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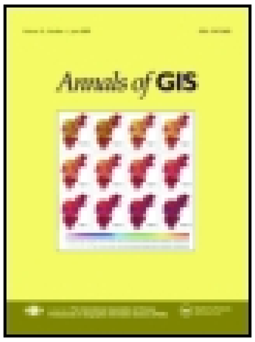

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Spatial homogeneity and heterogeneity of energy poverty: a neglected dimension

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ABSTRACT
Since the 1970s, a variety of studies has searched for the sociodemographic, housing and economic determinants of energy poverty. A central question, however, has not been answered by any of the previous studies: what are the national-level determinants, i.e. the determinants that homogeneously provoke a high level of energy poverty in all areas of a country? What are the neighbourhood-specific determinants, i.e. the characteristics that have a heterogeneous impact across the neighbourhoods of a country? This study seeks to answer these questions by analysing the level of energy poverty, the percentage of households' disposable income spent on energy expenditure, in 2473 neighbourhoods of the Netherlands in 2014. By employing a semi-parametric geographically weighted regression analysis, the effects of two of the determinants of energy poverty are found to be spatially homogeneous: (i) percentage of low-income households and (ii) percentage of pensioners. The results indicate that the impacts of six of the determinants are spatially heterogeneous: (i) household size, (ii) percentage of unemployment, (iii) building age, (iv) percentage of privately rented dwellings, (v) number of summer days and (vi) number of frost days. Subsequently, the effects of spatially homogeneous and heterogeneous determinants are estimated and mapped; the results are discussed and some policy implications are proposed.

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Household energy expenditure; energy poverty; household energy consumption; semi-parametric geographically weighted regression; Netherlands

1. Introduction

1.1. The neglected geographic dimension of energy poverty

Combating energy poverty has been matter of the policy-makers' interest in the European Union (EU) in the last decade. A European parliament legislation, the Third Energy Package on common regulations for domestic gas and electricity markets of the member states (European Parliament 2009a, 2009b), has required the member states to identify households that have difficulty meeting their energy expenses and to take actions to protect them. The member states, subsequently, have adopted a variety of measures to identify such households and granted a variety of supports in order to protect them. The policies proposed by the EU member states, however, have no geographic dimension. By offering financial aids to the household that are troubled with meeting their energy expenses, the policies merely aim to mitigate the 'effects' of energy poverty rather than addressing the geographic stimuli that 'causes' the high level of energy poverty. The policies, moreover, are spatially homogenous: the EU member states have merely introduced one-size-fits-all policies that are applicable for all locations of their respective countries; supplementary policy instruments specific to different regions, municipalities and neighbourhoods, however, are lacking (see the review by Dobbins and Pye 2016).

The geographic dimension of energy poverty is neglected by the previous scientific studies, too. By searching for the generalizable facts that explain the high level of energy poverty across all areas of a city, country, region or continent, most of the previous studies have implicitly presumed that the stimuli of energy poverty are homogenous across each and every energy-poor neighbourhood. A small portion of the previous studies that have accounted for heterogeneity of energy-poor neighbourhoods, oppositely, have ignored the possibility that some of the characteristic of these neighbourhoods may, in fact, be generalizable, and thus must be addressed by the national-level policies.

The standpoint of this study is that the questions of 'what are the geographic patterns associated with energy poverty, and are these patterns homogenous or heterogeneous?' need to be central to any exploration on energy poverty. This study aims to find the answers to this question by studying energy poverty in the neighbourhoods of the Netherlands in 2014. The article is

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divided into four main parts. In the next part, the previous studies on energy poverty, and the objective and the approach of this study are explained. In the second part, the method of analysis and the data used in the study are presented. In the third part, the results of the analysis are shown. In the fourth and final part of paper, the results are discussed and concluded.

1.2. Previous studies on homogeneity and heterogeneity of energy poverty

Subsequent to the publication of the two seminal studies on modelling geographic associations (Brunsdon, Fotheringham, and Charlton (1996) and Fotheringham, Charlton, and Brunsdon (1996)), and the follow-up book by Fotheringham, Brunsdon, and Charlton (2003), two types of geographic impact are distinguished by a variety of studies in different disciplines: (i) spatially homogeneous impacts, i.e. the insight that the stimuli of a phenomena provoke the same response in each and every geographical context; (ii) spatially heterogeneous impacts, i.e. the stimuli of a phenomenon vary across the locations of interest.

The concepts of spatial homogeneity of heterogeneity of geographic impacts could be adopted in order to categorize the previous studies on energy poverty. To examine impact of the determinants of energy poverty, two distinct approaches are adopted by the previous studies. First, many studies have presumed that there are some spatially homogeneous factors that explain the level of energy poverty across all areas of a city, country, region or continent. The conclusions drawn by these studies are location-free statements applicable to every location within a given study area. For instance, 'in Ireland … over half of elderly households endure [an] inadequate ambient household temperature in winter', Healy and Clinch concluded (2002, 329). In Vienna, 'energy-inefficient windows, buildings and housing sites are the cause of a heavy [energy] burden', Brunner et al. observed (2012, 7). 'Raising income can lift a household out of poverty, but rarely out of fuel poverty', Boardman observed in the United Kingdom (1991, xv). A low-income level is associated with energy poverty because 'low income people are more likely to be living in old buildings with poor envelope conditions', Santamouris et al. observed in Athens (2007, 893).

A second approach has emerged in the recent years. The underling presumption of this approach is that factors influencing energy poverty are spatially heterogeneous. The studies following this approach, therefore, try to disclose location-specific determinants of energy poverty. Living in a privately rented dwelling, for instance, has a significant impact on energy poverty 'in urban areas in the Midlands and Northern regions, in particular the north-east [of England]', Robinson et al. concluded (2018a, 11). 'Vulnerabilities [to energy poverty] associated with disability or illness … are stronger … in some southern cities [of England] including London, Luton and Southampton', Robinson et al. found (2018a, 12–13). Bouzarovski and Simcock (2017, 640) formulate the basic foundation of this approach as follows: 'there are clear geographic patternings associated with energy poverty, as well as the geographically embedded and contingent nature of … underlying causes'.

