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Mapping Energy Poverty in Lombardy Using a Fuzzy Multidimensional Index *

Raffaele Miniaci† Alessio Pirola ‡ Nicola Pontarollo § Massimiliano Rizzati ¶

This version: November 26, 2025

Abstract

The ecological transition and decarbonization agenda have brought energy poverty into sharp focus. However, despite growing policy and academic attention, consensus on its definition or measurement remains elusive. This paper proposes a novel multidimensional energy poverty index based on a fuzzy set approach (fMEPI), addressing three key principles: the multifactorial nature of energy poverty, the limitations of binary classifications, and the need for indicators computable at local scales. Drawing on administrative, census, and modelled data, the index integrates five dimensions: housing conditions and energy efficiency, residential energy consumption, financial capacity, climate conditions, and energy-related needs. Applied to the Lombardy region (Italy), results reveal that vulnerability is concentrated in mountainous and hilly areas, and that large municipalities exhibit significant intra-urban heterogeneity. The proposed methodology offers a practical tool for regional and local authorities to design and target policies against energy poverty.

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†University of Brescia, raffaele.miniaci@unibs.it.

‡University of Brescia, alessio.pirola@unibs.it.

§University of Brescia, nicola.pontarollo@unibs.it.

¶University of Brescia, massimilano.rizzati@unibs.it.

1 Introduction

The debate surrounding the ecological transition and decarbonization, compounded first by the COVID-19 pandemic and later by the Russian-Ukrainian conflict, has increasingly highlighted concerns about energy poverty—defined as households' difficulty in affording essential energy services. Within the European Union, these concerns prompted the European Commission (2020) to issue explicit recommendations: to "assess the distributional effects of the energy transition"; to "develop all policies to tackle energy poverty on the basis of meaningful and accountable processes of public participation"; and to "design measures to address energy poverty through close cooperation among all levels of administration," particularly regional and local authorities.

The question of which policies are most effective in addressing energy poverty remains highly discussed across both the Global North and Global South. Recent studies examine this issue from multiple perspectives: for instance, Adams et al. (2024) focus on the U.S.; Heller et al. (2025) compare European and U.S. experiences; Rotmann et al. (2025) provide a broader international outlook; and Wuebben et al. (2025) examine policy design in South America.

Despite the attention from academics, public opinion and policy makers, there is no consensus on the definition of energy poverty, let alone on how to measure it. This paper contributes to the ongoing debate by proposing a novel energy poverty indicator that recognises three fundamental aspects. First, energy poverty, like other forms of deprivation, is the outcome of the interaction of multiple factors. Secondly, in the presence of a nuanced concept for which there is no widespread agreement on its definition, adopting a binary classification (poor/not poor) may be overly reductive and misleading. Finally, to ensure practical relevance for regional and local authorities, the indicator should be computable with available data and at the appropriate spatial granularity to design and monitor local policies addressing energy poverty.

Given these three premises, we employ the fuzzy set approach to multidimensional poverty measurement (Lemmi and Betti, 2006) to develop a multidimensional energy poverty index that exploits administrative, census and modelled data available (or estimable) for small-scale areas. We apply this index to Lombardy, a NUTS-2 region in northern Italy.

Lombardy, with 10 million inhabitants[1] in 2024 across approximately 1,500 municipalities, is more populous than many European countries. Half of its population lives in the

[1] https://ec.europa.eu/eurostat/databrowser/view/demo_r_d2jan/default/table?lang=en&category=reg.reg_dem.reg_dempoar

Figure 1: Map of Lombardy, highlighting orography and main urban areas. Source: : https://www.italiadascoprire.net/regioni-italiane/italia-settentrionale/lombardia/mappa-lombardia.html

western portion, including Milan's metropolitan area; the remaining part is dispersed from the Alps to the Po Valley and between Lakes Como and Garda, with numerous sparsely populated areas (see Figure 1). The region's climate varies from Alpine to temperate sub-continental (Fratianni and Acquaotta, 2017). It is Italy's wealthiest region, with a 2023 GDP of €490 billion[2] —comparable to that of Austria or Ireland and exceeding that of Denmark or Portugal. Urban and lakeside areas are the richest, while mountain areas have faced depopulation since the 1980s (Emanuel, 2019). Immigrants account for 12 percent of residents[3], mainly in cities and plains. The Italian Observatory on Energy Poverty (OIPE) estimates that in 2023, 7.2 percent of Lombard households were energy-poor, below the national average of 9 percent (Osservatorio Italiano sulla Povertà Energetica (OIPE), 2024). Its size, climate and socio-economic diversity make Lombardy an emblematic case, offering insights transferable to other territories.

To develop our indicator, we combine information from a variety of sources: cartographic data; the Energy Performance Certificates (EPCs) registry; population and housing censuses, Ministry of Finance and Revenue Agency records; and large-scale models for climate and

[2] https://ec.europa.eu/eurostat/databrowser/view/nama_10r_2gdp/default/table?lang=en&category=reg.reg_eco10.reg_eco10gdp

[3] https://esploradati.istat.it/databrowser/#/it/dw/categories/IT1,POP,1.0/POP_FOREIGNIM/DCIS_POPSTRRES1/IT1,29_7_DF_DCIS_POPSTRRES1_1,1.0

land use data. We additionally use simulations of residential buildings' energy demand and renovation costs, which combine available information, physical models and relevant regulations.

Informed by the literature, the index considers five dimensions: housing conditions and energy efficiency; residential energy consumption; financial capacity; climate conditions and energy-related needs. The analysis shows that very rarely are areas vulnerable in all five domains. For instance, areas with poorer housing conditions and higher residential energy consumption are often those with better financial capacity. The overall multidimensional energy poverty index is the highest in the northern mountainous areas and the hilly areas to the southwest, identifying these predominantly rural zones of Lombardy as the most vulnerable. Interestingly, the granularity of the results also shows that contiguous areas in large municipalities as Milan can be noticeably heterogeneous.

