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Review

Emerging spatial clusters of energy poverty vulnerability in rural Finland—Byproducts of accumulated regional development

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A R T I C L E I N F O

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A B S T R A C T

This geospatial research on Finnish energy poverty reveals that rural areas have potentially higher energy poverty vulnerability than urban areas. The analyses focus on household energy expenditures (HEE) in postcode areas and detect local high or low HEE determinants. The urban-rural typology is applied and found relevant when studying energy poverty and identifying spatial dependencies. The findings demonstrate that rural areas are more vulnerable to energy price increases than urban areas, and the spatial clustering of vulnerability to energy poverty is evident and temporally permanent. The main reason for energy poverty is related to postcode areas' socioeconomic status and building stock characteristics, indicating the accumulation of the negative impacts of regional development on energy poverty vulnerability. The results also suggest that monitoring not only levels of energy poverty but also the temporal dynamics of energy poverty is essential to ensure the effectiveness of policy measures and solutions.

1. Introduction

Fluctuating energy prices across Europe likely increase energy poverty—a complex structural and socioeconomic challenge that affects tens of millions. In 2018, nearly 34 million Europeans could not keep their homes adequately heated [1]. Europe's most common causes of energy poverty are low income levels, low household energy efficiency, and high energy prices [2]. Energy poverty lacks a uniform definition but can be related to energy access, end-user energy costs, and regions' socioeconomic differences [1,3].

The energy vulnerability of households means their inability to secure adequate energy services, i.e., being at risk of energy poverty [4]. In Finland, energy poverty has been mainly unrecognized as a social issue due to energy-efficient housing, district heating infrastructure, and social security measures [5]. However, vulnerable groups in Finland experience energy poverty, with 1.3 % of the population in 2021 unable to keep their homes warm and 5.8 % having utility bill arrears [6].

In terms of structural energy poverty vulnerability [7], Finland is in a less vulnerable group of nations, including several Western European countries, where energy poverty is mainly restricted to specific demographic groups or those living in certain housing types. However, vulnerability to energy poverty has become a relevant topic in Nordic countries due to the recent fluctuation and peaking of electricity prices [8,9]. Like in Sweden and Norway, electricity-based heating is common in Finland, and most household electricity use is during the cold midwinter.

In the energy poverty framework, Bouzarovski and Petrova [10] identify access to energy, affordability, flexibility, energy efficiency, and a mismatch between needs and services as essential vulnerability factors. Vulnerable households may face challenges with energy efficiency, high energy losses, and lack of political recognition or knowledge of available support. Vulnerability analyses of energy poverty can consider risk factors and driving forces, capturing spatial and temporal dynamics and recognizing household status changes [10,11].

This regional study of Finnish energy poverty presents how remote rural areas can have higher energy poverty vulnerability than urban areas. The regional development trends are well known from the statistics, but energy poverty, which connects directly with regional development, needs to be better understood. Energy poverty can be associated with negative net migration rates and population losses, deteriorating living standards, falling housing prices, and accumulating societal disadvantage in general. Therefore, spatial analysis of energy

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poverty vulnerability is needed to increase understanding of spatio-temporal dynamics and to develop policy mechanisms.

These analyses apply the urban-rural typology to summarise regional development trends and local variations in the study region's energy poverty vulnerability. There has been limited focus on potential rural-urban disparities in earlier energy poverty studies [12,13]. The urban-rural factor is considered relevant in the context of energy poverty vulnerability in the literature because rural households are disadvantaged due to rural housing stock, and fewer energy options are accessible in rural locations [13]. In addition, the urban-rural classification accurately captures recent regional growth [14].

This study uses the expenditure-based approach with geospatial analyses to analyze the geographical and dynamic variation of postcode areas' energy poverty vulnerability and detect its local determinants. The analyses use GIS methodology to identify the energy poor by adding the geographical distribution of local vulnerabilities to household energy poverty. Household energy expenditure (HEE) is applied as a measure of energy poverty vulnerability in postcode areas [15]. The 10 % rule [see, e.g., [16,17]] and Low Income High Costs (LIHC) definitions [18] are used to estimate a household's vulnerability. The 10 % rule measures household conditions but cannot identify causes of energy poverty [19]. Therefore, the LIHC definition is modified for postcode areas, indicating vulnerability if HEE is higher than 10 % in a month and median income is below the study region's median.

The paper aims to generate a new understanding of the spatial pattern of energy poverty vulnerability as the dynamic and geographic dimension of energy poverty is often neglected [15]. Energy poverty research in Finland is limited, and no earlier geospatial analyses have presented urban-rural differences or local vulnerabilities to energy poverty.

The following research questions have guided our analysis:

- What are the geographic, spatial, and dynamic variations of vulnerability to energy poverty, and what are the urban-rural differences in vulnerability?
- What kind of areas are at the highest risk for energy poverty vulnerability?
- What are the opportunities to alleviate energy poverty vulnerability in those risk areas?

The following chapter discusses the data and methods used to measure and map vulnerability to energy poverty. The analyses use postcode area data from the case area North Karelia, located in Eastern Finland. The results present spatiotemporal patterns of household energy cost variation and vulnerability to energy poverty in the region, also bringing attention to the differences between urban and rural parts of the region. Finally, potential strategies for alleviating vulnerability to energy poverty are discussed.

2. Understanding the temporal and spatial aspects of energy poverty vulnerability in a peripheral region

In Finland, energy poverty has not been widely discussed as the country has a highly developed energy infrastructure, abundant energy resources, and well-established social security. The Ministry of Environment [20] estimated that in Finland, approximately 60,000–100,000 inhabitants might be at risk of energy poverty, mainly those living in unrenovated older (constructed in the 1960s to 1970s) private fossil-fuel-heated homes and apartments. The aging population, increased energy renovation needs of buildings, rising energy costs, and lack of support in peripheral regions are increasing the number of vulnerable households.

The case study region of North Karelia is located in the resource periphery of Eastern Finland, with socioeconomic challenges, long distances, and an aging population. It lies in a coniferous zone in the easternmost part of Finland that mainly encompasses North Karelia, with parts of Northern Savonia (Fig. 1). It is an example of a resource-dependent and rural NUTS3-level northern European region that struggles with the socioeconomic challenges caused by the restructuring of the economy, especially the wood industry [21]. The region was mentioned in 2015 as an energy poverty risk area if energy costs rose 2 % annually (Ibid.). Therefore, record-high increases in consumer prices (+11–15 %/a), fuel oil (+44 %), and traffic fuel (+27–28 %) in 2021–2022 have raised the importance of energy poverty research [22]. In addition, the peaking stock prices of electricity (08/2022) indicate a rising trend of consumer prices in the coming years.

This study analyses households' vulnerability to energy poverty using postcode areas as spatial units of the analyses. Postcode areas are the smallest functional areas in Finland, as those are based on the operation of post offices. The advantage of the postcode area data is that it is a small enough unit to describe local differences but large enough to control random variations in energy poverty vulnerability. Recent evidence suggests potential regional differences in vulnerability to energy price increases and volatility at the aggregate level [23]. The study region comprises 170 postcode areas with a total population of 104,726.

To describe the regional development trends and later analyze local variations of the energy poverty vulnerability in the study region, we use the urban-rural typology, which divides areas into seven categories: three urban and four rural (Fig. 1). The analyses utilize this typology because there has been little focus on potential rural-urban differences in energy poverty research [12] and because the urban-rural classification effectively describes the regional development of recent years [14]. In the literature, the urban-rural dimension is seen as relevant in the context of energy poverty because rural households are disadvantaged due to the nature of rural housing stock and the more limited choice of energy available in rural areas [12,13].

