially meets criteria*

## 6. Limitations

The use of aggregate data methods reduces pressure on data collection, however as energy poverty is occurring at the household level there is a limitation to the level of detail returned in the results, the most noticeable being the identification of households in hidden energy poverty. For these households characteristics such as data on floor area and insulation measures should be used to estimate required energy consumption and then compared to actual energy consumption. This increases data demands, the complexity of the calculation, and also raises privacy issues as household addresses are required. Furthermore, incomes and energy expenditures are not equivalised in this study. In household level studies such as with the British LIHC this is carried out as a prerequisite, to account for differences in household compositions and needs (Hills, 2011).

Validation of the model will determine how accurately the energy poverty index reflects the actual situation in Amsterdam. Due to restrictions in the amount of data available the logistic regression is performed on the WoON dataset, which contains values at the household level. This analyses the impacts of variables on energy poverty at the national scale and is then applied to the local level. A study by Mashhoodi et al. (2019) shows that some factors influencing energy poverty have a heterogenous effect throughout the Netherlands. The factors of private-rented households and residents over 65 are likely to have a similar effect on a local level in Amsterdam (Mashhoodi, 2019). The analysis would be improved by training the model on Amsterdam data. However, this requires a greater amount of data to be available which would increase costs of surveying. Variables in the Amsterdam dataset were transformed to binary values at the neighbourhood level to match the binary values at the household level in the trained model. The differences in the two data forms likely leads to increased errors in the test model.

Finally, the data collected on energy consumption is for the year 2015. This is the most recent and complete data set that corresponds to the neighbourhoods in the Amsterdam dataset. Energy prices are from 2018, and to improve accuracy data should be from the same year. It should be noted that differences in temperatures during certain years can impact consumption, for which an adjustment can be made using heating degree days. In the calculation of energy expenditure only gas and electricity consumptions are considered. Some neighbourhoods will have a greater proportion of alternative energy sources such as district heat, the price of which is not included in the calculations. It would be useful to also include alternative fuel types, particularly in future years as household gas consumption will decrease (PBL, 2018).

# 7. Conclusion

The energy transition in the Netherlands calls for municipalities to coordinate the strategy to take households off the gas network, which in the future will result in rising energy prices for all households. For those estimated 650,000-750,000 households already in energy poverty, there will be an even greater burden on the energy bill. Solutions are available to reduce energy consumption and costs, but there must be a method to identify and target these vulnerable households. The energy expenditure to income indicators that are used in Europe, such as in the UK and France, to measure energy poverty have been tested on the neighbourhood level in Amsterdam. The results estimate that around 40,000 to 126,000 households are in energy poverty in Amsterdam. At the national level the number is estimated around 560,000 to 1.1m households. The main factors which result in a higher risk of energy poverty are low-incomes, unemployment, private-rented households, single-parent household and households aged over 65 years old. Tuindorp Buiksloot, Tuindorp Nieuwendam, Volewijck, Holendrecht/Reigerbos and Slotermeer Noordoost are identified by all metrics to be in energy poverty. These are the neighbourhoods which are considered to have the highest levels and to be overall the most vulnerable to energy poverty.

The large deviation in estimated numbers of households between metrics highlights the uncertainty and complexity of defining and measuring energy poverty. One main weakness of the 2M indicator is the restrictive binary definition that is employed, which ignores varying levels of severity. The LIHC does include a measure for severity using the 'energy poverty gap', which is estimated at €253 in Amsterdam. However, the thresholds for LIHC are restrictive, which can easily lead to an exclusion of neighbourhoods on the boundary. Furthermore, the underlying construction of the relative twice the median threshold means the number in energy poverty may not increase if energy prices rise for all households. This is an inherent flaw as the increased burden of higher energy prices will not be reflected. It stresses the need for caution over the consequences of implementing a specific measurement method and the need to choose an indicator based on the desired outcomes over time.

The LIHC indicator gives more detail by highlighting the different groups through high/low energy costs, and high/low incomes. This has the benefit of targeting certain strategies at the different groups depending on the required needs. Moreover, it shows the weaknesses of utilising solely the 2M energy expenditure to income ratio to measure a complex problem. In attempts to overcome the criticisms of the energy expenditure to income indicators, the potential for machine learning models to build a composite index using proxy factors to incorporate vulnerability has been explored. A link is identified between certain factors and the occurrence of energy poverty. This shows the potential benefits that a composite indicator can give for improving the understanding of the complexity of energy poverty and the ability to target vulnerable local areas for support. This gives a wider perspective on the issue of energy poverty, in place of the narrower energy expenditure to income approaches. Effort is needed to further refine the model to improve certain parameters and ensure that neighbourhoods are not missed out. However, there is future potential in this method for use at the municipal level to improve on the current energy expenditure to income indicators. The further detail that is given into the factors and characteristics in neighbourhoods allows for better targeting of specific measures to alleviate energy poverty.

# 8. Recommendations

Whilst action is taking place at the municipal level there is further need for greater recognition of energy poverty, and further research into the dynamics and extent of the problem, for timely solutions to be put in place. A greater level of understanding can be improved through increased data collection and in-depth calculations allowing for the inclusion of those in hidden energy poverty. The co-operation of different institutions including ministries, municipalities, energy providers, housing associations and researchers is essential to put in place a strategic and effective plan to ensure that energy poverty does not increase in the coming years. The sharing of data sources into a collective database would be valuable.

Machine learning models are flexible in that they can incorporate different factors. For example, one factor that can be introduced into such a model that influences the energy consumption in urban areas is the heat island effect (Mashhoodi, 2019). The possibility of incorporating this into such an energy poverty/energy consumption model could be explored. The restrictive and rather arbitrary threshold values should be refined, for this a sensitivity analysis should be conducted on the impact of different thresholds. Furthermore, the definition of energy poverty can be further researched using social sciences and surveys, to gauge the perception of energy poverty in different groups.