We conduct a policy simulation from the perspective of a cost-minimising policymaker seeking to reduce CO2 emissions of the residential sector. Using an engineering model to estimate building-level renovation costs in our region of reference, we account for the heterogeneity in costs arising from differences in building characteristics such as age, size, and construction type. Our findings indicate that the areas prioritised for intervention do not always coincide with those at risk of energy poverty as identified by the fMEPI. This suggests that purely cost-efficient climate policies may raise distributional concerns, potentially bypassing the most vulnerable households in favour of areas where abatement is cheaper to achieve.

The paper is organised as follows: Section 2 provides a (non-exhaustive) literature review on the alternative approaches to the measurement of energy poverty in high-income countries. Section 3 illustrates the rationale of the proposed multidimensional energy poverty index based on a fuzzy set approach (fMEPI); Section 4 describes the dimensions, the variables and the data, which produce the indices used in Section 5 for the spatial analysis of energy poverty in Lombardy. Section 6 employs the fMEPI to evaluate whether cost-effective policies aimed at reducing CO2 emissions in the residential sector also affect regions that are vulnerable to energy poverty. Section 7 concludes the paper with a brief discussion on the potential use of the fMEPI for policy purposes.

2 Literature Review

There exists an extensive body of literature on how to define and appropriately measure energy poverty. For the concept of energy poverty to be relevant in policy terms, its definition must be context-specific. In limited-resource countries, the primary concern is the lack of access to modern energy sources, whereas in richer countries, where access to energy services is nearly universal, the focus shifts toward issues of affordability. The concept is also context-specific in terms of scope: policymakers and scholars need to decide which energy services are appropriate to be considered. For instance, whether to consider energy consumption for transport in addition to that for housing, and among the latter, which uses should be counted (e.g., only heating or heating and cooling).

There is broad agreement that energy poverty—like most forms of poverty and deprivation—arises from multiple, interconnected factors. Focusing on energy poverty related to housing services, Robinson et al. (2019) identify several key determinants: household characteristics (such as financial capacity and energy-related needs and practices); housing conditions (including the energy efficiency of dwellings and housing precarity); market conditions (which shape energy prices and access to suitable fuel and energy services); and the strength of the social safety net (both social networks and welfare state support).

Unidimensional energy poverty indicators condense the combined effects of these factors into a dichotomous classification (poor/not poor) based on a single variable. This variable can refer to an objectively measurable aspect (such as expenditure or income) or a subjective one (such as perceived living comfort).

Since Boardman's seminal work (Boardman, 1991) unidimensional income (or expenditure) based indicators have become the standard tool for monitoring energy poverty in high-income countries, both in academic research (e.g., Miniaci et al. (2014); Primc et al. (2019a)) and policy documents (e.g. Hills (2012); Ministry of Economic Development et al. (2019)). These indices have strengths: they are usually clearly defined, objective, easy to communicate and can be estimated from official survey data. However, they might prove to be excessively reductionist, often overlooking that households may under-consume to limit financial strain, leading to "hidden" energy poverty. See Faiella and Lavecchia (2015) and Cong et al. (2022) for alternative approaches to address this issue.

Unidimensional subjective indicators are also widely used. For instance, the European Commission uses the percentage of Europeans unable to keep their homes adequately warm as a measure of energy poverty.[4] However, Thomson and Snell (2013) highlight that such "consensual measures" of energy poverty are influenced by the heterogeneity of the individual perceptions and the social norms that shape what is considered an acceptable living condition. As a result, measures that appear to be intuitive and interpretable are, in practice, difficult to interpret and of limited value for policy purposes. An alternative approach to measuring energy poverty adopts a fundamentally different stance on the coexistence of the multiple factors that determine it. The multidimensional energy poverty indices (MEPIs) first identify the various dimensions of the phenomenon, then find a suitable representation for each dimension, and finally specify their (relative) importance in determining whether the households are deprived or not. Almost all the MEPIs in the literature implement the methodology proposed by Alkire and Foster (2011), consisting of dual cutoffs to identify dimensional deprivations and poverty. In high-income countries, this approach has been applied in several ways. For example, among the authors who propose MEPI based on objective indicators, there is Okushima (2017) for Japan; others use both subjective and objective indicators. Delugas and Brau (2021) follow this approach for Italy, Sokołowski et al. (2020) for Poland, and Tovar Reanos et al. (2025) for EU countries; finally, Halkos and Gkampoura (2021) and Cheikh et al. (2023) propose MEPIs for selected European countries that use only subjective indicators from the EU Survey on Income and Living Conditions (EU-SILC).

Although less reductionist than unidimensional indicators, MEPIs à la Alkire and Foster are ultimately an appropriately weighted combination of dichotomous states of deprivation. This binarisation may result in a loss of information, especially when the original underlying data are ordinal or continuous (e.g., expenditure or income). To overcome this limitation, Granzini (2025) proposes an index based on the partially ordered set theory, whereas Bollino (2017) adopt a fuzzy logic approach that yields a continuous degree of energy poverty for each household that is a function of its position in society for each dimension considered, rather than a simple deprived/not deprived classification.

All the metrics discussed thus far require household-level microdata. This makes these approaches difficult to implement whenever the geographical area of interest is (relatively) small. For instance, EU-SILC samples are representative only at the regional (NUTS2) level, but not at finer spatial scales. When policymakers and researchers seek to examine smaller areas or conduct spatial analyses, alternative approaches and different types of data are needed. In these cases, multidimensional approaches based on aggregated data (at the

[4] See https://energy.ec.europa.eu/topics/markets-and-consumers/energy-consumers-and-prosumers/energy-poverty_en. Accessed on 17/11/2025

municipality, county, or provincial level) are more appropriate. As (Sánchez-Guevara Sánchez et al., 2020) note (pp. 4), these methods do not allow "*to pinpoint the exact location of the energy-poor [...], but rather provide a snapshot of the most probable distribution of energy poverty, including the relative potential risks from a multifactorial perspective*".