The urban-rural typology used in the analysis is based on the population, labor, commute, building, and land use datasets. Based on these variables, the areas have been divided into urban-rural categories using various analyses and classification rules [14]. In the classification, urban categories contain inner urban areas, outer urban areas, and peri-urban areas. Local centers in rural areas are population centers located outside urban areas. Rural areas close to urban areas are areas with a rural character that are functionally connected and close to urban areas. Core rural areas have intensive land use, with a relatively dense population and a diverse economic structure at the local level. Sparsely populated rural areas consist of dispersed small settlements located far from each other, and most of the land area is forested. Because the typology is implemented using a nationwide 250 × 250 m grid of cells, the urban-rural category of the postcode areas was determined based on the biggest population of the typology in a postcode area. The study region is primarily rural since 77.6 % of the population and 95.9 % of the surface area belongs to rural categories.

The ongoing economic restructuring in the study region, characterized by the shrinking number of jobs, high unemployment rates, depopulation, and high proportions of pensioners, is deepest in the core rural and sparsely populated rural areas (Table 1). Demographic change in the study region reflects the general process of the rural areas in developed countries, in which young people move to growth centers for jobs and education, while the relatively larger elderly population tends to move to the municipal center for services and suitable housing [24]. In the study region, the urban-centric regional development is also reflected in income levels and dependence on social transfers, as the median income in rural areas is lower than in urban areas (Table 1). Differences in income levels are meaningful as they also indicate differences between regional categories in the ability to invest in energy efficiency, thus avoiding vulnerability to energy poverty.

The economic restructuring is also apparent in the study region's building stock characteristics. As population growth and construction are concentrated in urban areas, the rural building stock is decreasing, and it is the oldest, cheapest, and has lost the most value in the most rural areas, such as the core rural and sparsely populated rural areas

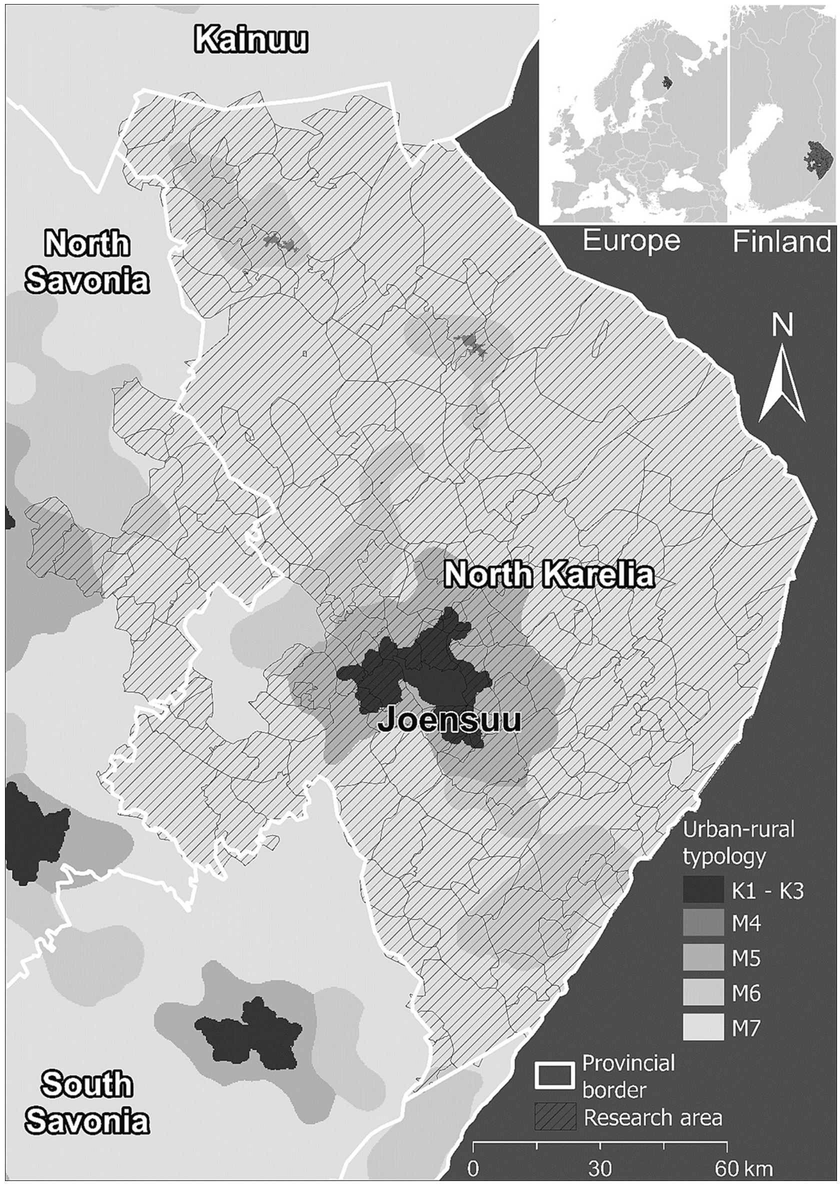

Fig. 1. Location of the case study area.

(Table 1). Investments in newer heating systems, such as geothermal heating, also reflect differences in building stock because such investments concentrate on urban areas with higher median income (Table 1). Altogether, these statistics suggest that the differences in the socioeconomic status between urban-rural categories are real, and rural areas are more vulnerable to energy poverty than urban areas based on their characteristics. In general, vulnerability to negative processes has been a characteristic of resource peripheries for a long time [25], but it has not been associated earlier with energy poverty as a byproduct of accumulated regional development processes.

3. Measuring and mapping energy poverty vulnerability

The concept of energy poverty vulnerability does not have a unified definition due to the complicated energy consumption patterns and socioeconomic differences in different regions and countries. This study uses household energy expenditure (HEE) to measure vulnerability to energy poverty in postcode areas. HEE is calculated as the percentage of disposable median income spent on average on the energy consumption costs of the household in postcode areas and has been used in many earlier studies [e.g., [15]]. Another reason for using HEE is that it allows the combination of the indicator with other definitions of energy poverty, such as the frequently used 10 % rule [16,17], which is also applied here to estimate the number of households vulnerable to energy poverty in the postcode areas. The rule can be understood as an indicator of household conditions, but it cannot identify the cause of energy poverty [19], and therefore, HEE is modeled with spatial regression models. The second approach for describing households' vulnerability to energy poverty in postcode areas is the Low Income High Costs (LIHC) definition [18]. This measure was modified to be more suitable for postcode areas: an area is considered vulnerable to energy poverty if HEE in the area was higher than 10 % in a month and median household income was below the study region's median income, adjusted for household size after energy costs are deducted. Both measures, the 10 % rule and LIHC, were used to demonstrate the extent of energy poverty vulnerability in postcode areas.

3.1. Calculation of HEE in postcode areas

HEE calculation in postcode areas depends on the households' total

Table 1
Descriptive statistics from the study area.