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# Appendix 1. Neighbourhood codes

The neighbourhood codes for Figure 3 are given in Figure 14 below. These can be used as a reference for neighbourhoods in the mapped results in section 5.

| wijk | naam wijk | wijk | naam wijk |
|---|---|---|---|
| A00 | Burgwallen-Oude Zijde | K44 | Hoofddorppleinbuurt |
| A01 | Burgwallen-Nieuwe Zijde | K45 | Schinkelbuurt |
| A02 | Grachtengordel-West | K46 | Willemspark |
| A03 | Grachtengordel-Zuid | K47 | Museumkwartier |
| A04 | Nieuwmarkt/Lastage | K48 | Stadionbuurt |
| A05 | Haarlemmerbuurt | K49 | Apollobuurt |
| A06 | Jordaan | K52 | Scheldebuurt |
| A07 | De Weteringschans | K53 | IJselbuurt |
| A08 | Weesperbuurt/Plantage | K54 | Rijnbuurt |
| A09 | Oostelijke Eilanden/Kadijken | K59 | Prinses Irenebuurt e.o. |
| B10 | Westelijk Havengebied | K90 | Buitenveldert-West |
| E12 | Houthavens | K91 | Buitenveldert-Oost |
| E13 | Spaarndammer- en Zeeheldenbuurt | M27 | Weesperzijde |
| E14 | Staatsliedenbuurt | M28 | Oosterparkbuurt |
| E15 | Centrale Markt | M29 | Dapperbuurt |
| E16 | Frederik Hendrikbuurt | M30 | Transvaalbuurt |
| E17 | Da Costabuurt | M31 | Indische Buurt-West |
| E18 | Kinkerbuurt | M32 | Indische Buurt-Oost |
| E19 | Van Lennepbuurt | M33 | Oostelijk Havengebied |
| E20 | Helmersbuurt | M34 | Zeeburgereiland/Nieuwe Diep |
| E21 | Overtoomse Sluis | M35 | IJburg-West |
| E22 | Vondelbuurt | M50 | IJburg-Oost |
| E36 | Sloterdijk | M51 | IJburg-Zuid |
| E37 | Landlust | M55 | Frankendael |
| E38 | Erasmuspark | M56 | Middenmeer |
| E39 | De Kolenkit | M57 | Betondorp |
| E40 | Geuzenbuurt | M58 | De Omval/Overamstel |
| E41 | Van Galenbuurt | N60 | Volewijck |
| E42 | Hoofdweg e.o. | N61 | IJplein/Vogelbuurt |
| E43 | Westindische Buurt | N62 | Tuindorp Nieuwendam |
| E75 | Chassébuurt | N63 | Tuindorp Buiksloot |
| F11 | Bedrijventerrein Sloterdijk | N64 | Nieuwendammerdijk/Buiksloterdijk |
| F76 | Slotermeer-Noordoost | N65 | Tuindorp Oostzaan |
| F77 | Slotermeer-Zuidwest | N66 | Oostzanerwerf |
| F78 | Geuzenveld | N67 | Kadoelen |
| F79 | Eendracht | N68 | Waterlandpleinbuurt |
| F80 | Lutkemeer/Ookmeer | N69 | Buikslotermeer |
| F81 | Osdorp-Oost | N70 | Banne Buiksloot |
| F82 | Osdorp-Midden | N71 | Noordelijke IJ-oevers-West |
| F83 | De Punt | N72 | Noordelijke IJ-oevers-Oost |
| F84 | Middelveldsche Akerpolder | N73 | Waterland |
| F85 | Slotervaart-Noord | N74 | Elzenhagen |
| F86 | Overtoomse Veld | T92 | Amstel III/Bullewijk |
| F87 | Westlandgracht | T93 | Bijlmer-Centrum (D,F,H) |
| F88 | Sloter-/Riekerpolder | T94 | Bijlmer-Oost (E,G,K) |
| F89 | Slotervaart-Zuid | T95 | Nellestein |
| K23 | Zuidas | T96 | Holendrecht/Reigersbos |
| K24 | Oude Pijp | T97 | Gein |
| K25 | Nieuwe Pijp | T98 | Driemond |
| K26 | Zuid-Pijp | | |