When aggregated data are used, the literature shows greater heterogeneity in the rationale of multidimensional indices, compared with studies that use microdata. Focusing on high-income countries, the Synthetic Multidimensional Energy Poverty Index by (Kryk and Guzowska, 2023) is the average of normalised national statistics for the 13 indicators on energy poverty identified by the European Commission (2020). (Kashour and Jaber, 2024) follow a similar strategy, but reduce the set to 6 items, one of which is a modelled energy efficiency score. Martínez Gorbig et al. (2025) built the Heat-or-Eat Risk Index (HERI) for the European (NUTS2) regions, which combines the indicators of the regional, lifestyle, socioeconomic and demographic dimensions into a single index using the Multicriteria Analysis Methodology (MCA). Studies differ in the dimensions and variables considered, the spatial granularity of the data and the weights used to combine the information across dimensions. Robinson et al. (2019) use principal component analysis (PCA) and Geographically Weighted PCA to analyse the sociospatial distribution of vulnerability to energy poverty across small areas in England; both Che et al. (2021) and Gouveia et al. (2019) use surveys to determine the relative weight of the dimensions considered by their multidimensional indices.

All these studies combine information from different data sources: the smaller the areas, the fewer survey data are used in favour of census and administrative data. In particular, Robinson et al. (2019) and Aguilar et al. (2025) exploit the information in the Energy Performance Certificates (EPCs) registers to assess the energy efficiency of the houses in the small areas under study. Lavecchia et al. (2024) leverage the EPCs of homes in the municipalities to conduct a spatial analysis of energy poverty in Lombardy, Italy. Although the EPCs contain crucial information on buildings' energy efficiency and the technical demand of energy, not all residential properties are certified, and the certified ones are not a random sample of the entire stock of houses. If sufficient cartographic and census data are available, an alternative strategy to estimate the energy requirement of the houses in a given area is to resort to physical models of the energy needs of buildings, as in Gouveia et al. (2019).

We contribute to the debate on energy poverty by investigating its spatial distribution in Lombardy with a fine level of spatial granularity, so as to be able to inform policies at the municipality level. In fact, the municipalities are simultaneously the main responsible for both urban planning and local social services, and are usually interested in having detailed information on the territories they administer. We propose a multidimensional indicator of energy poverty which applies the approach of the fuzzy multidimensional deprivation indicators to aggregate data rather than microdata.

3 A Fuzzy Multidimensional Energy Poverty Index

The fuzzy approach to the construction of multidimensional deprivation indices is becoming common in the socio-economic literature on inequalities (see Lemmi and Betti (2006) and more recently Betti and Lemmi (2021)). As the concept of energy poverty is nuanced, the use of fuzzy logic is particularly appealing because the method to produce indices does not impose reference levels and formalises a continuum of grades of poverty without defining thresholds. The methodology is typically applied to household survey microdata. For instance, Ayala et al. (2022) and Ulman and Cwiek (2021) use microdata and the fuzzy approach to analyse housing deprivation. For energy poverty,Oyekale and Molelekoa (2023) use South African microdata, whereas Primc et al. (2019b) adopt a fuzzy logic to study energy poverty from a macro-level perspective, analysing national data. Here, we use the fuzzy multidimensional energy poverty indices (fMEPI) for small areas, which allow spatial analysis of the phenomenon in Lombardy.

In the construction of the fMEPI, we implement a five-step procedure. We first refer to the abundant literature on energy poverty to identify the main dimensions that have a potential impact on it. Among the available data, we select those variables x_{dk} that better describe each of the dimensions, where $d = 1, \ldots, D$ are the dimensions, and $k = 1, \ldots, K_d$ the variables used to describe them, with higher values of x_{dk} associated with lower vulnerability to energy poverty. Some of these variables can be expressed in monetary terms, some in physical one, and others are pure numbers. At the second step, all the items are transformed into scores in the interval [0,1] using the non-linear transformation:

$$s_{i,dk} = \frac{F(x_{i,dk}) - \min F(x_{i,dk})}{1 - \min F(x_{i,dk})} \tag{1}$$

where i identifies the observation (in our case, the area) and is the cumulative distribution function. In our context, all the variables are continuous, and in many cases, their dispersion is considerable. This transformation has the advantage of underweighting the gaps between areas that fall in the top (bottom) tails of the distributions and magnifying the differences between observations in the central parts of the distributions. Notice that if $x_{i,dk} > x_{j,dk}$, then $s_{i,dk} > s_{j,dk}$.

The next step requires the definition of the weights to be applied to each score in the aggregation phase, that is, when we move from the set of items to an indicator that synthesises the information of all items into a single indicator. Here, we follow Crescenzi et al. (2025) and define the weight in a way that tends to give more relevance to the most dispersed and least correlated (redundant) items. In detail, the weight of item k belonging to the dimension d is

$$w_{dk} = w_{dk}^{a} \times w_{dk}^{b}. \tag{2}$$

The first component is proportional to the standard deviation of the score:

$$w_{dk}^{a} = \frac{\sigma_{s_{dk}}}{1 - \overline{s_{dk}}}. \tag{3}$$

The second is

$$w_{dk}^{b} = \frac{1}{1 + \sum_{j=1}^{K_d} \rho_{jk} 1\left(\rho_{jk} < r_k\right)} \times \frac{1}{1 + \sum_{j=1}^{K_d} \rho_{jk} 1\left(\rho_{jk} \geq r_k\right)}. \tag{4}$$

where ρ_{jk} is the Kendall correlation between the scores s_{dk} and s_{dj} belonging to the same dimension d, $r_k = \max\left(\rho_{jk}\right) - \min\left(\rho_{jk}\right)$ and 1() is the indicator function, which equals one if the inequality in parentheses is true, zero otherwise. At the aggregation step, the dimension scores are defined as weighted averages of the scores of the pertinent variables:

$$s_{i,d} = \frac{\sum_{k=1}^{K_d} s_{i.dk} w_{dk}}{\sum_{k=1}^{K_d} w_{dk}}. \tag{5}$$