Category	Variable	Urban-rural category					Region	F-test
		Urban areas	Local centers in rural areas	Rural areas close to urban areas	Core rural areas	Sparsely populated rural areas		F statistics (*p*-value)
Socio-economic status	Median income in 2020, €	41,850	26,357	37,353	31,185	29,662	31,975	31.83 (<0.001)
	Average change in the household median income in 2016–2020, € (%)	1989 (4.8)	1592 (6.4)	3170 (9.7)	2408 (8.5)	2148 (8.5)	2315 (8.3)	0,62 (0.648)
	Unemployment in 2020, %	12.1	16.6	14.2	18.5	21.7	19.1	3.36 (0.011)
	Pensioners in 2020, %	27.8	46.8	35.0	44.9	50.9	45.5	43.13 (<0.001)
	Population density in 2020, inh./km^2	25.9	13.1	11.3	4.5	2.0	6.1	28.31 (<0.001)
	Population in 2020, n	23,382	14,513	17,602	21,216	27,526	104,239	–
	Total population change in 2016–2020, n (%)	−52 (−0.2)	−1458 (−10.0)	−1157 (−6.6)	−2004 (−9.4)	−3628 (−13.2)	−8299 (−7.9)	–
	Total change in the number of jobs in 2016–2020, n (%)	71 (1.4)	−291 (−5.4)	−777 (−9.7)	−821 (−13.5)	−1065 (−14.8)	−2883 (−10.5)	–
Building stock	District heating in 2020, %	4.8	7.6	1.4	0.8	0.8	1.4	3.85 (0.005)
	Electrical heating in 2020, %	55.1	35.6	48.1	37.9	33.4	38.2	23.11 (<0.001)
	Oil heating in 2020, %	7.8	26.0	5.4	7.0	5.6	6.5	16.40 (<0.001)
	Geothermal heating in 2020, %	7.8	2.1	5.0	2.1	1.7	2.8	29.89 (<0.001)
	Average year of construction in 2020	1982	1969	1973	1964	1962	1966	38.95 (<0.001)
	Average price in 2020, €/m^2	1248.1	725.7	794.9	537.9	469.2	600	56.88 (<0.001)
	Change in the average price in 2010–2020, %	−4.6	−5.6	−15.0	−28.6	−34.4	−27.4	1.31 (0.267)
	Change in the amount of building stock in 2016–2020, n	209	12	56	9	−120	166	–

energy consumption costs, which are based on the area's average electricity and heat consumption. In this article, the total energy consumption cost ($T_{i,j}$) in a postcode area is calculated as follows.

$$T_{i,j} = E_{i,j} + H_{i,j}, \quad (1)$$

where $E_{i,j}$ denotes electricity consumption costs and $H_{i,j}$ denotes heat consumption costs in postcode i in month j, respectively. The total energy consumption costs are calculated with monthly statistics because there are large variations in energy consumption in the study region between the seasons.

By definition, the average electricity consumption costs ($E_{i,j}$) in postcode area i for month j is calculated as follows:

$$E_{i,j} = C_{k,I}{}^{*} P_i, \quad (2)$$

where $C_{k,i}$ refers to electricity consumption in month j in postcode area i (kWh), and Pi refers to the price of electricity (kWh/€). Data on the monthly consumption of electricity is extracted from Pohjois-Karjalan Sähkö's database, which contains hourly electricity consumption from almost 65,000 places of use and was further aggregated with the monthly electricity consumption data of 170 postcode areas in the operational region of Pohjois-Karjalan Sähkö Oy. The data also includes electricity consumption as heat.

The price of electricity consumption in postcode area i in month j (Pi, j) (€/kWh) is calculated based on the housing stock by dividing it into apartments and small residential buildings as follows:

$$P_{i,j} = A_i{}^{*} \left(P_{a,j} + Pt_{a,j}\right) + R_i{}^{*} \left(P_{r,j} + Pt_{r,j}\right), \quad (3)$$

where A_i denotes the proportion of the apartments in the total number of residential buildings in the postcode area, $P_{a,j}$ denotes the price of electricity in month j for apartments, R_j denotes the proportion of the small residential buildings in the total number of the residential buildings in the postcode area, and $P_{r,j}$ denotes the price of electricity in month j for small residential houses. $Pt_{r,j}$ and $Pt_{a,j}$ denote the transfer prices of electricity in month j for apartments and small residential houses. The calculation is done separately for apartments and small residential buildings because transfer prices of electricity differ between house types. The monthly electricity prices and transfer tariff parameters were collected from the official statistics [26]. The average heat energy consumption costs ($H_{i,j}$) of the postcode areas were calculated by utilizing the information on the heating systems of residential buildings. The heating systems data is derived from the Building and Dwelling Register (BDR) [27], which contains information about the size of residential houses, their age, and the type of heating system. From this database, it was possible to calculate the average values of the building stock by postcode areas.

The heat energy consumption costs are calculated by summing up the consumption cost of the district heating ($DH_{i,j}$) and oil heating ($OH_{i,j}$) in postcode areas i for month j as follows:

$$H_{i,j} = DH_{i,j} + OH_{i,j}. \quad (4)$$

The consumption cost of the district heat energy is calculated as follows:

$$DH_{i,j} = \sum \left(S_{k,i}{}^{*} Hu_k{}^{*} Pdh_k\right)^{*} M_j, \quad (5)$$

where $S_{k,i}$ denotes the average size of house type k in postcode area i (m^2), and H_{uk} denotes heat usage (kWh/m^2), which was set to 88 kWh/m$_2$ for small residential buildings (terraced and detached houses) and 90 kWh/m$_2$ for apartment buildings. The term Pdh_k denotes the district heat energy price of house type k (€/kWh), which in 2019 was 98.69 €/MWh for detached houses, 90.20 €/MWh for terraced houses, and 85.66 €/MWh for apartments [28]. M_j refers to the monthly proportion of heat energy use from the total annual consumption, estimated from the monthly electricity consumption data. Based on calculations, heat energy consumption as a percentage of total yearly consumption was 22.4 % in January, 7.0 % in April, 0 % in July, and 8.6 % in October. The use of wood as an additional source of heat energy was excluded from the calculation because there are no reliable statistics for its consumption in the postcode areas.

The consumption cost of oil heating ($Oh_{i,j}$) is calculated as follows:

$$OH_{i,j} = \sum \left(S_{k,i}{}^{*} Hu_{k}{}^{*} Poh^{*} B\right)^{*} M_{j}, \tag{6}$$

where Poh refers to the price of domestic oil based on the national monthly statistics on energy prices [22], and B denotes the boiler's efficiency rate. The parameters for B were obtained from the Motiva statistics [29]. The efficiency rates varied from 90 % (boiler acquired since 2010) to 65 % (boiler acquired before the 1970s).

Finally, HEE for postcode areas is calculated from the total energy consumption costs ($T_{i,j}$) by dividing it by the median income (I_j) of the households in the postcode area i as follows:

$$HEE_{i,j} = \left(T_{i,j}/I_{i}\right)^{*} 100. \tag{7}$$

The median income refers to households' disposable monetary income in postcode area i, obtained from the Paavo statistical service [30].

3.2. Mapping temporal-spatial patterns of HEE in postcode areas

The spatial variation of HEE in postcode areas is analyzed with spatial autocorrelation statistics, which describe the distribution of spatial data in a geographical space [31]. In spatially autocorrelated data, the values observed or measured by the spatial units for that variable are not independent, meaning that the value of each observation also reflects the values of the adjacent spatial units, suggesting that the phenomenon under consideration is geographically spread across areas. When spatial autocorrelation is positive, high values of HEE are located geographically close to other high values, and average and low values are similarly clustered together [31]. A negative autocorrelation, in turn, describes a situation in which nearby postcode areas differ considerably more in HEE than randomness would suggest.