A knowledge gap in the previous studies is apparent. An earlier study on energy poverty could be based on the presumption that the determinants of energy poverty are spatially homogeneous, as many studies are, or on the presumption that the determinants are spatially heterogeneous, as some studies are. None of the studies, however, has examined the validity of the presumption which it followed.

1.3. Objective and approach of this study

This study aims to identify the spatially homogeneous and heterogeneous determinants of energy poverty in neighbourhoods of the Netherlands in 2014, and to estimate the impact of such factor across the neighbourhoods. To do so, two research questions are put forward: first, what are the spatially homogeneous determinants of energy poverty, i.e. the factors that can increase, or decrease, levels of energy poverty in all neighbourhoods of the Netherlands? Secondly, what are the spatially heterogeneous determinants of energy poverty, i.e. the factors whose impact is specific to some neighbourhoods of the Netherlands?

The methodology of this study is twofold. First, by means of a geographical variability test (Nakaya et al. 2009), the spatially homogeneous and heterogeneous determinants of energy poverty are identified. Secondly, in order to estimate the impact of the homogeneous and heterogeneous determinants, a semi-parametric geographically weighted regression (SGWR) model is developed. The model estimates the global impact of the homogeneous determinants on energy poverty of all neighbourhoods, as well as the neighbourhood-specific impact of the heterogeneous determinants.

As a proxy for the level of energy poverty, the percentage of disposable income spent on household energy expenditure (HEE) is used. The reason for using HEE instead of the common measures of energy poverty proposed by EU member states is that the proposed measures are all binary indicators allowing only for a 'yes/no' categorization (Herrero 2017). In the Netherlands, for instance, the policies merely distinguish vulnerable consumers from others: a vulnerable consumer is a person whose supply of electricity or gas is halted by the energy supplier, thus posing a risk to her/his health. In Ireland and Scotland, for example, a household that spends more than 10% of its disposable income on energy bills is considered to be in energy poverty. This study uses HEE instead of the binary measurements of energy poverty for two reasons: first, the criteria proposed by Dutch policies merely accommodate the most severe circumstances and do not provide a wide angle on the issue of energy poverty; secondly, binary definitions of energy poverty are highly threshold-sensitive, as a minor change in the criteria could result in a complete different picture of energy poverty (for instance, see the test carried out by Robinson, Bouzarovski, and Lindley 2018b).

Seven types of independent variables are used to illustrate the socio-economic and housing characteristics of the neighbourhoods. The variables were previously considered as effective determinants of energy poverty:

(1) Household size, as the number of both children and economies of scale in the use of the energy increases in larger households (Middlemiss and Gillard 2015; Anderson, White, and Finney 2012);
(2) Percentage of privately rented dwellings, as the investment in the maintenance of privately rented dwellings could be less than in owner-occupied and publicly rented dwellings (Robinson, Bouzarovski, and Lindley 2018a; Kholodilin, Mense, and Michelsen 2017; Bouzarovski and Petrova 2015);
(3) Unemployment, as it reflects a modest income level and low motivation for investment in buildings' energy efficiency (Phimister, Vera-Toscano, and Roberts 2015; Buzar 2007);
(4) Building age, as a proxy for buildings' energy efficiency (Brunner, Spitzer, and Christanell 2012; Fahmy, Gordon, and Patsios 2011);
(5) Percentage of low-income inhabitants, as energy bills could account for a relatively larger portion of the disposable income of such inhabitants (Chakravarty and Tavoni 2013; Bouzarovski 2009);
(6) Percentage of pensioners, as it is associated with a higher sensitivity to climate conditions and longer hours spent inside the dwellings (Legendre and Ricci 2015; Harrison and Popke 2011);
(7) Number of cooling and heating degree days as they affect level of energy consumption (Wiedenhofer, Lenzen, and Steinberger 2013; Reinders, Vringer, and Blok 2003)

2. Method and data

2.1. Method

The methodology of this study is twofold. The first step of the analysis aims at identifying spatially homogeneous and heterogeneous determinants of energy poverty, and to test whether the multicollinearity between the independent variables is at an acceptable level. To do so, an ordinary least square (OLS) model and a geographically weighted model (GWR) are developed. The OLS model is used for examining the level of multicollinearity between the independent variables. The GWR model is employed for the identification of the spatially homogeneous and heterogeneous determinants of energy poverty. The OLS model is formulated as follows:

$$y_i = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i, \tag{1}$$

where y_i is the estimated value of HEE at location i, β_0 shows the intercept and β_k shows the coefficient of the kth independent variable. x_{ik} and ε_i are the kth independent variable and random error term in location i, respectively. Subsequently, a GWR model of HEE is developed:

$$y_i = \beta_0(\mu_i, v_i) + \sum_k \beta_k(\mu_i, v_i) x_{ik} + \varepsilon_i, \tag{2}$$

where (μ_i, v_i) denotes the x–y coordinate of location i. $\beta_k(\mu_i, v_i)$ and $\beta_0(\mu_i, v_i)$ are the estimated local coefficient and local intercept of independent variable k in location i, respectively. The local coefficients are calculated as follows:

$$\hat{\beta}(\mu, \vartheta) = \left(X^T W(\mu, \vartheta) X\right)^{-1} X^T W(\mu, \vartheta) y, \tag{3}$$

where $\hat{\beta}(\mu, \vartheta)$ is the unbiased estimate of β, and $W(\mu, \vartheta)$ is a fixed bisquare spatial weight matrix adopted for location i:

$$W_{ij} = \begin{cases} \left(1 - \left(\frac{d_{ij}}{\theta}\right)^2\right)^2, & if\ d_{ij} < \theta \\ 0, & otherwise \end{cases}, \tag{4}$$

where W_{ij} quantifies the weight of neighbourhood$j$in the GWR model developed for neighbourhood i. d_{ij} is the metric distance between neighbourhood i and neighbourhood j. θ denotes the bandwidth size. The optimal value of θ, the bandwidth size at the corrected Akaike Information Criterion of GWR model is minimized. To identify the spatially homogeneous and heterogeneous determinants of HEE, the geographical variability test of GWR 4.0 tool is employed (developed by Nakaya et al. 2009). The test is based on the conduction of multiple GWR models and comparing their performance. In order to assess whether the impact of the *k*th independent variable is homogeneous or heterogeneous, two models are developed: first, a model that holds all the variables as heterogeneous determinants and the *k*th variables as homogeneous determinants; secondly, a model that holds all the independent variables, among them the *k*th variables, as heterogeneous determinants of HEE. Should the AICc of the second model be lower than that of the second model, reflected by the negative value of 'DIFF of Criterion' in the geographical variability test, the *k*th independent variable is a homogeneous determinant of HEE. Otherwise, the variable is a heterogeneous determinant. Subsequent to the identification of local and global variables, in the second step, a SGWR model is employed. The model estimates the global impact of the independent variables identified as homogeneous variables, as well as the neighbourhood-specific impact of the variables identified as heterogeneous determinants. The SGWR model is formulated as follows:

$$y_i = \beta_0(\mu_i, v_i) + \sum_m \beta_m(\mu_i, v_i)x_{im} + \sum_n \gamma_n z_{ni} + \varepsilon_i, \quad (5)$$

where $\beta_m(\mu_i, v_i)$ is the estimated coefficient of the *m*th local determinant of HEE at location *i*, and γ_n denotes the estimated coefficient of the *n*th global determinant. The spatial weight matrix is a fixed bisquare function, and the bandwidth size is specified in order to minimize AICc. Ultimately, in order to select the best model for estimating HEE, the performance of OLS, GWR, and SGWR models are compared by means of four tests: adjusted R^2, AICc, cross-validation (CV) and randomness of spatial distribution of the intercept values (assessed by Moran's Index).

2.2. Dependent variable

This study analyses HEE in the neighbourhood units of the Netherlands, *wijken* in Dutch (Figure 1). The premises of the neighbourhood are designated by the Central Bureau of Statistics (CBS) in Netherlands. Data on the annual consumption of gas and electricity within dwellings is extracted from CBS data (Centraal Bureau voor de Statistiek 2014). The average price of gas and electricity for households in 2014 is taken from Eurostat data (Eurostat 2015). This study includes 2473 residential neighbourhoods of the Netherlands.

2.3. Independent variables

This study uses six independent variables (Table 1). *Household size* describes the average number of residents in a household. *Private rent* denotes the percentage of dwellings that are neither owner-occupied nor owned by a municipality or a housing corporation. *Low income* is percentage of low-income inhabitants. According to the CBS definition, a low-income inhabitant is a resident whose disposable income is ranked among the four lowest deciles of income in the Netherlands. *Unemployment* denotes the percentage

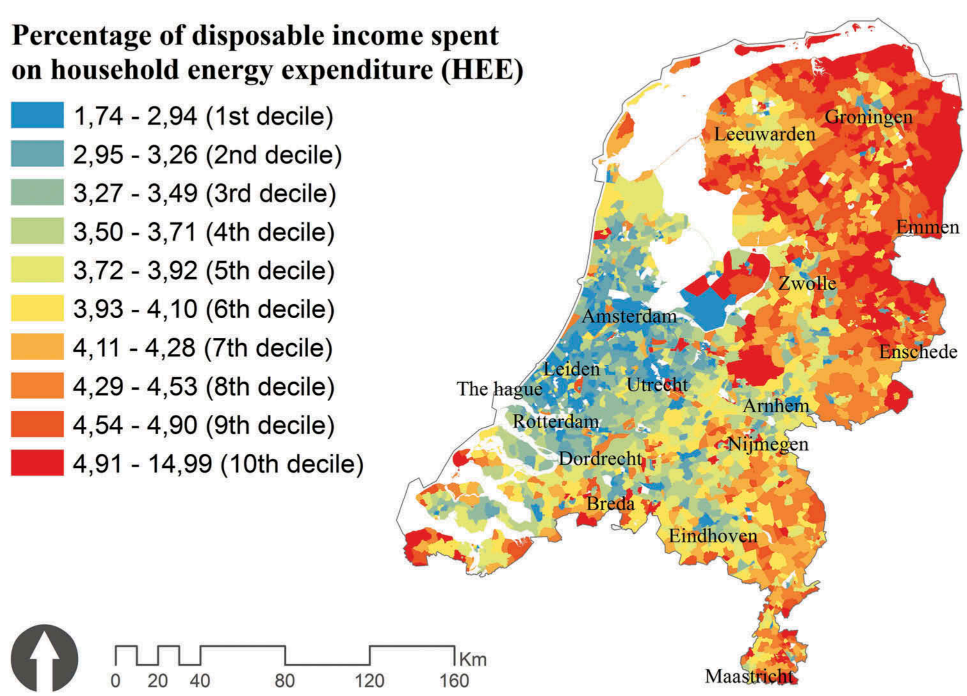

Figure 1. Case study area and dependent variables.

Table 1. Descriptive statistics of independent variables.