Figure 15 - Neighbourhood codes

# Appendix 2. Input data for maps

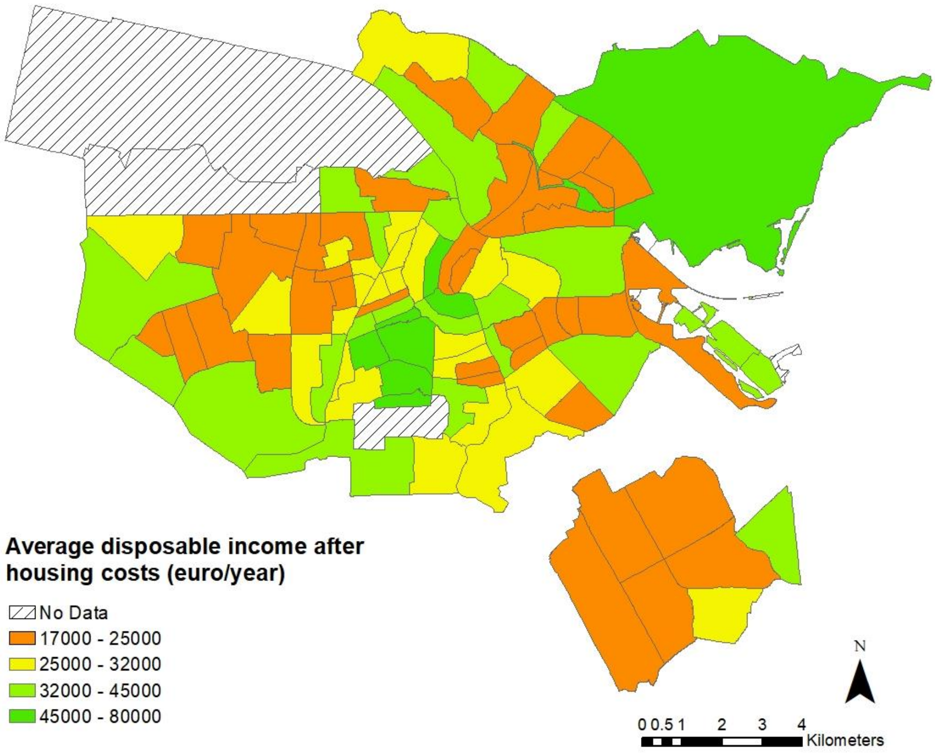


*Figure 16 - Disposable income in Amsterdam*

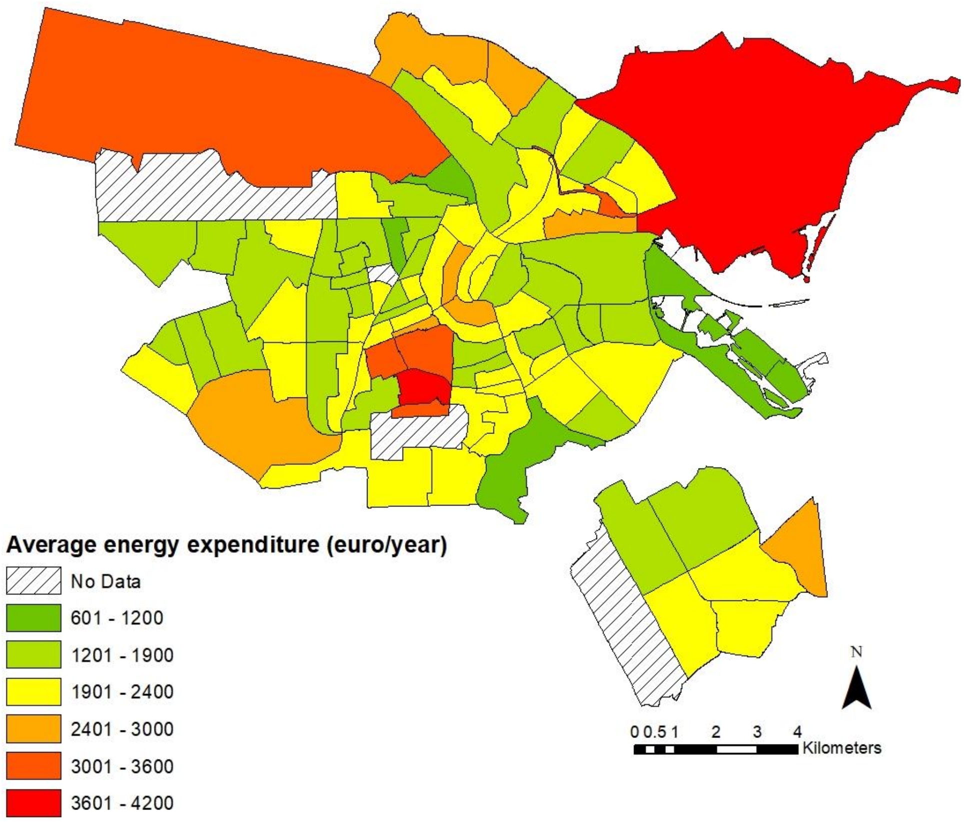


*Figure 17 - Energy expenditure in Amsterdam*

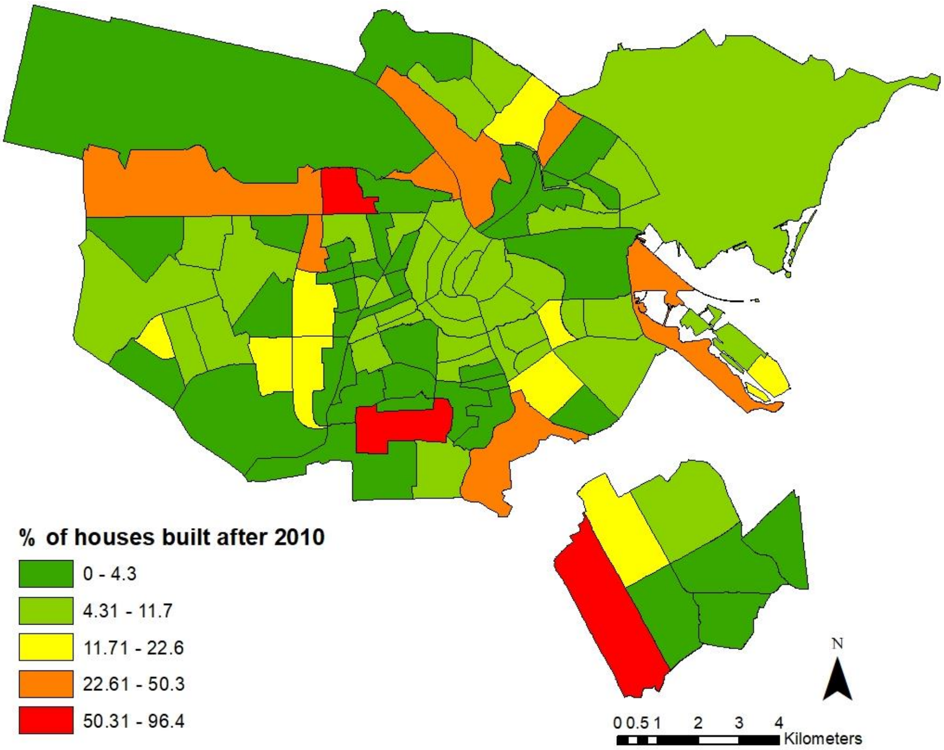


*Figure 18 - Houses built after 2010 in Amsterdam*

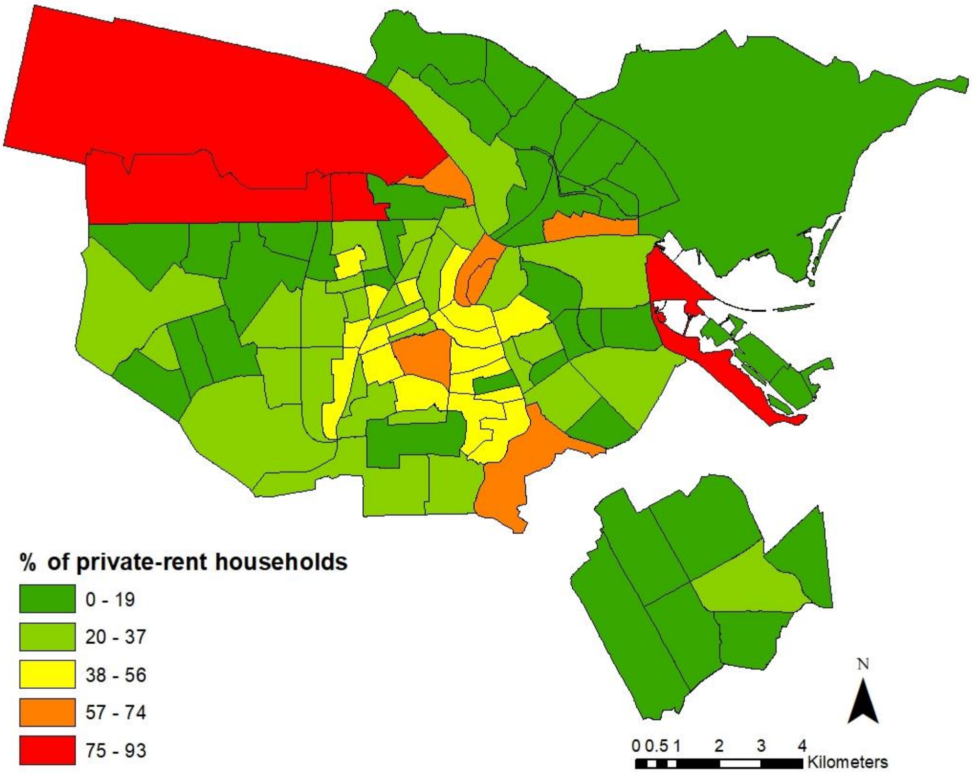


*Figure 19 - Private-rented houses in Amsterdam*

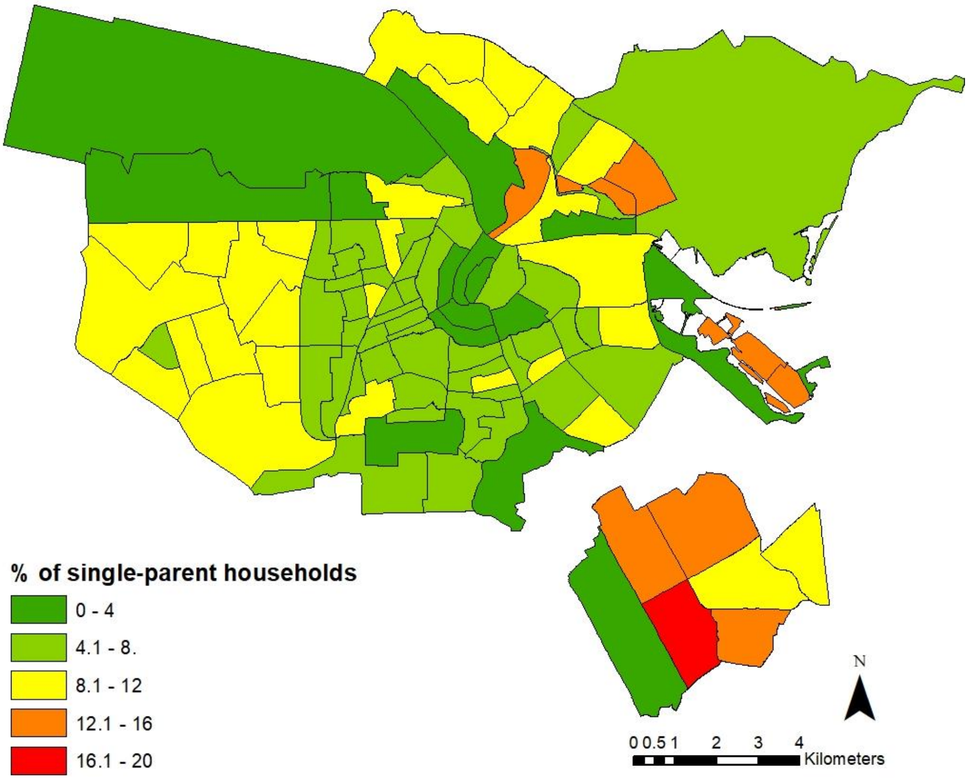


*Figure 20 - Single-parent households in Amsterdam*

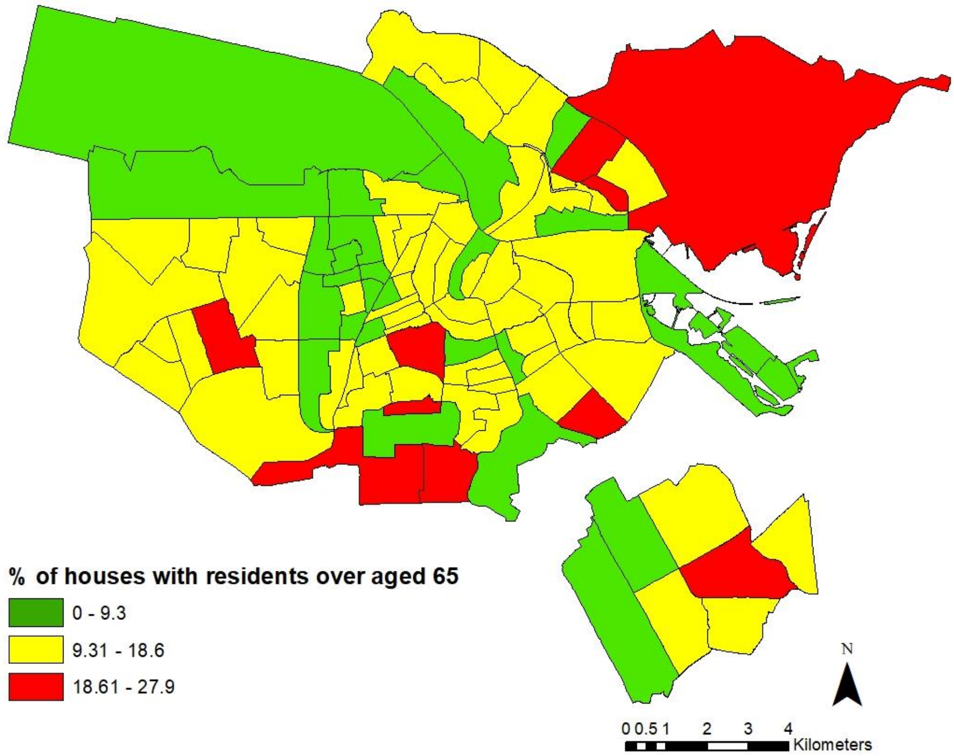


*Figure 21 - Households over the age of 65 in Amsterdan*

# Appendix 3. The Confusion matrix

In building the predictive models in python an evaluation is given of the model trained on the WoON dataset, this indicates its performance on the national level. In the Amsterdam dataset the data is at neighbourhood level, therefore another evaluation is needed to show the performance of the model working at this level. This is done by comparing the 2M and LIHC indicator results given in section 5.1 and 5.2 for Amsterdam neighbourhoods to the predictive models produced in 5.3 and 5.4. The confusion matrix gives information from which accuracy, precision, recall and F1 scores can be calculated. The formulas used to calculate these scores are given below.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