Moran's *I* statistic, one of the most common measures of spatial autocorrelation, reveals that HEE is spatially concentrated on postcode areas (Fig. 2). This indicates that energy poverty vulnerability is not independently located in the study region, meaning that it is a spatially autocorrelated phenomenon, and thus, vulnerability is concentrated spatially in the study region. The spatial autocorrelation is highest with small distances as it becomes diluted when the spatial weight matrix's distance parameter increases. There are also remarkable differences between months because spatial autocorrelation is higher in January than in July (Fig. 2). This demonstrates that the extent of the spatial formations increases in the study region during the winter when the total energy consumption is higher.

The local spatial autocorrelation of HEE is analyzed with the LISA (Local Indicator of Spatial Association) index developed by Luc Anselin [32] to map local spatial concentration and learn more about the spatial structure of HEE. The spatial units that deviate from the statistically random spatial distribution are divided into four groups based on the values of the LISA index. Postcode areas in the high-high group (HH) have high positive index values with the surrounding postcode areas, meaning the spatial concentration of high HEE values. Correspondingly, postcode areas in the low-low group (LL) have low negative index values along with their surrounding postcode areas, corresponding to the spatial concentration of relatively low HEE values. In the low-high group (LH) of postcode areas, HEE is lower than in surrounding postcode areas, whereas, in the high-low group (HL), the HEE of the postcode area is higher than in the surrounding postcode areas. When interpreting the results of the local autocorrelation, it should be remembered that the result of each postcode area only applies to the postcode area in the middle of the postcode areas to be analyzed. The postcode areas included in the LISA groups are statistically significant because the occurrence of the observed co-variability in randomly arranged data is very unlikely [33].

3.3. Spatial modeling of the determinants of HEE in postcode areas

The spatial regression models are fitted with the data from January, April, July, and October to understand the temporal variation of HEE in postcode areas and potential energy poverty vulnerability. The regression model used in the analysis can be written as follows:

$$HEE_{i,j} = \alpha + \beta Pop_{i} + \beta Loc_{i} + \beta Se_{i} + \beta H_{i} + \varepsilon, \tag{8}$$

where the household energy expenditure ($HEE_{i,j}$) in postcode area i at month j is explained by row vectors that describe the variables used to demonstrate the population structure and density (Pop_i), location (Loc_i), socioeconomic status (Se_i), and housing characteristics (H_i) of the postcode areas. The selection of these variables is based on the previous literature, in which these variables were considered effective

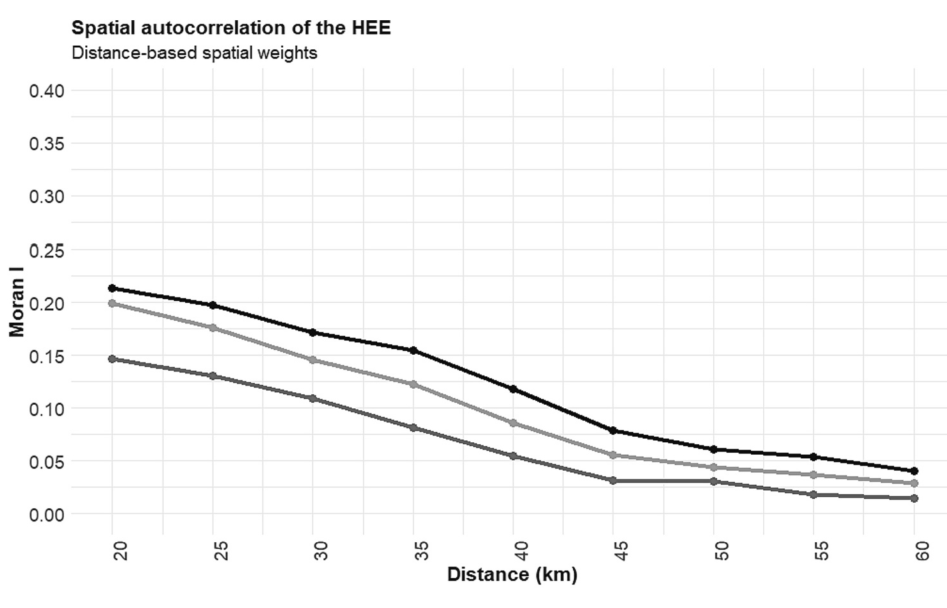

Fig. 2. Spatial autocorrelation of the HEE with various distance-based spatial weight matrices.

determinants of energy poverty [12,15]. All variables in the row vectors used in the stepwise Akaike information criteria selection are collected and described in Appendix 1. The stepwise selection function was used from R software's olsrr package.

The determinants of HEE are modeled with spatial regression analysis as the spatial autocorrelation of HEE is significant. If spatial modeling were not used, the regression coefficients of the determinants could be either biased or ineffective [34], which might lead to wrong interpretations and conclusions of the associations between HEE and determinants. Regression models were estimated with spatial autoregression models (SAR). Based on the spatial dependence diagnostics, the SAR model is estimated using the spatial error model, where the error terms across different spatial units are correlated. The spatial error model is defined as follows:

$$\mathrm{Y} = X\beta + \mathrm{e}, \text{ where } \mathrm{e} = \lambda \mathrm{We} + \xi, \tag{9}$$

where λ is the spatial autoregressive coefficient for the error lag, We refers to the spatially lagged error term, and ξ is an uncorrelated and homoskedastic error term. Spatial error dependence may be interpreted as a nuisance (and the parameter λ as a nuisance parameter) in the sense that it reflects spatial autocorrelation in measurement errors or in variables that are otherwise not crucial to the model. The spatial error models were fitted using R's spdep package.

4. Results

4.1. Mapping the variation in energy consumption and energy poverty vulnerability

The spatial variation of HEE in postcode areas is greatest in more remote areas, which suffer from lower average household income and older houses with energy-inefficient heating. The temporal variation of HEE is high between summer and winter when heating is needed most. In July, there are only a few postcode areas where HEE exceeds the 10 % threshold, while in January, only a few areas do not exceed the threshold. Looking at the whole year average, most areas that exceed the threshold are remotely located in the study regions' border areas and far from urban centers. Yearly average HEE shows that most areas in the study region still spend <10 % of household income on energy during the year, and energy poverty vulnerability remains low (Fig. 3).

In addition to spatial variation, the temporal variation of HEE is remarkable during the year (Fig. 4, Table 2), which indicates that energy poverty vulnerability in postcode areas fluctuates during the year. HEE is at its highest in January, during the winter, and energy poverty vulnerability affects most of the population. In summer, HEE and energy poverty vulnerability are lower than in winter, affecting a significantly smaller part of the study region's population. In the study region, approximately 353 inhabitants were vulnerable to energy poverty in July, whereas in January, the corresponding number was 30,731 inhabitants based on the LIHC measure (Table 2). These figures demonstrate that vulnerability to energy poverty is strongly associated with the time of the year.