The higher the score in dimension d for area i, the less problematic dimension d is for that area. The overall score is the simple average of the dimension scores:

$$s_i = \sum_{d=1}^{D} s_{i.d}/D. \tag{6}$$

The fifth and final step maps the overall score in the fMEPI through the membership function, $\mu_i = \mu\left(s_i\right)$. Given the score s_i, the membership function tells us to what extent the area i is energy poor. The choice of the membership function is arbitrary, and we follow Betti and Verma (2008), who suggest an 'Integrated Fuzzy and Relative' (IFR) approach, suitable for multidimensional indices:

$$\mu_i = \mu\left(s_i\right) = \left(1 - F\left(s_i\right)\right)\left(1 - L\left(s_i\right)\right), \tag{7}$$

where $F()$ is the cumulative distribution function, and $L()$ is the Lorenz curve. The function takes into account both the proportion of areas less vulnerable than the area i,$1 - F(s_i)$, and an inequality index given by the share of the overall score $s = \sum_i s_i$ received by all areas less vulnerable than the area i,$1 - L(s_i)$. The same membership function is applied to the dimension scores to obtain dimension-specific indices $\mu_{i,d}$.

4 Dimensions, data and descriptive statistics

We leverage the available literature to select the most relevant dimensions to consider when investigating energy poverty. The thirteen objective and subjective indicators on energy poverty identified by the European Commission (2020) and used by Kryk and Guzowska (2023) can be traced back to three dimensions: the affordability of households' residential energy services; the market conditions (which are reflected in prices) and the housing conditions (which include an indicator on the energy consumption per square metre, climate corrected). The set of indicators used by Kashour and Jaber (2024) can be categorised in the same way, with a richer description of the housing conditions that includes a modelled energy efficiency score. Martínez Gorbig et al. (2025) explicitly consider four dimensions: energy accessibility (that is represented by items as energy prices, household disposable income and the share of household budget for energy expenditure); resilience of energy systems (described by the shares of electricity produced by the main producer, that of renewable energy in consumption, and that of energy imported); food security (with food prices indices) and what they call household relative expenditure in lifestyle domains, that gathers the shares of household budgets for food and energy services. For worldwide comparison, Che et al. (2021) consider three dimensions named energy availability, which includes per capita energy consumption and the percentage of the population with access to electricity; energy affordability (captured by per capita GDP and household final consumption, and diffusion of cellphones); and energy cleanability, with indicators on the energy mix and emissions.

When moving to a finer level of spatial granularity, Robinson et al. (2019) refer to eighteen indicators that they organise into eight (somewhat overlapping) dimensions: house and appliances energy efficiency; access to appropriate fuel types and new technologies; energy-related needs and practices; energy prices; financial capacity; social networks; precarity of housing, and welfare and state support. Gouveia et al. (2019) consider only two dimensions, namely the energy gap, which combines buildings' final energy demand and consumption, and households' ability to implement alleviation measures, which combines socio-economic information and data on buildings' state of conservation. Similarly, Aguilar et al. (2025) have a single dimension that includes all the socio-economic indicators of vulnerability, one for the built environment vulnerability indicators (which include an indicator on housing energy efficiency) and the third one for the energy costs. In their spatial analysis of energy poverty risk in Lombardy, Lavecchia et al. (2024) consider four components: the expenditure required to satisfy residential energy needs (estimated based on EPC data), the severity of climate conditions, the quality of the building stock (which combines information on houses' age, energy efficiency and prices) and the income and the level of education of the residents of the municipalities.

Our choice of dimensions and items is summarised in 1, and it is the result of the balance between the indications of the literature and the availability of data with adequate granularity. To carry out a spatial analysis of energy poverty that adequately reflects the heterogeneity of urban and non-urban territories, our units of observation are 4400 small areas (OMI areas) defined by the Italian Revenue Agency as portions of the municipalities' territories with homogeneous real estate characteristics. Given this level of granularity, the only suitable data for these small 4400 zones comes from administrative registries, censuses or macro models that produce environmental and energy measurements with adequate territorial details. We thus consider twenty-five indicators organised in five dimensions. All the indicators are transformations of the original variables such that the higher the value of the indicator, the less likely the area is to be vulnerable to energy poverty.

The dimension "Housing conditions and energy efficiency", which is assessed in all the literature reviewed above, is captured by an indicator of the energy performance of the houses in the area; the age of the residential buildings in the area and the average number of dwellings per building. For the latter two, unfortunately, the most recent available information can be obtained from the general census of population and housing run by the Italian Statistical Office (ISTAT) in 2011. The information is available at the census tract level, portions of territory that are smaller and included in the OMI areas; data for the OMI areas is therefore obtained by upscaling. And this is what happens whenever the original data comes from censuses. For the energy performance indicator, we combine different sources. We first exploit the georeferenced EPC register and consider the average thermal energy required for heating for all certified houses in the area. At the same time, we use data available from the regional geoportal for all the buildings, the age of construction of the buildings in the area and a physical model for the energy demand to estimate the same index for each residential building in the area (see Grassi et al. (2025)). The final thermal performance index for the

Table 1: Dimensions, items, data sources and modelled used.