The output tables from python in Figure 22 and Figure 16 show the values for the actual and predicted number of households, these are transformed into percentages in the results section for easy comparison with the test results.

| Actual | 0 | 1 |
|---|---|---|
| **Predicted** | | |
| **0** | 911 | 298 |
| **1** | 641 | 1300 |

*Figure 22 - Output confusion matrix for LIHC training set*

| Actual | 0 | 1 |
|---|---|---|
| **Predicted** | | |
| **0** | 1655 | 616 |
| **1** | 104 | 1195 |

*Figure 23 - Output confusion matrix for 2M training set*

## Appendix 4. Model results with confidence intervals

Detailed results of the predictive models are presented in Table 20 and 21, for the 2M and the LIHC metrics, respectively. Significance levels for the independent variables are indicated by the P values. The coefficients are reported on a different scale however are similar to the odds ratios given in Table 6 and Table 12.

*Table 20 - Detailed 2M model results*

Dependent variable: LIHC, No. of observations: 6394

| Indep. variable | Coefficient | Std. error | z | P>[z] | CI 0.025 | CI 0.975 |
|---|---|---|---|---|---|---|
| **Low income** | 2.82 | 0.087 | 32.42 | 0.000 | 2.65 | 2.99 |
| **Private-rent** | 0.21 | 0.084 | 2.45 | 0.014 | 0.04 | 0.37 |