In urban-rural typology, the differences in HEE and proportion of the people vulnerable to energy poverty are evident, especially in the winter (Table 2), when the difference between urban areas (and rural areas close to urban areas) increases in relation to other rural categories (Fig. 4). This reveals that energy poverty vulnerability increases more in rural areas than in urban areas in winter. The impact of the urban-rural typology on vulnerability is also evident in July because only residents of the core rural and sparsely populated rural areas are then vulnerable to energy poverty, as the differences in average HEE values in postcode areas are weakly statistically significant (Table 2). The highest HEE values and highest vulnerability to energy poverty are found in January in rural areas' local centers and sparsely populated and core rural areas; the lowest HEE values are observed in urban areas and rural areas close to urban areas (Table 2). The extent of vulnerability in winter is illustrated by the LIHC measure, according to which, in January, 50 % of the population is vulnerable to energy poverty in local centers in rural areas. Energy poverty vulnerability is also high in the core rural areas, at 39.6 % of the population, and sparsely populated rural areas at 41.6 % (Table 2). The difference between the highest average HEE values (local centers in rural areas) and the lowest (rural areas close to urban areas) is 51 % (Table 2).

4.2. Spatial patterns of energy poverty vulnerability

The spatial structure and variation of HEE in postcode areas are further analyzed with the LISA index (Fig. 5), which reveals the spatial

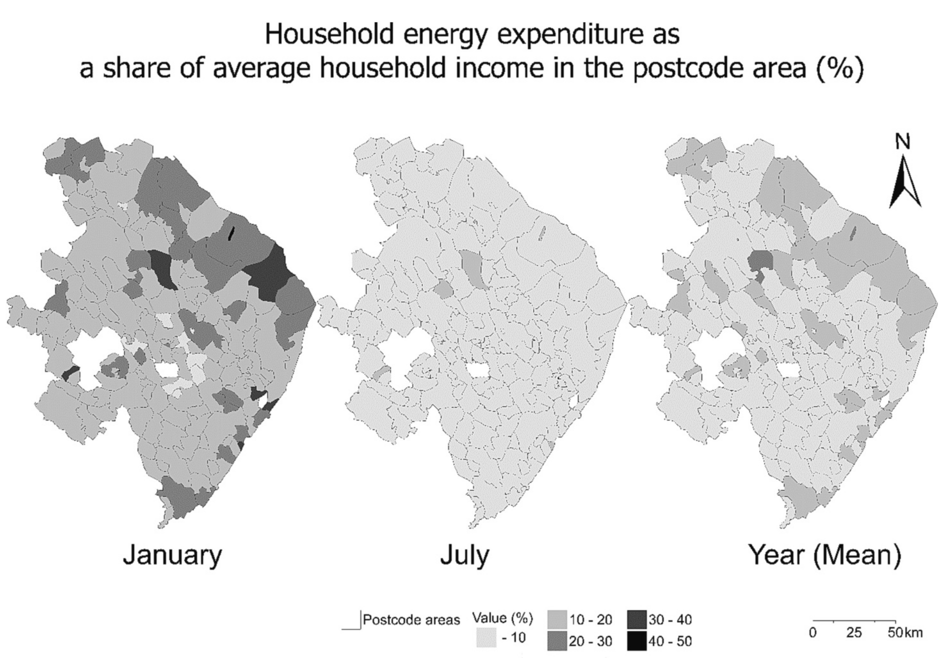

Fig. 3. Household energy expenditure as a share of average household income by postcode area. Temporal variation is high between the summer and winter months.

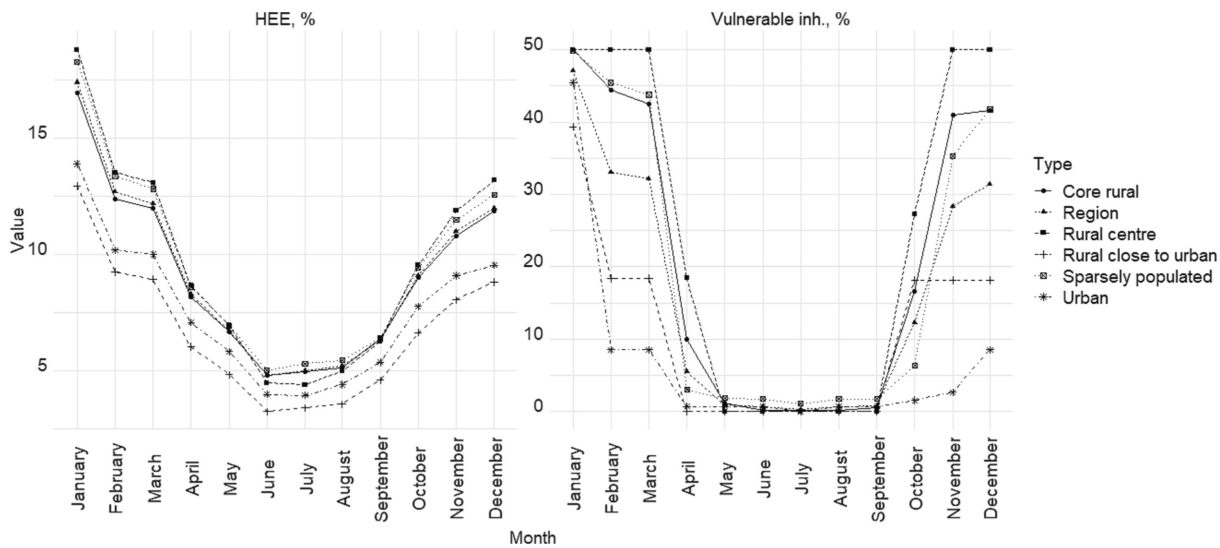

Fig. 4. Temporal variation of the HEE and potential energy poverty in the study region.

Table 2
HEE and amount of population vulnerable to energy poverty by urban-rural categories.

Variable	Month	Urban-rural category					F-test	
		Urban areas	Local centers in rural areas	Rural areas close to urban areas	Core rural areas	Sparsely populated rural areas	F statistics	p-Value
HEE, % (€)	January	13.2 (478.9)	18.4 (411.8)	12.2 (386.4)	16.1 (432.5)	17.2 (418.3)	3.896 (1.353)	0.005 (0.253)
	July	3.9 (139.2)	4.3 (96.5)	3.3 (102.4)	4.8 (126.7)	5.2 (122.1)	2.201 (0.896)	0.071 (0.468)
	Whole year	7.4 (3097.1)	9.5 (2505.1)	6.5 (2340.7)	8.9 (2715.7)	9.4 (2582.4)	2.829 (1.379)	0.026 (0.243)
Inhabitants vulnerable to energy poverty based on the 10 % rule, n (%)	January	10,620 (45.4)	7256 (50)	6929 (39.4)	10,608 (50)	13,710 (49.8)	–	–
	July	0 (0)	0 (0)	0 (0)	46 (0.2)	307 (1.1)	–	–
	Whole year	206 (0.8)	3951 (27.2)	1983 (11.3)	2232 (10.5)	1864 (6.8)	–	–
Inhabitants vulnerable to energy poverty based on the LIHC measure, n (%)	January	33 (0.1)	7256 (50)	3594 (20.4)	8397 (39.6)	11,451 (41.6)	–	–
	July	0 (0)	0 (0)	0 (0)	46 (0.2)	307 (1.1)	–	–
	Whole year	0 (0)	0 (0)	1301 (7.4)	1389 (6.5)	897 (3.3)	–	–

formations and tendency to energy poverty vulnerability at the local level. Therefore, the regional structure contains spatial formations with higher and lower energy poverty vulnerabilities. The LL cluster with low vulnerability is concentrated around Joensuu City, whereas the HH cluster with high vulnerability is dispersed throughout the study region. Spatial outliers, LH and HL clusters, are mostly located next to the larger spatial formations of HH and LL clusters. The spatial clusters seem to be constant over time, as most are permanent in July and January (Fig. 5), and the differences in the descriptive statistics between January and July are only minor (Table 3). These statistics underline that in the study region, the relative differences in vulnerability between postcode areas seem to be spatially and temporally permanent, and vulnerability expands to local concentrations; thus, vulnerability does not apply only to individual postcode areas.