Variable	Mean	Minimum	Maximum	SD
Household size	2.35	1.20	4.00	0.31
Private rent (%)	12.06	1.00	78.00	7.25
Low income (%)	40.05	18	72	5.47
Unemployment (%)	2.13	0.00	7.14	0.81
Pensioner (%)	17.81	1	62	5.34
Building age	38.58	1	163	15.01
Number of summer days	23.27	5.98	37.70	7.96
Number of frost days	68.79	50.40	81.06	6.62

of the population aged between 15 and 65 receiving unemployment benefits as their main source of income. *Pensioner* is the percentage of the population that receives a pension. *Building age* shows the median age of residential, or partially residential, buildings in the neighbourhoods.

Annual air temperature in the neighbourhoods is reflected by the use of two variables, defined by Royal Netherlands Meteorological Institute (KNMI): *number of summer days*, the number of days in which maximum temperature outnumbers 25°C, and *number of frost days*, the number of days in which minimum temperature falls below 0 °C. To obtain these variables, based on the KNMI guideline (Sluiter 2012), the measurements of the summer and frost days of the 28 meteorological stations of KNMI are interpolated across the country.

3. Results

3.1. Identification of spatially homogeneous and heterogeneous determinants

In the first step, an OLS model is employed. The results of the model show that coefficients of all six independent variables are significant (p value <0.01). All the estimated coefficients are positively signed – indicating that higher values of all the variables are associated with higher levels of HEE. The variance inflation factor (VIF) of all six independent variables is well below the threshold value of 2.5. This shows that the multicollinearity between the variables is low and the effect they represent is fairly unique. Subsequently, a GWR model is employed. The bandwidth size of the model is 30 km – the optimal bandwidth size to minimize AICc. The geographical variability test shows that the DIFF of criterion is positive in the case of two of the independent variables. This identifies these variables as spatially homogeneous determinants of HEE (Table 2):

(I) *Low income*,
(II) *Pensioner*.

The results of the test identify four of the independent variables as spatially heterogeneous determinants of HEC (indicated by negative values of DIFF of criterion):

(I) *Household size*,
(II) *Private rent*,
(III) *Unemployment*,
(IV) *Building age*,
(V) *Number of summer days*,
(VI) *Number of frost days*.

The findings of the first step of the analysis are used to develop the SGWR model.

3.2. Results of the SGWR model and its performance compared to the GWR and OLS models

In the second step of the analysis, a SGWR model is developed. The identification of the spatially homogeneous and heterogeneous variables is used as the basis for the SGWR model, as the model estimates the spatial stationary impact of the former variables as well as the spatial non-stationary impact of the latter (Table 3).

Table 2. Geographical variability test and estimates of OLS and GWR models.

	OLS results		GWR results				Geographical variability test	
Variable	β	VIF	β mean	β min	β max	β SD	DIFF of Criterion †	Type of determinant impact
Intercept	0.000**		−0.205	−26.673	18.538	3.037	−3897.98	Heterogonous
Household size	0.382**	1.91	0.302	−0.384	1.308	0.176	−54.14	Heterogonous
Private rent (%)	0.192**	1.21	0.188	−0.119	1.146	0.163	−297.64	Heterogonous
Low income (%)	0.537**	1.16	0.401	−0.311	1.032	0.083	2.84	Homogenous
Unemployment (%)	0.072**	1.40	0.023	−0.249	0.435	0.094	−22.89	Heterogonous
Pensioner (%)	0.201**	1.29	0.137	−0.243	0.646	0.092	4.61	Homogenous
Building age	0.127**	1.33	0.148	−0.164	0.526	0.095	−22.58	Heterogonous
Number of summer days	−0.121**	1.33	0.540	−17.380	13.487	2.016	−13.68	Heterogonous
Number of frost days	0.230**	1.64	−0.153	−6.849	5.229	1.377	−23.30	Heterogonous
R^2	0.514		0.74					
Adjusted R^2	0.512		0.71					

β: standardized regression coefficient.
**p value* <0.05.
***p value* <0.01.

Table 3. Estimates of SGWR model.

	Spatially homogeneous determinants		Spatially heterogeneous determinants			
Variable	*B*	SE	*β* mean	*β* min	*β* max	*β* SD
Intercept			−0.083	−66.402	24.721	4.040
Household size			0.308	−0.393	3.108	0.183
Private rent (%)			0.188	−0.275	3.072	0.216
Low income (%)	0.403**	0.014				
Unemployment (%)			0.014	−0.443	0.671	0.122
Pensioner (%)	0.128**	0.014				
Building age			0.155	−0.182	2.425	0.130
Number of summer days			0.636	−29.257	17.760	2.556
Number of frost days			−0.24617	−16.0184	10.76843	1.769067
R^2	0.759					
Adjusted R^2	0.725					

β: standardized regression coefficient.
***p value* <0.01.

The map of the local R^2 values of the SGWR model (Figure 2) shows that the values of R^2 range from 18% to 99%, with an average of 57% and a standard deviation of 12%. The highest values are observed in Eindhoven and Leeuwarden where the observed values of R^2 outnumber 90%. The two areas with relatively low level of R^2 are rural areas in vicinity of Groningen and the city of Amsterdam, where the values are significantly lower than other large cities of the country.

A comparison between performance of the three models shows that SGWR model provides a better estimate of HEE. The lowest level of AIC, AICc and CV as well as the highest adjusted R^2 are obtained in the SGWR model. Random spatial distribution of residual is merely observed in case of the SGWR model. This indicates that distinguishing between spatially homogeneous and heterogeneous determinants of the HEE provides a better understanding of the phenomenon compared to the holding all variables as homogeneous determinants, in the case of the OLS model, or as heterogeneous determinants, in the case of the GWR model (Table 4).