Dimensions (d = 1,...,5)	**Items** $x_{d,k}$	**Data sources**
Housing conditions and energy efficiency	1/Thermal performance index (kWh/m^2/year)	EPC registry, cartographic data and energy modelling
	% of living space in renovated houses	
	% of living space in houses built after 1976	
	% of living space in houses built between 1976 and 1990	EPC registry and cartographic data
	% of living space in residential buildings in old city centres	
	% of living space in houses, not single or terraced houses	
	% of residential buildings built since 2000	Census 2011
	Average number of dwellings per building	Census 2011
Residential energy consumption	1/Per capita energy consumption in the residential sector	EU energy atlas 2019 (kTOE/year) and Census 2021
	Population/Number of inhabited houses	Census 2021
	1/Average size of houses inhabited by residents (m^2)	Census 2011
Financial capacity	% of population $>$ 9 yrs old with a university degree	Census 2021
	% of employed population 15-64 yrs old	Census 2021
	Per capita taxable personal income (€)	
	% of taxpayers in the population	Ministry of Finance 2022 tax data and Census 2021
	Per capita taxable personal income/house prices	
	Per capita taxable personal income/ Envelope renovation cost (€$/m^2$)	Ministry of Finance 2022 tax data, Census 2021, cartographic data and energy modelling
	% of resident homeowner households	Census 2011
Climatic conditions	Heating degree days	ERA5-Land Copernicus CDS
	1/Altitude	Copernicus Digital Elevation Model
	Share of urbanised land	Copernicus Corine Land Cover
	Monthly average of no frost days	ERA5-Land Copernicus CDS
Energy-related needs	% population $>$ 6 yrs old	Census 2021
	% population $<$ 75 yrs old	
	% non extra UE population	

area is a weighted average of the two measures, with weights given by the estimated overall surface of the certified/not certified dwellings. We use a mix of cartographic, census and EPCs data to account for the share of living space by age of construction, renovation status and location of the houses in the city centres.

The residential energy consumption is described by a housing crowding index and the average size of the houses of the residents (both from censuses). Moreover, we use the EU energy atlas for energy demand in 2019, combined with 2021 census data, to estimate the per capita energy consumption in the residential sector.

The dimension "Financial capacity" combines data on human capital, occupation and homeownership from the censuses, with data on taxable personal income and the number of taxpayers provided by the Revenue Agency. We use information on the selling prices of the houses in the areas recorded by the Revenue Agency to compute an indicator of homeownership availability as the ratio (per capita taxable personal income/house prices). Finally, we take advantage of the data available from the regional geoportal for all the buildings, of an engineering model and regulations to estimate the cost (per square metre) of renovating the envelope of the building, where appropriate and suitable. We use the average of this cost to compute an indicator of the affordability of the renovation costs in the area (as per capita taxable personal income/ envelope renovation cost). Although in this paper we investigate the spatial distribution of energy poverty in just one Italian region, the climate conditions in Lombardy are so heterogeneous to consider an ad hoc dimension for climate as one of the domains with an impact on the spatial distribution of energy poverty. As items of this dimension, we consider the heating degree days, the altitude and the number of frost days. Moreover, we also account for the share of urbanised land, as one of the factors with an impact on micro-climate conditions.

Finally, we consider three variables that correlated with differential energy needs across households: the share of elderly residents, that of the pre-school children and that of extra-EU residents.

It is apparent that, differently from most of the reviewed literature, the fMEPI does not consider the market conditions as determinants of energy poverty. This is not because we claim they are irrelevant, but rather because the market conditions are substantially homogeneous across areas in Lombardy, and there is no granular information on the retail prices of electricity, gas and other energy sources. Moreover, the accessibility of gas and district heating networks, potential alternatives to increase market competition, is proxied by variables already considered, such as the altitude and the degree of urbanisation of the areas.

Table 2 shows the basic descriptive statistics for the items considered. The marginal and joint distributions of the scores determine the weights to be used in the aggregation weights, which are displayed in the last three columns of the same table. The correlations between the scores of the items belonging to each dimension are typically low. For the housing conditions and energy efficiency the highest values (0.55) are (as expected) for the correlation between the scores of the share of living space of houses built after 1976 and the that of the share of living space of houses built between 1976 and 1990, and the correlation between the energy performance indicator and the share of living space of houses built after 1976. Correlations of similar magnitudes are found between the scores of the per capita taxable income, the indicator of the renovation costs affordability and the percentage of the population with a tertiary degree. Unsurprisingly, the highest correlations are recorded between the scores of the items in the climate dimension, between altitude, heating degree days and frost days, with a peak of 0.84. Despite the risk of using redundant items, we decided to maintain these variables in the set of indicators because altitude is also a proxy for access to the gas network, and the number of frost days accounts for extreme situations, not captured by the average heating degree days.

Given the scores for each item in the dimensions and the associated weights, we can now compute the dimension and total scores, whose statistics are displayed in Table 3 and 4. By construction, all the scores have a mean equal to $\frac{1}{2}$, but the dispersion can vary. In particular, the score of the dimension referred to the climate conditions is remarkably higher than the others. The correlation matrix highlights that the dimensions have a rather limited pattern of linear dependency. The negative signs for the correlations of some scores indicate that the relative disadvantage in a specific dimension can be compensated for by an advantage in another one. For instance, a lower score in the energy consumption dimension (i.e. areas that consume more energy than average) is associated with a higher score in the finance capacity domain (that is, areas richer than average), or areas with better climate are those with higher energy-related needs. Consistently, all the scores are positively associated with the total score, although with a different degree of correlation.

5 Spatial Distribution of Energy Poverty in Lombardy

Figures 2 and 3 use maps to illustrate the spatial distribution of the five dimension-specific indices $\mu_{i,d}$ across the 4,407 OMI areas in Lombardy. They all have a sample mean of about

Table 2: Items' descriptive statistics and relative weights.