Descriptive statistics from the LISA clusters from January show that the most common spatial cluster is "not significant," which means that around two-thirds of the population in the study region lives in postcode areas where there is no spatial concentration nor spatial dependency of HEE, indicating that spatial formations in energy poverty vulnerability are rare at the regional level (Table 3). The second most common spatial formation is the LL cluster, which indicates the spatial concentration of low vulnerability to energy poverty. This formation covers about a quarter of the population and about 15 % of the postcode areas in the study region (Table 3). The HH cluster is the third most common spatial cluster, representing high vulnerability to energy poverty. This formation covers about 6 % of the population and about 5 % of the postcode areas in the study region. Spatial outliers, LH and HL clusters, are rare as they cover only about 5 % of the population and about 8 % of the postcode areas in the study region (Table 3).

The differences in HEE between spatial formations are remarkable. For instance, in the HH cluster, HEE is 2.5 times higher in January than in the LL cluster, showing the depth of vulnerability to energy poverty between spatial formations (Table 3). The HH spatial cluster's energy poverty vulnerability is illustrated by the average HEE value, which is much higher in January than the corresponding values in rural categories. Overall, the differences between spatial formations are greater than the differences between the urban and rural categories. Energy poverty vulnerability is thus more pronounced in the spatial structure than in the urban-rural typology, although it was more common in rural areas.

According to Fisher's exact test, there seems to be a connection between the spatial formations of HEE and the urban-rural classification (p-value <0.001). Based on the cross-tabulation, the HH cluster is more common in core and sparsely populated rural areas than the LL cluster, which is commoner than expected in the study region's urban areas. For example, in January, most of the HH clusters were in core rural areas

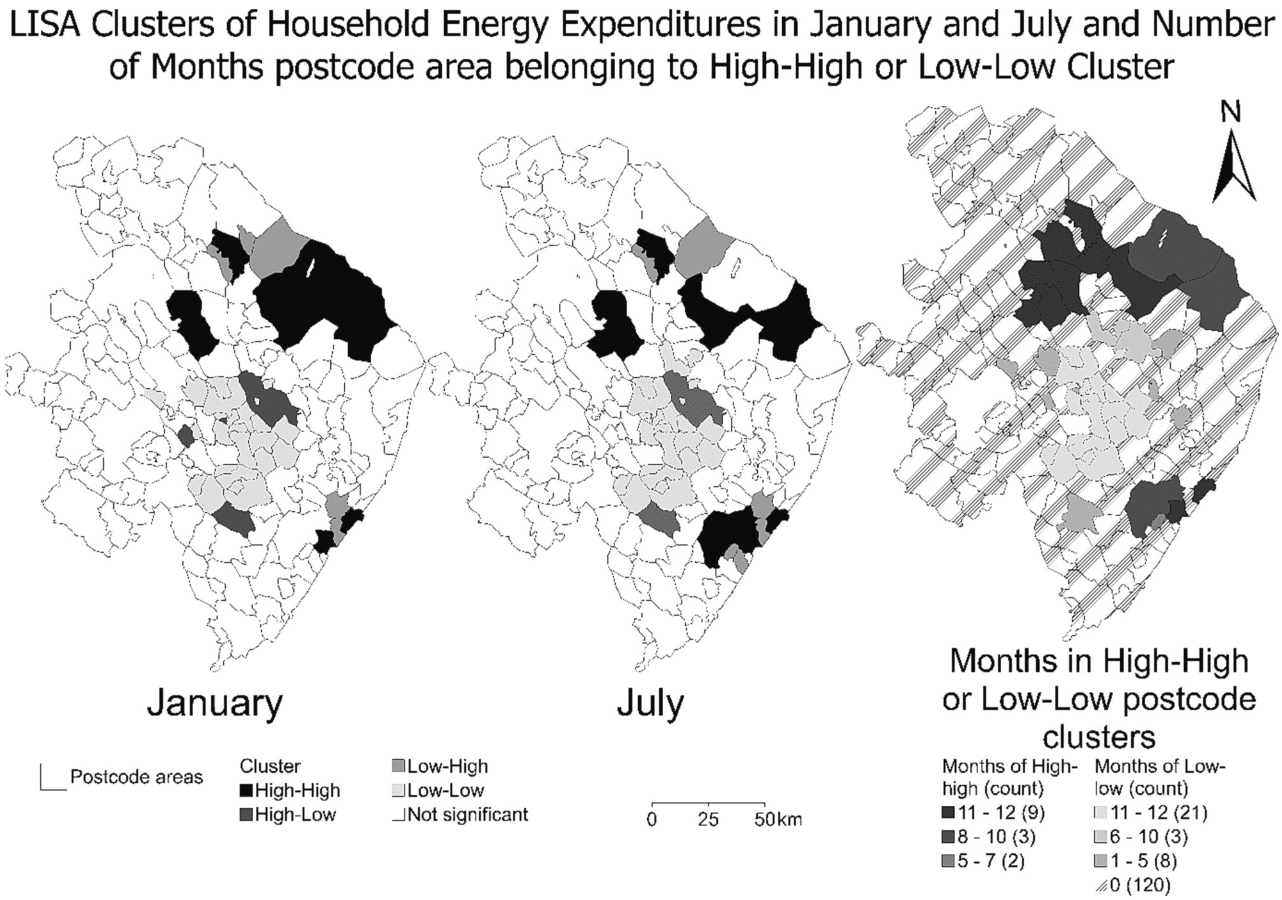

Fig. 5. LISA HEE clusters by postcode area and the number of months postcode area belonged to a High-High or Low-Low cluster in a year.

(five) and sparsely populated rural areas (seven), and most of the LL clusters were in urban (seven) and rural areas close to urban areas (11). The finding suggests that spatial autocorrelation widens urban-rural differences, as high vulnerability to energy poverty appears to be also spatially concentrated with higher risk around the rural postcode areas.

4.3. Modeling the risks of energy poverty vulnerability

The determinants for energy poverty vulnerability in postcode areas in different months are analyzed with spatial regression modeling. The results from the models are collected in Table 4, showing that the coefficients of six independent variables are significant (p-value <0.05). All the estimated coefficients except population density are positively signed, indicating that higher values of all variables are associated with higher levels of HEE and, thus, higher energy poverty vulnerability. Variables describing the housing characteristics, such as the average age of buildings or type of heating systems, were not significant in the regression models and were left out of the analysis.

The regression results confirm earlier findings highlighting the association between energy poverty vulnerability and low income levels. Low income has a positive regression coefficient every month (Table 4), meaning that areas with high low-income rates are highly vulnerable to energy poverty. The importance of socioeconomic status is also supported by the regression coefficient of rental apartments, which indicates that an increasing proportion of rental houses in building stock is associated with increasing energy poverty vulnerability due to increased HEE (Table 4).

Energy poverty vulnerability is also related to housing characteristics. The average price of apartments has a positive association with the expected July HEE (Table 4), which means that a high average price increases energy poverty vulnerability while a low average price decreases it. This observation can be explained by net migration because, among other things, pensioners and students have been moving to areas with new apartments. Therefore, a proportionally higher share of revenue is spent on energy costs, leading to higher energy poverty vulnerability. Increasing living space per inhabitant also has a positive regression coefficient every month and underlines the role of housing characteristics on energy poverty vulnerability (Table 4). This variable indicates that individuals living in large houses are at risk for high HEE due to increased energy consumption required for heating.