| **Aged over 65** | -0.66 | 0.069 | -9.48 | 0.000 | -0.08 | -0.52 |
| **Built after 2010** | -1.36 | 0.148 | -9.18 | 0.000 | -1.65 | -1.07 |
| **Single-parent HH** | -0.31 | 0.096 | -3.27 | 0.001 | -0.50 | -0.13 |
| **Aged over 75** | 0.58 | 0.098 | 5.99 | 0.000 | 0.39 | 0.78 |

*Table 21 - Detailed LIHC model results*

Dependent variable: 2M energy ratio, No. of observations: 7246

| Indep. variable | Coefficient | Std. error | z | P>[z] | CI 0.025 | CI 0.975 |
|---|---|---|---|---|---|---|
| **Low income** | 1.09 | 0.076 | 14.36 | 0.000 | 0.95 | 1.25 |
| **Private-rent** | 0.57 | 0.081 | 7.09 | 0.000 | 0.42 | 0.73 |
| **Aged over 65** | 0.31 | 0.046 | 6.93 | 0.000 | 0.23 | 0.41 |
| **Single-parent HH** | 0.34 | 0.085 | 4.04 | 0.000 | 0.18 | 0.51 |
| **Built after 2010** | -1.44 | 0.155 | -9.27 | 0.000 | -1.74 | -1.13 |
| **Unemployment** | 1.24 | 0.318 | 3.90 | 0.000 | 0.61 | 1.86 |

# Appendix 5. Data for factors influencing energy poverty occurrence in Amsterdam

For predictions to be made in Amsterdam based on the WoON dataset, the same factors influencing energy poverty occurrence in Amsterdam that are given in percentage shares for each neighbourhood need to be transformed into binary form. For example, the percentage of low-income households needs to be given a 1 or 0 to define a high or low boundary. Below are binary transformations.