Dimension	Item (x_{dk})	Mean	Std. Dev.	Weight
Housing conditions and energy efficiency	1/Thermal performance index (kWh/m^2/year)	0.0066	0.0029	0.0731
	% of living space in renovated houses	1.54	4.08	0.1135
	% of living space in houses built after 1976	42.69	24.41	0.0777
	% of living space in houses built between 1976 and 1990	17.83	16.44	0.3618
	% of living space in residential buildings in old city centres	18.73	21.43	0.0976
	% of living space in houses, not single or terraced houses	52.49	23.64	0.0971
	% of residential buildings built since 2000	17.53	11.41	0.0842
	Average number of dwellings per building	2.85	2.19	0.0950
Residential energy consumption	1/Per capita energy consumption (TOE/year)	1.44	1.72	0.2480
	Population / Number of inhabited houses	2.32	0.27	0.4150
	1/Average size of houses inhabited by residents (m^2)	0.0099	0.0014	0.3370
Financial capacity	% pop. $>$ 9 yrs old with a university degree	12.08	5.93	0.1338
	% of employed population 15–64 yrs old	66.74	5.99	0.1178
	Per capita taxable personal income (€)	17007	3789.7	0.0805
	% of taxpayers in the population	74.78	6.63	0.0860
	Per capita taxable personal income / house prices	16.22	5.68	0.2041
	Per capita taxable personal income / envelope renovation cost (€/m^2)	255.91	876.27	0.1158
	% of resident homeowner households	72.72	16.94	0.2620
Climate conditions	1/Heating degree days	0.0071	0.0018	0.1981
	1/Altitude	0.0081	0.0109	0.2159
	Share of urbanised land	30.67	33.76	0.3737
	Monthly average of no frost days	26.31	3.93	0.2124
Energy-related needs	% population $<$ 75 yrs old	88.25	4.25	0.4512
	% population $>$ 6 yrs old	96.46	1.51	0.3325
	% non–extra EU population	97.78	3.18	0.2163

Table 3: Descriptive statistics of dimension and total scores $s_{i,d}$.

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Housing conditions	0.5000	0.1418	0.0354	0.8769
Energy consumption	0.5000	0.1404	0.0275	0.9665
Financial capacity	0.5000	0.1385	0.0395	0.8974
Climate conditions	0.5000	0.2201	0.0096	0.9507
Energy-related needs	0.5000	0.1448	0.0182	0.9972
Total score	0.5000	0.0817	0.1643	0.7351

Table 4: Correlations of dimension and total scores $s_{i,d}$

	Housing	**Energy**	**Financial**	**Climate**	**Needs**	**Total**
Housing conditions	1.0000					
Energy consumption	0.4336	1.0000				
Financial capacity	0.0444	-0.1043	1.0000			
Climate conditions	0.3355	0.1945	0.1691	1.0000		
Energy-related needs	-0.0698	0.0815	-0.0450	-0.2893	1.0000	
Total Score	0.6673	0.5926	0.3938	0.6770	0.1871	1.0000

0.37 and a standard deviation of 0.31, whereas the correlations are almost equal to those of the scores in Table 4. Each colour in the maps corresponds to a group that contains 20% of the areas, from those with the lowest level of the index to the highest, that is, from the least to the most vulnerable areas.

The maps make evident that areas that are among the most advantaged ones in one dimension can be among the most disadvantaged ones in others. For instance, the zones in the extreme south west of the region (the hilly Oltrepò Pavese) have poor housing conditions, high energy consumption and adverse climate conditions, but good financial capacity. Similarly, in the extreme south east, the favourable climate conditions and financial capacity are somewhat counterbalanced by high energy consumption and poor housing conditions. The spatial distribution of the overall, fuzzy, multidimensional energy poverty index is illustrated in the bottom panel of Figure 3. The northern mountainous zones, together with those in the south-west, are the areas most exposed to the risk of energy poverty. The central areas of Lombardy, which are flat or at the foot of the mountains, are the ones with the least vulnerability. The granularity of the data also allows us to investigate the intra-urban heterogeneity of the phenomenon. Figure 4 focuses on the territories of Milan and Brescia, the most populated municipalities in the region (about 1,400 and 200 thousand inhabitants, respectively). It can be observed that spatially contiguous areas in the same municipality can be characterised by rather different levels of the index, and thus exposure to the risk of

Figure 2: Membership function values for the housing conditions and energy efficiency dimension, the residential energy consumption dimension and the financial capacity dimension. The higher the value, the higher the vulnerability to energy poverty due to this dimension. Different colours correspond to different quintiles.