Urban and rural characteristics are indirectly seen in the regression coefficients. Based on the negative regression coefficients every month, low population density is associated with higher energy poverty vulnerability (Table 4). Thus, increasing population density decreases the HEE of the postcode areas. Distance to a grocery market positively correlates with HEE only in January, when the increasing distance to the closest market also increases HEE in the postcode areas (Table 4). These observations indicate that rural areas with low population density and poor accessibility to services have a higher energy poverty vulnerability than urban areas. This finding supports earlier findings from the urban-rural categories where high HEE rates were observed in sparsely populated and core rural areas (see Table 2).

5. Discussion

Due to natural causes, energy poverty seems to be associated with strong temporal variability. During the winter, the population vulnerable to energy poverty increases; for instance, in January, 29.5 % of the population in the study region was vulnerable to energy poverty. In July, when energy consumption for heating is less, the corresponding proportion was only 0.3 % of the population. This temporal variability also means that traditional renewable energy sources for alleviating energy

Table 3
Descriptive statistics from the LISA clusters.

Month	Variable	High-High (HH)	Low-Low (LL)	Low-High (LH)	High-Low (HL)	Not significant
January	Population, n (%)	6323 (6.0)	23,943 (22.9)	2158 (2.1)	3409 (3.3)	68,716 (65.7)
	HEE, %	28.7	11.4	13.0	19.8	16.1
	Number of areas, n	9	25	9	4	120
	Surface area, %	10.6	7.4	2.9	2.2	76.8
	Inhabitants living under potential energy poverty based on the 10 % rule, n (%)	6658 (100)	18,453 (77.5)	1293 (100)	3409 (100)	68,715 (99.0)
July	Population, n (%)	9214 (8.8)	23,592 (22.6)	1388 (1.3)	2996 (2.9)	67,359 (64.4)
	HEE, %	6.0	3.2	3.8	5.0	4.9
	Number of areas, n	7	25	7	2	126
	Surface area, %	9.1	7.3	3.0	2.0	78.6
	Inhabitants living under potential energy poverty based on the 10 % rule, n (%)	133 (1.4)	0 (0)	0 (0)	0 (0)	418 (0.6)
Whole year	Population, n (%)	7284 (7.0)	23,171 (22.1)	2256 (2.2)	3444 (3.3)	68,394 (65.4)
	HEE, %	14.2	5.9	6.9	10.7	8.6
	Number of areas, n	13	22	8	5	119
	Surface area, %	16.0	7.5	3.8	2.2	70.5
	Inhabitants living under potential energy poverty based on the 10 % rule, n (%)	9156 (71.4)	0 (0)	0 (0)	3014 (88.4)	8378 (13.5)

poverty, i.e., small-scale combustion of chopped firewood for household heating, remain essential in rural North Karelia. Zhao, Dong, Dong & Shahbaz [35] notice that studies on energy poverty alleviation through renewable energy focus mainly on the energy poverty reduction effect of solar photovoltaic energy and the role of other renewables and the overall production system in energy poverty alleviation are less studied. According to our experience in the RE sector, biomass is essential in North Karelia for reducing electricity use for heating, but investments in solar PV are also growing fast.

The results of the study demonstrated that the urban-rural dimension seems relevant when studying energy poverty as well as detecting spatial formations. The findings support earlier research in which rural areas appeared more vulnerable to energy price increases than urban areas, while the experience of energy poverty in urban areas is longer with a higher probability of persistence [12]. The higher vulnerability of the rural areas, except rural areas close to urban areas, was also evident from the results, as in January, 88 % of the population vulnerable to energy poverty lived in local rural centers, core rural areas, or sparsely populated rural areas. Only 12 % of the vulnerable population lived in urban areas or rural areas close to urban areas.

The spatial clustering of HEE was evident, and the spatial clusters were also temporally permanent and covered geographically extensive, sparsely populated areas. The spatial clustering of energy poverty vulnerability was problematic because the differences between HH and LL clusters were deeper than those between urban and rural categories. The finding demonstrates that spatial structures have emerged in the study region in which energy poverty vulnerability has accumulated. The most optimistic finding was that the most common spatial cluster was “not significant,” indicating that around two-thirds of the population lived in postcode areas where no spatial clustering existed in their neighborhood. The spatial clusters and urban-rural categories had an association as, for instance, most of the HH clusters were in the core or sparsely populated rural areas.

Regression modeling revealed no major differences between months in determinants of HEE. Nevertheless, it must be stated that although the location of residence and the characteristics of the building stock affected energy poverty vulnerability, the main determinant of vulnerability was the low socioeconomic status of certain postcode areas, as is also noted in the systematic literature review [13]. Energy poverty can also be associated with transport poverty, which refers, among other aspects, to the inability to meet the cost of transport [36]. The results could be very different, and the differences between urban and rural areas or spatial clusters would probably be larger if transport poverty were also considered, as infrastructure is poorer and distances to services are farther in rural areas than in urban areas, simultaneously increasing vulnerability to energy and transport poverty [13]. The regression modeling weakly supported this assumption as poor accessibility increased HEE and vulnerability to energy poverty in postcode areas.

6. Conclusions

The geographic distribution of energy poverty vulnerability has not been extensively studied at small area levels such as postcode areas. The results of this study indicate substantial temporal and spatial variations in HEE and energy poverty vulnerability. The results suggest that, like the various phenomena of regional development, energy poverty appears to be spatially concentrated, and urban-rural differences are clearly verifiable. Spatial analysis, which detected vulnerability determinants, indicated that the main reason for energy poverty is related to the socioeconomic status of postcode areas, and the characteristics of building stock and location also impacted HEE.

The link between regional development and energy poverty vulnerability appears to be due in the short term to changes in the socioeconomic status of postcode areas through negative net migration and population development, but in the longer term, the link also manifests itself in deteriorating building stocks in postcode areas creating a vicious cycle of spatial development. For instance, reliance on expensive heating fuels and disinvested and inefficient housing markets seem to impact energy poverty vulnerability in rural areas more than in urban areas. Rural areas, therefore, appear to be more vulnerable to energy poverty and have more risk factors due to the negative effects of economic restructuring and regional development, as noted by O'Sullivan et al. [37], predisposing them to energy poverty vulnerability more than urban areas. However, the results do not mean energy poverty is only a rural problem. The findings are consistent with results from a study that found, based on extensive literature, that the highest level of energy vulnerability is among households that face a combination of multiple socio-demographic disadvantages alongside relative spatial peripheralization [13].

Based on the findings of this study, remote rural areas have greater vulnerability to long-term energy poverty than urban areas because, for example, house price trends make it difficult to make new energy investments and get bank loans since the value of residential buildings has fallen sharply. Therefore, the transition and use of new renewable energy sources can even strengthen the polarization of energy poverty vulnerability because investment capacity varies between areas and might be lowest in areas with the lowest housing prices. Regional development and its association with housing prices are already reflected to some extent in the difficulty of obtaining loans in rural areas,

Table 4
Results of the spatial error models explaining energy consumption costs as a percentage of disposable income in different months in 2019.