3.3. Estimates of the impact of spatially homogeneous determinants

Estimates of both of the spatially homogeneous determinants of HEE are significant at the *p* value <0.01 level. The results show that the impact of the first homogeneous determinant, *low income*, is more than three times larger than that of the second homogeneous determinant of HEE, *pensioners*. The estimates of the standardized coefficient of *low income* show that the factor outnumbers the

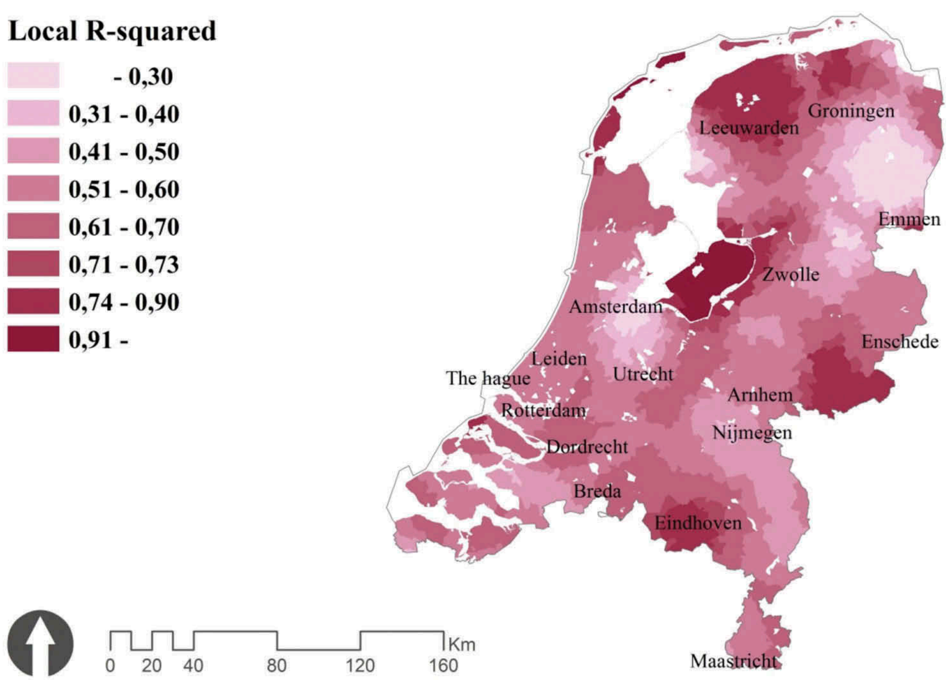

Figure 2. Local R^2 produced by the SGWR model.

Table 4. Diagnostics of the OLS, GWR and SGWR models.

Method	OLS	GWR	SGWR
AIC	5251.55	4091.24	3502.29
AICc	5251.64	4123.15	3975.18
CV	0.4951	0.3795	0.3723
R^2	0.514	0.737	0.759
Adjusted R^2	0.512	0.709	0.725
Residuals Moran's I	0.1668	0.0241	0.0100
Bandwidth (metre)	NA	40.047.96	29.847.42

neighbourhood-specific impacts of the heterogeneous determinants in almost all of the neighbourhoods. The impact of *Low income* outnumbers the neighbourhood-specific impacts of *household size* in more than 72% of the neighbourhoods. The corresponding numbers compared to the neighbourhood impacts of *private rent*, *unemployment*, *building age*, *number of summer days* and *number of frost days* are 93%, 99%, 98%, 88% and 87%, respectively. *Low income*, in short, is found to be the strongest, or one of the strongest determinants of HEE across all neighbourhoods of the Netherlands.

The comparison between the estimated effect of the second homogeneous determinant, *pensioners*, and the neighbourhood-specific impacts of heterogeneous determinants, illustrates a diverse picture. The impact of *pensioners* is smaller than that of *household size* in more than 74% of the neighbourhoods. The impact, however, outnumbers that of *unemployment* in 91% of the neighbourhoods. In almost two-thirds of the neighbourhoods, the impact of *pensioners* is outnumbered by that of *private rent* and *building age* (59% and 68%), whereas in almost 88% of the neighbourhood, the presence of pensioners has a larger contribution to HEE than *number of summer days* or *number of frost days* (Figure 3).

3.4. Estimates of the impact of spatially heterogeneous determinants

The results show that the impact of heterogeneous determinants of HEE is not necessarily significant in all neighbourhoods. The localized coefficients of *household size* are significant (p value <0.01) in 74% of neighbourhoods (Figure 4(a)). The corresponding numbers for that of *private rent* (Figure 4(b)) and *building age* (Figure 4(d)) are 42% and 35%. In the case of *number of summer days* (Figure 4(e)) and *number of frost days* (Figure 4(f)), the localized coefficients are significant in 20% of the neighbourhoods. The smallest percentage of significant neighbourhood-specific coefficients is observed in the case of *unemployment* where the HEE of a mere 13% of neighbourhoods is significantly affected by the factor (Figure 4(c)). In the case of *household size*, *private rent* and *building age*, the sign of almost all the neighbourhood-specific coefficients is positive. In the case of *unemployment*, *number of summer days* and *number of frost days*, however, the sign of the neighbourhood-specific coefficients varies across the neighbourhoods: the sign of three-fifth of the coefficients is positive and that of one-third of the coefficients is negative. The latter indicates that the nature of the association between HEE and these variables varies from one neighbourhood to another.

Figure 5 illustrates the most influential localized determinant of HEE, the heterogeneous determinant with the largest estimated standardized coefficient in the neighbourhood in question, in the neighbourhoods of Netherlands. The results indicate that in almost 55% of the neighbourhoods, *household size* is the most influential localized determinant of HEE. Such neighbourhoods comprise the major cities of the province of Zuid-Holland, Rotterdam and The Hague, as well as the city of Maastricht. In more than 12% of the neighbourhoods, *private rent* is the most influential localized determinant of HEE. The neighbourhoods of Enschede, Amsterdam, Almeer as well as those of the so-called green heart, central areas of the Randstad region, fall in this group. In almost 5% of the neighbourhoods, *building age*, as a proxy of building energy efficiency, is the most influential localized determinant of HEE. The neighbourhoods of Groningen and Dordrecht fall in this group.