*Table 22 - Binary transformation data for factors influencing energy poverty*

| Wijk | % HH low income | | % HH Private Rent | | % HH Over 65 | | % HH Single parent | | % HH After 2010 | | % HH Out of work | | % HH Over 75 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Amstel III/Bullewijk | 67 | 1 | | 0 | 1 | 0 | 1 | 0 | 96 | 1 | | 0 | 1 | 0 |
| Apollobuurt | 8 | 0 | 47 | 0 | 18 | 0 | 6 | 0 | 2 | 0 | 3 | 0 | 8 | 0 |
| Banne Buiksloot | 27 | 1 | 5 | 0 | 16 | 0 | 12 | 0 | 13 | 0 | 15 | 0 | 7 | 0 |
| Bedrijventerrein Sloterdijk | 16 | 0 | 90 | 1 | 1 | 0 | | 0 | 45 | 0 | | 0 | 0 | 0 |
| Betondorp | 31 | 1 | 2 | 0 | 24 | 1 | 10 | 0 | 0 | 0 | 18 | 1 | 11 | 1 |
| Bijlmer-Centrum (D,F,H) | 31 | 1 | 13 | 0 | 8 | 0 | 16 | 1 | 17 | 0 | 18 | 1 | 2 | 0 |
| Bijlmer-Oost (E,G,K) | 31 | 1 | 9 | 0 | 12 | 0 | 16 | 1 | 10 | 0 | 16 | 0 | 4 | 0 |
| Buikslotermeer | 20 | 0 | 11 | 0 | 22 | 1 | 10 | 0 | 1 | 0 | 14 | 0 | 12 | 1 |
| Buitenveldert-Oost | 14 | 0 | 35 | 0 | 28 | 1 | 6 | 0 | 8 | 0 | 8 | 0 | 17 | 1 |
| Buitenveldert-West | 13 | 0 | 34 | 0 | 23 | 1 | 6 | 0 | 2 | 0 | 7 | 0 | 13 | 1 |
| Burgwallen-Nieuwe Zijde | 14 | 0 | 66 | 1 | 8 | 0 | 3 | 0 | 9 | 0 | 5 | 0 | 2 | 0 |
| Burgwallen-Oude Zijde | 17 | 0 | 63 | 0 | 9 | 0 | 4 | 0 | 9 | 0 | 6 | 0 | 2 | 0 |
| Centrale Markt | 19 | 0 | 15 | 0 | 11 | 0 | 10 | 0 | 0 | 0 | 11 | 0 | 3 | 0 |
| Chassébuurt | 11 | 0 | 40 | 0 | 9 | 0 | 10 | 0 | 10 | 0 | 12 | 0 | 3 | 0 |
| Da Costabuurt | 17 | 0 | 45 | 0 | 12 | 0 | 6 | 0 | 4 | 0 | 7 | 0 | 4 | 0 |
| Dapperbuurt | 27 | 1 | 15 | 0 | 13 | 0 | 8 | 0 | 16 | 0 | 13 | 0 | 5 | 0 |
| De Kolenkit | 27 | 1 | 11 | 0 | 8 | 0 | 8 | 0 | 43 | 0 | 13 | 0 | 4 | 0 |
| De Omval/Overamstel | 8 | 0 | 74 | 1 | 5 | 0 | 2 | 0 | 49 | 0 | 4 | 0 | 1 | 0 |
| De Punt | 21 | 0 | 32 | 0 | 13 | 0 | 8 | 0 | 16 | 0 | 13 | 0 | 6 | 0 |
| De Weteringschans | 13 | 0 | 47 | 0 | 13 | 0 | 4 | 0 | 6 | 0 | 5 | 0 | 4 | 0 |
| Driemond | 13 | 0 | 6 | 0 | 17 | 0 | 11 | 0 | 2 | 0 | 8 | 0 | 7 | 0 |
| Eendracht | 14 | 0 | 4 | 0 | 16 | 0 | 10 | 0 | 0 | 0 | 8 | 0 | 5 | 0 |
| Elzenhagen | | 0 | | 0 | 8 | 0 | 7 | 0 | 39 | 0 | 6 | 0 | 3 | 0 |
| Erasmuspark | 18 | 0 | 41 | 0 | 8 | 0 | 7 | 0 | 2 | 0 | 9 | 0 | 3 | 0 |
| Frankendael | 19 | 0 | 28 | 0 | 15 | 0 | 7 | 0 | 19 | 0 | 10 | 0 | 6 | 0 |
| Frederik Hendrikbuurt | 21 | 0 | 32 | 0 | 12 | 0 | 6 | 0 | 3 | 0 | 11 | 0 | 4 | 0 |
| Gein | 22 | 0 | 14 | 0 | 14 | 0 | 16 | 1 | 0 | 0 | 14 | 0 | 3 | 0 |
| Geuzenbuurt | | 0 | | 0 | 8 | 0 | 6 | 0 | 2 | 0 | 9 | 0 | 3 | 0 |
| Geuzenveld | 26 | 1 | 10 | 0 | 10 | 0 | 11 | 0 | 6 | 0 | 13 | 0 | 4 | 0 |
| Grachtengordel-West | 9 | 0 | 47 | 0 | 17 | 0 | 4 | 0 | 5 | 0 | 4 | 0 | 5 | 0 |
| Grachtengordel-Zuid | 13 | 0 | 48 | 0 | 14 | 0 | 4 | 0 | 7 | 0 | 3 | 0 | 5 | 0 |
| Haarlemmerbuurt | 20 | 0 | 29 | 0 | 17 | 0 | 7 | 0 | 5 | 0 | 10 | 0 | 5 | 0 |
| Helmersbuurt | 16 | 0 | 42 | 0 | 11 | 0 | 6 | 0 | 5 | 0 | 7 | 0 | 3 | 0 |
| Holendrecht/ Reigersbos | 29 | 1 | 8 | 0 | 16 | 0 | 20 | 1 | | 0 | 17 | 1 | 5 | 0 |
| Hoofddorppleinbuurt | 15 | 0 | 48 | 0 | 10 | 0 | 6 | 0 | 2 | 0 | 7 | 0 | 4 | 0 |
| Hoofdweg e.o. | 26 | 1 | 37 | 0 | 9 | 0 | 7 | 0 | 2 | 0 | 13 | 0 | 4 | 0 |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Houthavens | 11 | 0 | 71 | 1 | 8 | 0 | 5 | 0 | 34 | 0 | 6 | 0 | 2 | 0 |
| IJburg-Oost | | 0 | . | 1 | | 0 | | 0 | | 0 | | 0 | | |
| IJburg-West | 14 | 0 | 18 | 0 | 5 | 0 | 13 | 1 | 6 | 0 | 8 | 0 | 1 | 0 |
| IJburg-Zuid | 17 | 0 | 15 | 0 | 4 | 0 | 14 | 1 | 19 | 0 | 9 | 0 | 1 | 0 |
| IJplein/Vogelbuurt | 32 | 1 | 6 | 0 | 12 | 0 | 12 | 0 | 0 | 0 | 17 | 1 | 4 | 0 |
| IJselbuurt | 24 | 0 | 38 | 0 | 13 | 0 | 8 | 0 | 3 | 0 | 11 | 0 | 5 | 0 |
| Indische Buurt-Oost | 30 | 1 | 11 | 0 | 13 | 0 | 10 | 0 | 7 | 0 | 16 | 1 | 5 | 0 |
| Indische Buurt-West | 26 | 1 | 18 | 0 | 9 | 0 | 8 | 0 | 7 | 0 | 13 | 0 | 3 | 0 |
| Jordaan | 20 | 0 | 34 | 0 | 16 | 0 | 5 | 0 | 5 | 0 | 9 | 0 | 5 | 0 |
| Kadoelen | 13 | 0 | 7 | 0 | 16 | 0 | 10 | 0 | 7 | 0 | 7 | 0 | 6 | 0 |
| Kinkerbuurt | 21 | 0 | 36 | 0 | 8 | 0 | 6 | 0 | 9 | 0 | 14 | 0 | 2 | 0 |
| Landlust | 27 | 1 | 26 | 0 | 8 | 0 | 8 | 0 | 6 | 0 | 13 | 0 | 3 | 0 |
| Lutkemeer/Ookmeer | 20 | 0 | 28 | 0 | 15 | 0 | 9 | 0 | 6 | 0 | 10 | 0 | 4 | 0 |