Dependent variable: energy consumption costs as a percentage of disposable income					
Independent variables	January	April	July	October	Whole year
sqrt(rental apartments (%))	**0.153*****	**0.104*****	**0.054****	**0.121*****	**0.115*****
	(0.027)	**(0.026)**	**(0.026)**	**(0.026)**	**(0.025)**
Low income rate (%)	**0.028*****	**0.020*****	**0.019*****	**0.022*****	**0.021*****
	(0.006)	**(0.006)**	**(0.006)**	**(0.006)**	**(0.006)**
Average price €/m^2	**0.001****	**0.0004***	0.0004	**0.001***	**0.0005***
	(0.0003)	**(0.0003)**	(0.0003)	**(0.0003)**	**(0.0003)**
Average age of apartments	−0.010	−0.004	−0.001	−0.005	−0.004
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Average living space (m^2/inh.)	**0.026*****	**0.015***	**0.013***	**0.018****	**0.019****
	(0.008)	**(0.008)**	**(0.008)**	**(0.008)**	**(0.008)**
Population density (inh./km^2)	**−0.011****	**−0.010***	**−0.010****	**−0.011****	**−0.011****
	(0.005)	**(0.005)**	**(0.005)**	**(0.005)**	**(0.005)**
Distance to closest grocery shop (km)	**0.005***	0.003	0.002	0.003	0.003
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
Constant	20,830	9569	2260	9538	8484
	(14,435)	(13,685)	(13,596)	(13,893)	(13,441)
Observations	153	153	153	153	153
Log likelihood	−89.899	−81.561	−80.324	−83.807	−80.023
Sigma^2	0.184	0.165	0.165	0.170	0.163
Akaike Inf. Crit.	199.799	183.121	180.647	187.614	180.045
Wald test (df = 1)	17.404***	14.696***	7.658***	13.651***	13.162*** (df = 1)
LR test (df = 1)	12.188***	10.910***	5.632**	10.277***	9.640*** (df = 1)

Note.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

which boosts the depopulation of rural regions [24]. Moreover, high temporal variations and exceptionally high energy costs in winter can be one factor that increases seasonal housing in rural areas and thus strengthens the decrease of permanent housing in rural areas. In Finland, the seasonal population has increased in sparsely populated rural areas due to growth in the number of second homes during the last decades [38], and some properties used as summer cottages are former residential buildings.

Energy poverty is a complex phenomenon requiring solutions such as shifting from fossil energy systems to renewables and structural renovations of public and private buildings [e.g., [39]]. One solution that requires investment capacity and social innovation is the establishment of citizen-led energy communities to create shared benefits through production allocation for community members [40]. In Finland, some energy companies have started offering contracts only for customers in their operating region, providing prices below the market average and at reasonable levels for households. Contract strategies and energy pricing mechanisms could be further investigated as one measure to protect households from energy poverty and peaking energy prices, especially during the winter when high demand creates volatility in electricity prices. Aggravating energy poverty gradually damages the economy and social quality [35]. Those vulnerable to energy poverty are those most unlikely to have the capacity to invest in energy efficiency or modern energy systems due to falling property values, especially in core and sparsely populated rural areas. Therefore, new energy community models and social enterprises could be developed, considering energy transition, energy poverty alleviation, and inclusion of those most vulnerable to peaking energy prices.

Energy poverty in Finland has not been high on the political agenda despite the extreme socioeconomic, urban-rural, and spatial clustering of the problem. However, from a policy perspective, this article has three key messages. First, spatial analysis can facilitate an understanding of the geographical development processes in energy poverty. Urban-rural targeting alone is not likely an effective means of allocating policies because most problematic areas were spatially clustered and dependent. Second, extra attention needs to be paid to energy poverty vulnerability in rural areas in periods of urban-centric regional development. If the structural change in the economy continues with the current regional priorities and observed development trends, the differences in energy poverty vulnerability between regions are likely to deepen. Third, monitoring not only levels of energy poverty but also the temporal and spatial dynamics of energy poverty is important to ensure the effectiveness of policy mechanisms. Public policy decisions should be directed to affect when and where energy poverty vulnerability is the most significant, i.e., during winter, by a holistic and dynamic approach considering decentralized energy investments, infrastructure, and provisioning systems without excluding or marginalizing peripheral rural areas. This aim is also recognized in the Finnish Rural Policy Programme, which promotes decentralized bioenergy production [41].

Finally, a few critical remarks and limitations of the research design should be considered while interpreting the results. First, the results in postcode areas are generalized based on median values, and therefore, the problems of ecological fallacy in predicting energy poverty vulnerability are present in the results. Second, the heat energy usage calculation was based on average estimates, which overlooks that households can reduce their energy consumption if disposable income decreases. Therefore, the results describe the temporal and spatial variation of energy poverty vulnerability as a geographical phenomenon. Nevertheless, the results are important because there are few similar spatial analyses since data on electricity consumption is not generally available at small spatial scales. Third, the examination of energy poverty vulnerability focused only on electricity consumption, but the accentuated regional differences also highlighted the need to combine energy poverty analysis with transport poverty analysis. Fourth, the relationship between energy poverty vulnerability and regional development must be continuously monitored, as the emerging seeds of spatial inequality are already found in the regional structure as well as in the urban-rural divide.

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CRediT authorship contribution statement

Olli Lehtonen: Writing – review & editing, Writing – original draft, Software, Project administration, Methodology, Formal analysis, Data curation. **Antti Petteri Hiltunen:** Writing – original draft, Visualization. **Lasse Okkonen:** Writing – review & editing, Writing – original draft, Conceptualization. **Kim Blomqvist:** Writing – original draft, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix 1. Variables used in the regression modeling

Variable	Row vector	Description	Data source	Year
Pensioner	Population	Percentage of the population that receives a pension (%).	Paavo	2020
Population density	Population	Population density (inh./km^2).	Paavo	2020
Average age of inhabitants	Population	The average age by area.	Paavo	2020
High education	Population	Percentage of the inhabitants with university/tertiary-level degrees, doctoral degrees, or equivalent (%).	Paavo	2020
Low education	Population	Percentage of the inhabitants that have no qualifications other than basic or qualifications unknown (%)	Paavo	2020
Low income	Socioeconomic status	Percentage of low-income inhabitants (%). According to the Paavo definition, households in the lowest income category are in the lowest 1–2 decilies of earnings.	Paavo	2020
Unemployment	Socioeconomic status	Percentage of the population aged between 15 and 65 receiving unemployment benefits as their main source of income.	Paavo	2020
Building age	Housing	*Building age* is the median age of residential or partially residential buildings in neighborhoods.	Building and Dwelling Register	2019
Price of dwellings	Housing	Average price of residential buildings (€/m^2).	Reaktor	2019
Change in price of dwellings	Housing	Change in the price of residential buildings between 2010 and 2019.	Reaktor	2019
Living space	Housing	The average size of residential buildings.	Building and Dwelling Register	2019
One-person households	Housing	Percentage of one-person households.	Paavo	2020
Households living in rented dwellings	Housing	Households with rented dwellings are households whose tenure status is rental, subsidized, interest subsidized rental, and right of occupancy dwellings.	Paavo	2020
Distance to schools	Location	Distance to the nearest primary school (km).	Own calculations, Statistics Finland	2020
Distance to markets	Location	Distance to the nearest market (km).	Own calculations, YKR database	2020
Distance to supermarket	Location	Distance to the nearest supermarket (km).	Own calculations, YKR database	2020
Availability of broadband	Location	Percentage of the inhabitants having access to broadband internet (%).	Own calculations, Traficom	2020
Rural areas	Location	Dummy variable indicating belonging to the rural classes.	SYKE	2018

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