In more than 11% of the neighbourhoods, *number of summer days* is the most influential localized determinant. Such neighbourhoods are mostly located by the coast in the North of the country, the northern neighbourhoods of the provinces of Groningen and Friesland, as well as in the vicinity of the largest rivers in the province of Zeeland. In more than 12% of the neighbourhoods, *number of frost days* is the most influential localized determinant of HEE. Most of these neighbourhoods are located in the east side of the country, with large agglomerations observed in the provinces of Overijssel between the cities of Zwolle and Enschede. In more than 3% of the neighbourhoods, the level of HEE is explained by global determinants only. Such neighbourhoods are partially located in the province of Zeeland. *Unemployment* is the most influential local determinant in a mere 0.4% of the neighbourhoods.

4. Discussion

4.1. Homogeneous determinants

The results show that the impacts of two of the determinants of HEE are spatially homogeneous. It is found that low-income inhabitants, i.e. those within the lowest four deciles of income, are in danger of energy

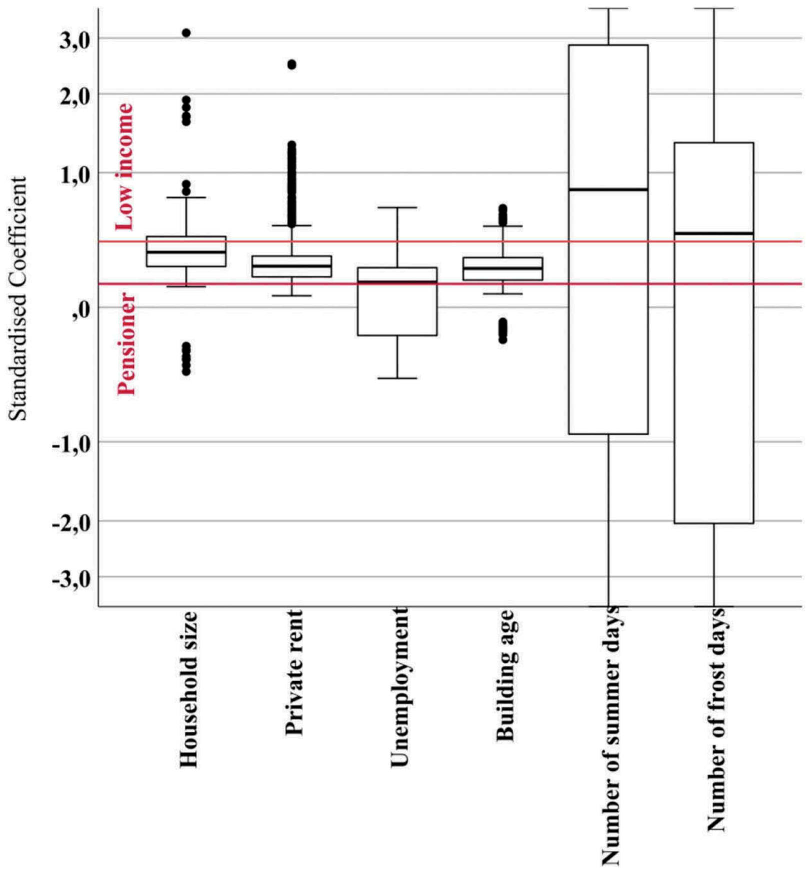

Figure 3. The box plot represents the standardized coefficient of the spatially homogeneous determinants of HEE (in red) compared to significant (p value <0.01) localized coefficients of the heterogeneous determinants.

poverty in all neighbourhoods of the Netherlands. As the financial resources available to this social group are relatively limited, such an observation is not unexpected. The finding, however, should serve as a warning of the social consequences of the implementation of the policies aimed at phasing out gas used for cooking and heating in the Dutch residential sector before 2050 (Energieagenda 2016). Replacing natural gas, a relatively cheap source of energy, with electricity, a more expensive energy source, could push this social group further into energy poverty. Further studies need to analyse the impact of the energy transition on the budget of low-income households and offer respective support measures. Low-income households could, for instance, be equipped with energy-efficient heating and cooking appliances. Insulating the dwellings of low-income households could be supported by the national government. A new tax scheme could allow low-income households a refund of the Regulatory Energy Tax – a levy on gas and electricity consumption imposed by the government, accounting for 28% of the total tariff in 2013 (Deloitte Conseil 2015) – included in energy prices.

Another social group that is homogeneously in danger of energy poverty is the pensioners. Given the demographic trends in the Netherlands – rising single-person elderly households – such a danger will most probably continue to rise in the coming decades. According to CBS projections (Centraal Bureau voor de Statistiek 2011), in 2060 the average household size will be 2.08 persons (compared to 2.25 in 2011) and single-person households will account for 44% of all households (compared to 36% in 2011). Furthermore, nearly half of one-person households are expected to be older than 65 in 2050 (compared to just 31% in 2011). Policies need to accommodate these demographic trends. A variety of policy instrument, ranged from improving energy-efficiency of the dwellings of senior citizens to promotion of communal places to curb the number of lonely-at-home-hours of the elderlies, could be adopted.