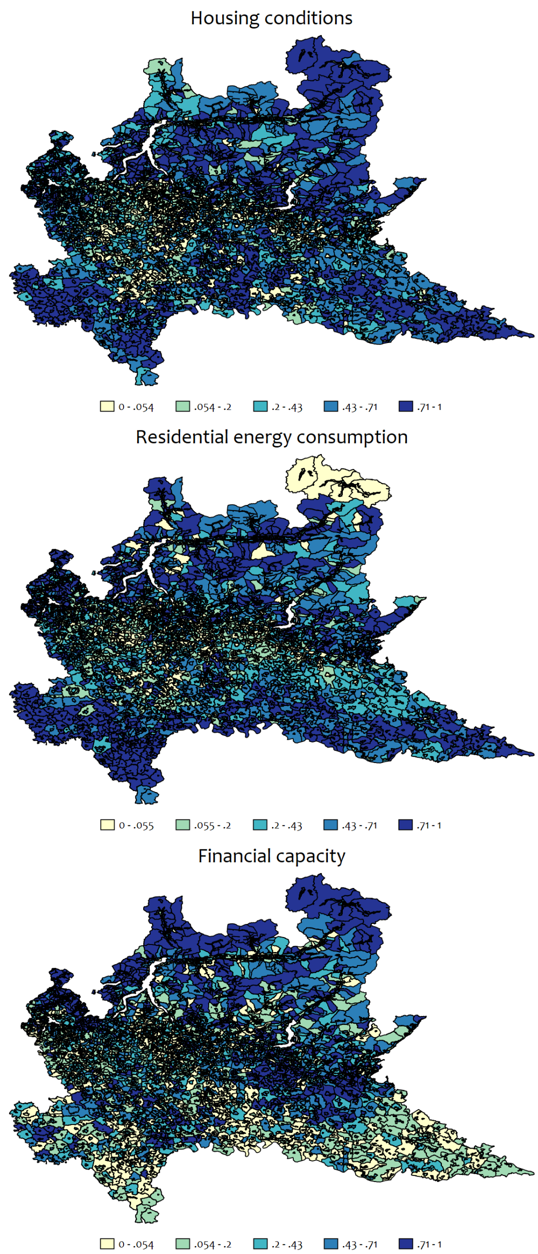


Figure 3: Membership function values for the climate conditions dimension, the energy-related needs dimension and the overall membership function. The higher the value, the higher the vulnerability to energy poverty due to this dimension. Different colours correspond to different quintiles.

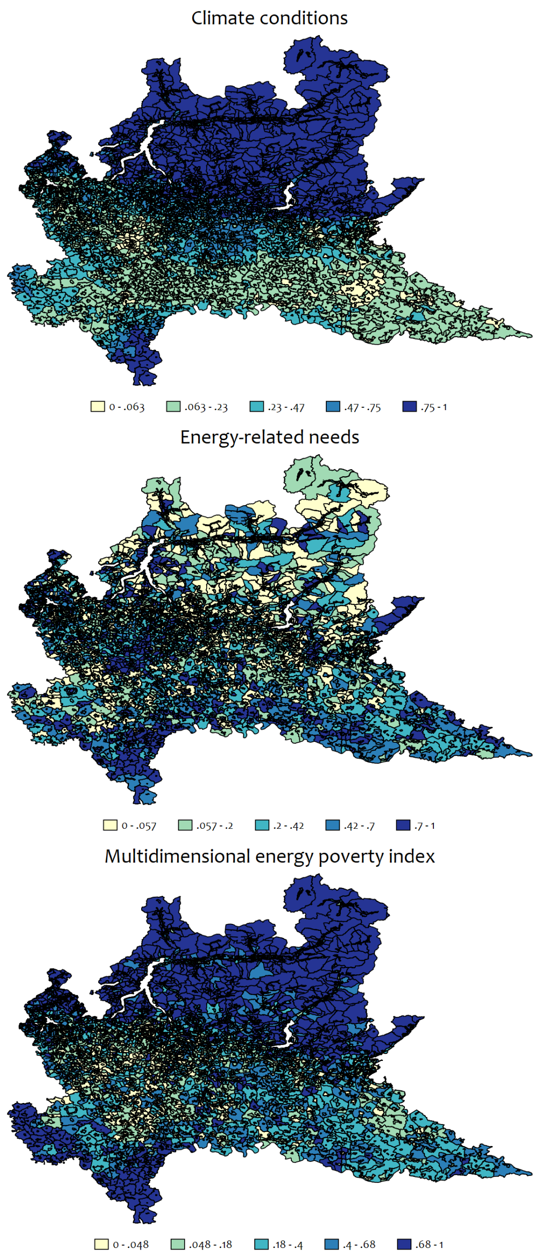
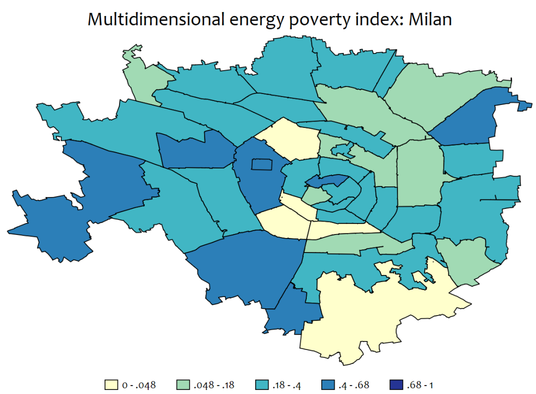
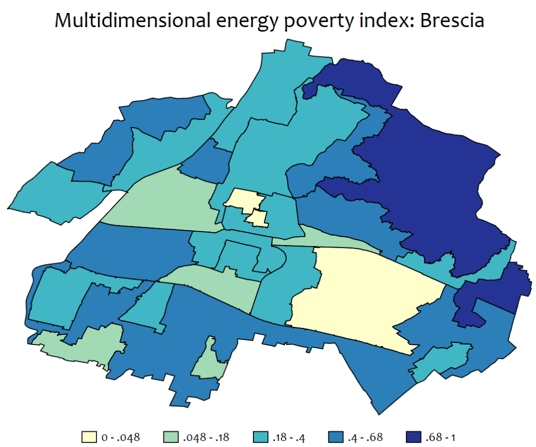


Figure 4: Overall membership function values for the municipalities of Milan and Brescia. The higher the value, the higher the vulnerability to energy poverty. Different colours correspond to different quintiles.



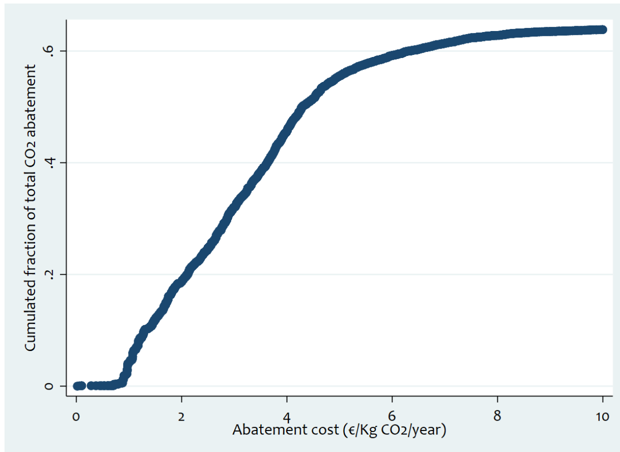


energy poverty.