| Middelveldsche Akerpolder | 12 | 0 | 16 | 0 | 12 | 0 | 10 | 0 | 1 | 0 | 7 | 0 | 5 | 0 |
| Middenmeer | 9 | 0 | 30 | 0 | 11 | 0 | 6 | 0 | 12 | 0 | 5 | 0 | 4 | 0 |
| Museumkwartier | 12 | 0 | 57 | 0 | 19 | 1 | 6 | 0 | 3 | 0 | 4 | 0 | 7 | 0 |
| Nellestein | 12 | 0 | 36 | 0 | 20 | 1 | 9 | 0 | | 0 | 9 | 0 | 7 | 0 |
| Nieuwe Pijp | 21 | 0 | 39 | 0 | 12 | 0 | 6 | 0 | 6 | 0 | 10 | 0 | 5 | 0 |
| Nieuwendammerdijk/Buiksloterdijk | 5 | 0 | 10 | 0 | 15 | 0 | 6 | 0 | 7 | 0 | 4 | 0 | 5 | 0 |
| Nieuwmarkt/Lastage | 19 | 0 | 32 | 0 | 18 | 0 | 5 | 0 | 8 | 0 | 8 | 0 | 5 | 0 |
| Noordelijke IJ-oevers-Oost | 30 | 1 | 64 | 0 | 4 | 0 | 2 | 0 | 6 | 0 | | 0 | 1 | 0 |
| Noordelijke IJ-oevers-West | 8 | 0 | 24 | 0 | 6 | 0 | 3 | 0 | 50 | 0 | 7 | 0 | 1 | 0 |
| Oostelijk Havengebied | 13 | 0 | 21 | 0 | 9 | 0 | 10 | 0 | 4 | 0 | 8 | 0 | 2 | 0 |
| Oostelijke Eilanden/Kadijken | 22 | 0 | 14 | 0 | 15 | 0 | 8 | 0 | 10 | 0 | 12 | 0 | 4 | 0 |
| Oosterparkbuurt | 24 | 0 | 19 | 0 | 11 | 0 | 8 | 0 | 8 | 0 | 13 | 0 | 3 | 0 |
| Oostzanerwerf | 17 | 0 | 4 | 0 | 15 | 0 | 12 | 0 | 0 | 0 | 11 | 0 | 7 | 0 |
| Osdorp-Midden | 24 | 0 | 14 | 0 | 11 | 0 | 11 | 0 | 7 | 0 | 13 | 0 | 6 | 0 |
| Osdorp-Oost | 22 | 0 | 18 | 0 | 19 | 1 | 9 | 0 | 4 | 0 | 14 | 0 | 10 | 0 |
| Oude Pijp | 19 | 0 | 46 | 0 | 9 | 0 | 5 | 0 | 6 | 0 | 8 | 0 | 2 | 0 |
| Overtoomse Sluis | 16 | 0 | 44 | 0 | 9 | 0 | 5 | 0 | 7 | 0 | 6 | 0 | 2 | 0 |
| Overtoomse Veld | 24 | 0 | 30 | 0 | 7 | 0 | 7 | 0 | 15 | 0 | 11 | 0 | 3 | 0 |
| Prinses Irenebuurt e.o. | 4 | 0 | 23 | 0 | 23 | 1 | 5 | 0 | 1 | 0 | | 0 | 11 | 1 |
| Rijnbuurt | 24 | 0 | 40 | 0 | 14 | 0 | 8 | 0 | 2 | 0 | 11 | 0 | 6 | 0 |
| Scheldebuurt | 15 | 0 | 52 | 0 | 14 | 0 | 7 | 0 | 4 | 0 | 5 | 0 | 6 | 0 |
| Schinkelbuurt | 20 | 0 | 37 | 0 | 10 | 0 | 7 | 0 | 2 | 0 | 10 | 0 | 3 | 0 |
| Sloter-/Riekerpolder | 10 | 0 | 29 | 0 | 15 | 0 | 10 | 0 | 1 | 0 | 6 | 0 | 6 | 0 |
| Sloterdijk | 9 | 0 | 86 | 1 | 4 | 0 | 2 | 0 | 77 | 1 | | 0 | 1 | 0 |
| Slotermeer-Noordoost | 31 | 1 | 11 | 0 | 10 | 0 | 10 | 0 | 2 | 0 | 17 | 1 | 4 | 0 |
| Slotermeer-Zuidwest | 30 | 1 | 11 | 0 | 11 | 0 | 10 | 0 | 5 | 0 | 16 | 0 | 5 | 0 |
| Slotervaart-Noord | 21 | 0 | 22 | 0 | 15 | 0 | 11 | 0 | 0 | 0 | 12 | 0 | 8 | 0 |
| Slotervaart-Zuid | 21 | 0 | 22 | 0 | 14 | 0 | 9 | 0 | 23 | 0 | 12 | 0 | 7 | 0 |
| Spaarndammer- en Zeeheldenbuurt | 28 | 1 | 12 | 0 | 13 | 0 | 9 | 0 | 3 | 0 | 15 | 0 | 4 | 0 |
| Staatsliedenbuurt | 23 | 0 | 21 | 0 | 10 | 0 | 7 | 0 | 6 | 0 | 12 | 0 | 3 | 0 |
| Stadionbuurt | 22 | 0 | 31 | 0 | 15 | 0 | 10 | 0 | 2 | 0 | 10 | 0 | 6 | 0 |
| Transvaalbuurt | 29 | 1 | 15 | 0 | 11 | 0 | 10 | 0 | 7 | 0 | 14 | 0 | 3 | 0 |
| Tuindorp Buiksloot | 27 | 1 | 1 | 0 | 18 | 0 | 15 | 1 | 2 | 0 | 15 | 0 | 7 | 0 |
| Tuindorp Nieuwendam | 24 | 0 | 2 | 0 | 23 | 1 | 13 | 1 | 1 | 0 | 14 | 0 | 10 | 1 |
| Tuindorp Oostzaan | 24 | 0 | 3 | 0 | 17 | 0 | 12 | 0 | 6 | 0 | 13 | 0 | 8 | 0 |
| Van Galenbuurt | 47 | 1 | 28 | 0 | 7 | 0 | 8 | 0 | 1 | 0 | 24 | 1 | 2 | 0 |
| Van Lennepbuurt | 25 | 1 | 24 | 0 | 14 | 0 | 6 | 0 | 4 | 0 | 13 | 0 | 5 | 0 |
| Volewijck | 34 | 1 | 5 | 0 | 13 | 0 | 14 | 1 | 2 | 0 | 19 | 1 | 5 | 0 |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Vondelbuurt** | 17 | 0 | 36 | 0 | 18 | 0 | 6 | 0 | 11 | 0 | 6 | 0 | 9 | 0 |
| **Waterland** | 11 | 0 | 15 | 0 | 20 | 1 | 6 | 0 | 7 | 0 | 4 | 0 | 7 | 0 |
| **Waterlandpleinbuurt** | 27 | 1 | 6 | 0 | 12 | 0 | 14 | 1 | 12 | 0 | 14 | 0 | 6 | 0 |
| **Weesperbuurt/Plantage** | 18 | 0 | 41 | 0 | 15 | 0 | 4 | 0 | 5 | 0 | 10 | 0 | 5 | 0 |
| **Weesperzijde** | 18 | 0 | 31 | 0 | 9 | 0 | 5 | 0 | 9 | 0 | 6 | 0 | 2 | 0 |
| **Westelijk Havengebied** | | 0 | 84 | 1 | 9 | 0 | 4 | 0 | | 0 | | 0 | 0 | 0 |
| **Westindische Buurt** | 18 | 0 | 50 | 0 | 9 | 0 | 7 | 0 | 1 | 0 | 8 | 0 | 3 | 0 |
| **Westlandgracht** | 17 | 0 | 37 | 0 | 7 | 0 | 5 | 0 | 21 | 0 | 12 | 0 | 3 | 0 |
| **Willemspark** | 9 | 0 | 43 | 0 | 13 | 0 | 7 | 0 | 5 | 0 | 4 | 0 | 5 | 0 |
| **Zeeburgereiland/ Nieuwe Diep** | 9 | 0 | 93 | 1 | 4 | 0 | 4 | 0 | 47 | 0 | 5 | 0 | 1 | 0 |
| **Zuid Pijp** | 31 | 1 | 13 | 0 | 16 | 0 | 11 | 0 | 1 | 0 | 15 | 0 | 5 | 0 |
| **Zuidas** | 14 | 0 | | 0 | 3 | 0 | 3 | 0 | 66 | 0 | 2 | 0 | 1 | 0 |