4.2. Heterogeneous determinants

In 55% of the neighbourhoods, household size is the main localized determinant of energy poverty. Energy expenditure rises in larger households, say the

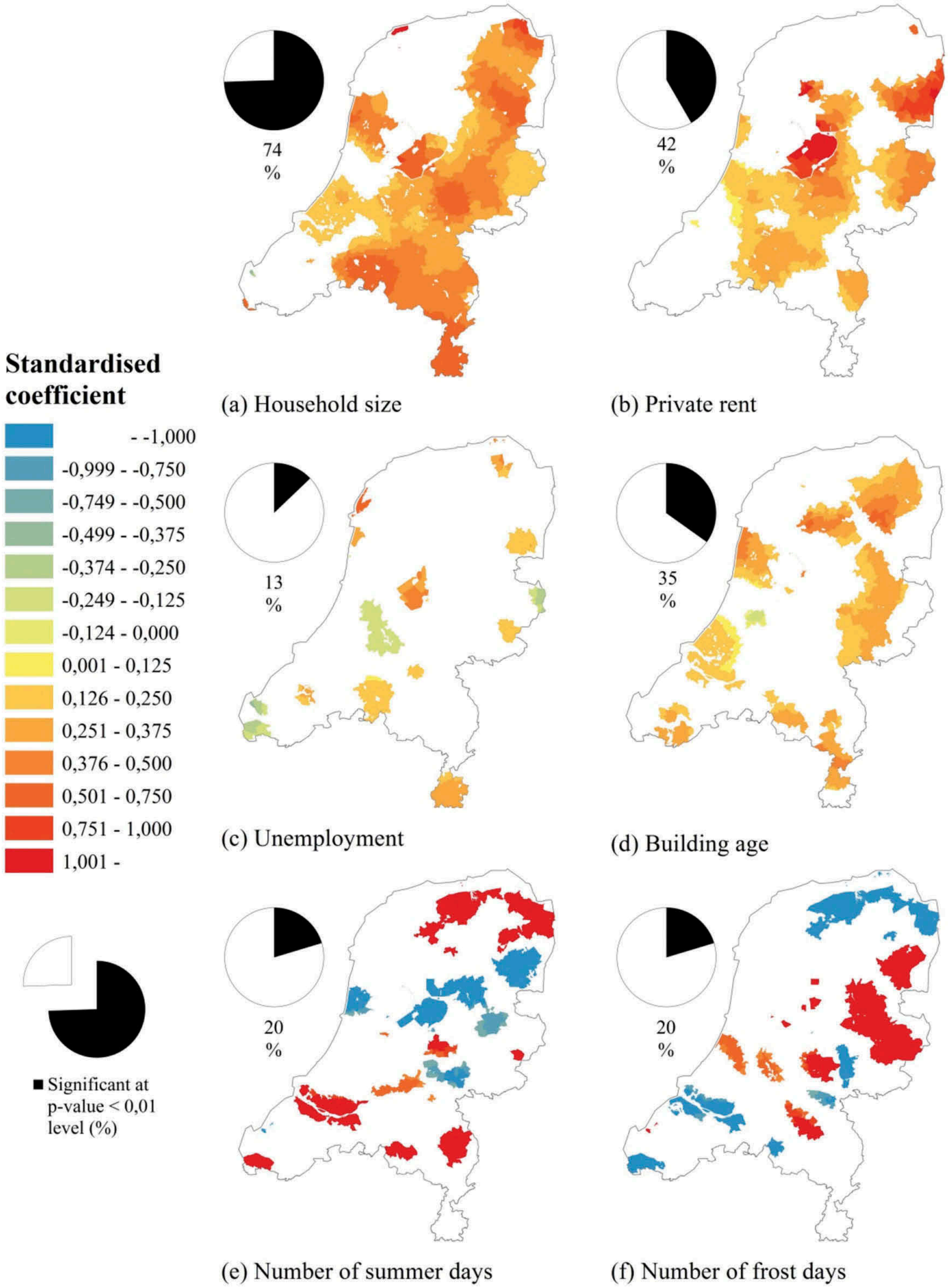

Figure 4. Maps show the localized coefficients of the heterogeneous determinants of HEE.

households with children, due to higher consumption for cooking, space warming and cooling, water heating, appliances, etc. (see Weber and Perrels 2000). Additionally, given the trend in Netherlands and the increased use of laptop, desktops, smartphones and tablets (Centraal Bureau voor de Statistiek 2017), the gap between electricity consumption of households with school-aged children and other households could further widen in years to come. Further studies need to survey the detailed energy use of the households in

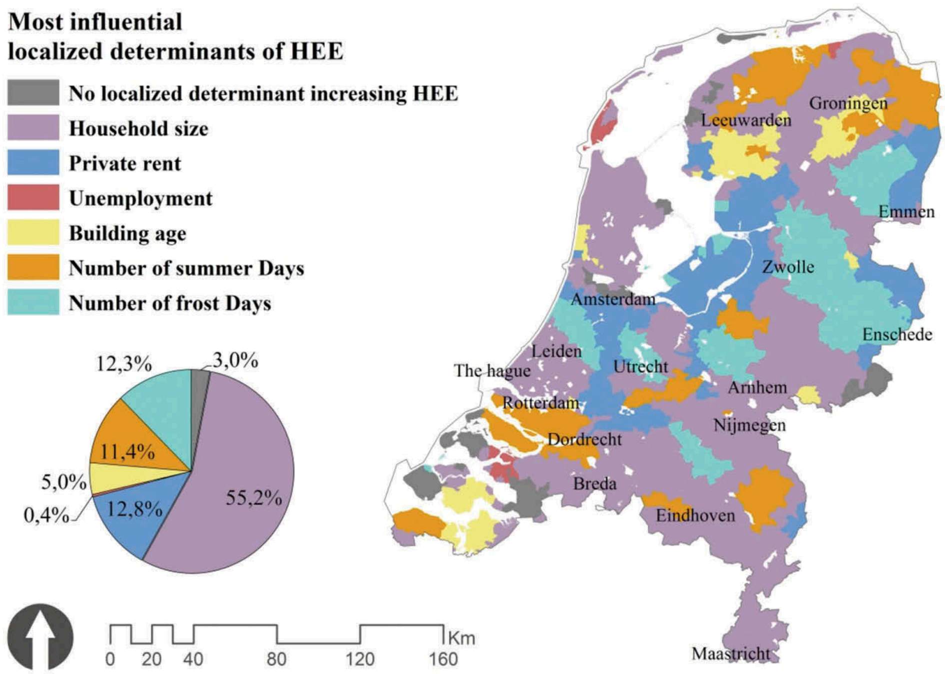

Figure 5. The most influential localized determinants of HEE. The pie-chart represents the frequency of the most influential localized determinants.

energy-poor neighbourhoods and determine whether or not energy expenses affect the health, education and personal development of children. Neighbourhood-specific support measures to satisfy such demands need to be introduced.