The boundaries for the binary transformation are given below.

| *Low income* | *Private-rent* | *Over 65* | *Single-parent* | *After 2010* | *Out of work* | *Over 75* |
|---|---|---|---|---|---|---|
| *23* | *64* | *19* | *13* | *67* | *16* | *12* |

# Appendix 6. Comparison of neighbourhoods in energy poverty

Table 23 contains neighbourhoods which have returned a positive energy poverty result.

*Table 23 - All neighbourhoods identified as in energy poverty*

| Neighbourhood | 2M | LIHC | 2M Predict | LIHC Predict |
|---|---|---|---|---|
| Banne Buiksloot | | | • | |
| Betondorp | • | | • | • |
| Bijlmer-Centrum (D,F,H) | | | • | • |
| Bijlmer-Oost (E,G,K) | | | • | • |
| Buikslotermeer | | | • | • |
| Buitenveldert-Oost | | | | • |
| Buitenveldert-West | | | | • |
| Dapperbuurt | | | • | |
| De Kolenkit | | | • | |
| De Omval/Overamstel | | | | • |
| Frankendael | | | • | |
| Gein | | | | • |
| Geuzenveld | | | • | |
| Holendrecht/Reigersbos | • | • | • | • |
| Hoofdweg e.o. | | | • | |
| Houthavens | | | | • |
| IJplein/Vogelbuurt | • | • | • | |
| Indische Buurt Oost | | | • | |
| Indische Buurt West | | | • | |
| Landlust | | | • | |
| Lutkemeer/Ookmeer | • | | | |
| Museumkwartier | | | • | |
| Nellestein | | | | • |
| Noordelijke IJ-oevers-Oost | • | • | • | |
| Prinses Irenebuurt e.o. | | | | • |
| Slotermeer-Noordoost | • | • | • | • |
| Slotermeer-Zuidwest | | | • | |
| Slotervaart-Zuid | | • | | |
| Spaarndammer- en Zeeheldenbuurt | | | • | |
| Transvaalbuurt | | | • | |
| Tuindorp Buiksloot | • | • | • | • |
| Tuindorp Nieuwendam | • | • | • | • |
| Van Galenbuurt | | | • | |
| Van Lennepbuurt | | | • | |
| Volewijck | • | • | • | • |
| Waterlandpleinbuurt | | | • | • |
| Zeeburgereiland/Nieuwe Diep | | | | • |
| Zuid Pijp | | | • | |
| Total no. of neighbourhoods | 9 | 8 | 25 | 19 |