In more than one-eighth of the neighbourhoods of the Netherlands, privately rented dwellings are the main localized determinant of energy poverty. The low motivation of the renter for investing in the building's energy efficiency is, presumably, the main reason for this observation. The housing subsidy (*huurtoeslag*) offered by the government, meanwhile, could be a reason for low motivation of the landlords. The subsidy is granted if the amount of rent and the income of the renter fall below certain thresholds (Voorwaarden voor huurtoeslag in 2016). The cap on rent price may encourage landlords to not renovate older buildings in order to keep the rent lower than the threshold and thus attract low-income renters. Renters who apply for a housing subsidy therefore receive a subsidy on their rent in exchange for a higher energy expenditure – a hidden rent in effect. Since July 2014, a sharp-eyed 'energy saving' scheme in the Dutch government's energy policy has proposed 400 million euros of funding to renovate rental houses receiving subsidies, on the condition that the rent does not exceed 700 euros (Government of the Netherlands 2014). As a complementary policy instrument, in neighbourhoods with high levels of energy poverty, applying for this fund could be mandatory.

In 5% of the neighbourhoods, the energy efficiency of buildings is the main local determinants of energy poverty. Currently, improving the energy efficiency of buildings is the keystone of the Third National Energy Efficiency Action Plan (Ministry of Economic Affairs 2014) as most of the actions, incentives and resources proposed by the policy target buildings' energy efficiency, among them the so-called block-by-block approach, large-scale projects to improve the energy efficiency of the existing housing stock. The notion of energy poverty could be utilized in order to prioritize the blocks in which the low quality of the buildings causes higher levels of energy poverty.

Number of summer days and *number of frost days* are the most influential determinants of energy poverty in one-fifth of the neighbourhoods. This observation could be explained from two different perspectives: thermal comfort and user behaviour. The former refers to circumstances in which thermal comfort in a warm, or a cold, neighbourhood is reduced by an additional number of summer, or frost, day. The latter refers to a circumstance when the number of warm days has a great influence on HEE of a cold area, and vice versa. In such circumstances, as inhabitants are exposed to a climate condition that they do not used to, energy consumption may drastically increase. This result shows that climate change could have a very complex impact on energy poverty. Further explorations need to study the impacts of climate change, see the scenarios by KNMI (2015), and urban heat islands, see the study by van der Hoeven and Wandl (2015), on energy poverty, and bring forward location-specific policy measures that accommodate these trends.

In a relatively small portion of the neighbourhoods, unemployment is the main neighbourhood-specific determinant of energy poverty. In order to offset the high burden of energy expenditure, the government could utilize smart technologies, i.e. smart meters providing detailed information about the energy use of consumers, to cover expenses directly related to the health of energy-poor unemployed people, e.g. expenses related to space heating on days with sub-zero temperatures.

5. Concluding remarks

Energy poverty is a geographic phenomenon spatially coinciding with a complex and reciprocal landscape of people, physical infrastructures, institutions and natural climate. How energy poverty interacts with its embedding geography remained unanswered, and unnoticed, by the policy-makers and scholars. The policies on energy poverty need to shift their perspective, and to acknowledge the embedding geography of the energy-poor neighbourhoods. Policies, to do so, need to target the geographic patterns which 'cause' energy poverty rather than offering financial aid to mitigate the 'effects' of energy poverty.

The results of this study show that the impact of the determinants of energy poverty could be spatially homogeneous (national-level determinants) or heterogeneous (neighbourhood-specific determinants). Policies need to accommodate this fact by diversifying in their spatial extent. To do so, two types of policies could be adopted. First, national-level policies offering a safety net to social groups who are intrinsically in danger of energy poverty, low-income households and pensioners in the case of the Netherlands, of all the neighbourhoods of a country. Secondly, neighbourhood-level funds come into effect when a particular social group of a neighbourhood is in danger of energy poverty due to its sociodemographic characteristics, employment or the conditions of housing tenure, or climate conditions. In order to offer support at the neighbourhood level, it is essential to carefully study the geographic context of each and every energy-poor neighbourhood, and, by introducing location-specific policies, to address the local factors that foster the high level of energy poverty – for example, see the studies by Guo (2008) and Mu et al. (2015). To do so, a close collaboration between energy network companies, the ministry of economic affairs, and municipal authorities is essential. Combating energy poverty is, and must be, a shared responsibility of all decision-makers on the national, regional and local levels.

The result of this study urge for a shift in the methodologies of the studies on energy poverty. By application of aspatial methods, most of the previous studies have effectively ignored spatial heterogeneity of the determinants of energy poverty. A variety of previous studies, meanwhile, have shown that the best understanding of a wide range of phenomena – among them academic achievement (Figueroa, Lim, and Lee 2016), effects of ozone pollution (Lin and Lu 2009), vulnerability to terrorism (Eisman, Gebelein, and Breslin 2017), household energy consumption (Mashhoodi 2018; Mashhoodi and van Timmeren 2018) and social vulnerability in slums (Jankowska, Weeks, and Engstrom 2011) – is achieved only when spatial heterogeneity of the effects is taken into consideration. The result of this study is beneficial for future studies on energy poverty; there is a central question to start with: what are the spatially homogeneous and heterogeneous determinants of energy poverty?

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