6 Subsidies for Home Renovation and Energy Poverty

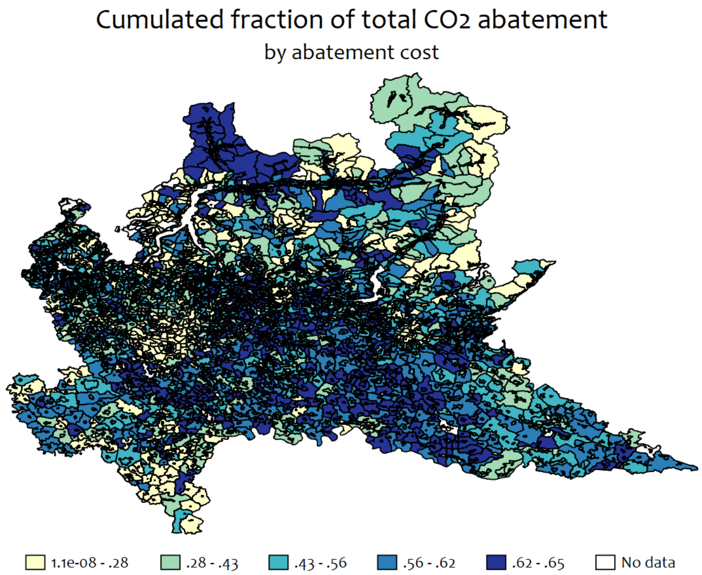
A possible consistent utilisation of fMEPI is to assess if an optimally designed policy of subsidisation of energy renovation, aimed at reducing CO2 emissions from the residential sector, affects the areas more exposed to energy poverty or not. We follow Camboni et al. (2023) and argue that, given a CO2 emissions reduction target , a rational policymaker should prioritise the areas in which the energy renovations are the most cost-effective, that is, those in which the unitary CO2 abatement cost is the lowest. We use engineering models to estimate the energy required for heating, the associated CO2 emissions, and the renovation costs for each residential building in the area. A standard renovation package is considered, typically including window replacement and attic or roof insulation. The type of intervention—if any—depends on the building's characteristics (type, age, renovation status) and its

Figure 5: Cumulated fraction of total CO2 emissions abatement due to renovations in areas ordered by unitary cost of CO2 emissions abatement.



location (urban, rural, or historical city centre). As a result, not all areas undergo the same type or extent of renovation, and both CO2 abatement and renovation costs vary across zones. We estimate that if all proposed renovations were implemented, emissions would fall by about 65%. To prioritise interventions, we rank areas by their unit abatement cost (€/kg CO2/year), from the most cost-effective to the least. The policy activates renovations starting with the lowest-cost areas and proceeds until the reduction target is met. Figure 5 shows that renovating areas with a unit abatement cost of lower than 2 €/kg CO2/year, considering only homes occupied by residents, would achieve roughly a 20% reduction in emissions. To reach the standard 30% reduction target, the threshold must increase to about 3 €/kg CO2/year. We now describe the spatial distribution of priority areas across the region and compare it with the distribution of fMEPI. In Figure 6, lighter-colored areas represent zones where renovations are most cost-effective for reducing CO2 emissions. Renovating all areas in the first group would reduce emissions by 28% compared to the baseline without renovations; including the second group would increase the reduction to 43%, and so forth. A comparison with Figure 3 reveals that some zones with high fMEPI also belong to the priority group for CO2 reduction—such as those in the south-west and north-east of the region. In these cases, policies aimed at reducing residential-sector emissions would simultaneously improve housing conditions in areas vulnerable to energy poverty. However, this alignment does not occur everywhere. For example, zones in the north-west exhibit high fMEPI but fall into the group where renovations are least cost-effective. Conversely, some south-eastern areas have low fMEPI yet should be prioritised for renovation. The analysis shows that policies aimed at reducing the environmental impact of the residential sector—such as those inspired

Figure 6: Cumulated fraction of total CO2 emissions abatement due to renovations in areas ordered by unitary cost of CO2 emissions abatement. Different colours correspond to different quintiles.



by the European Commission's Green Homes Directive (European Commission (2024))—do not necessarily benefit the areas most vulnerable to energy poverty.

7 Discussion and Conclusions

This study developed a novel fuzzy multidimensional energy poverty index (fMEPI) to assess the spatial distribution of energy poverty vulnerability. It provides an application across 4,400 small areas (OMI zones) in the Lombardy region of Italy. By integrating twenty-five indicators from diverse administrative, census, and modelled data sources, we constructed a comprehensive assessment framework encompassing five critical dimensions: housing conditions and energy efficiency, residential energy consumption, financial capacity, climate conditions, and energy-related needs. The methodology employed a fuzzy set approach that transforms raw variables into standardised scores through cumulative distribution functions, applies dimension-specific weighting schemes based on dispersion and correlation patterns, and generates continuous vulnerability indices through a relative membership function. Our results show that the predominantly rural areas in the north and in the south-west of Lombardy are those most exposed to the risk of energy poverty.

The proposed multidimensional fuzzy index of energy poverty fMEPI does not estimate the percentage of households in energy poverty for each area. Instead, it provides a probabilistic representation of how energy poverty is distributed across the territory, adopting a multifactorial perspective and leveraging diverse data sources. This approach highlights the relative strengths and weaknesses of different areas, making the index a valuable tool for identifying priority zones for intervention—once policymakers have established energy poverty as a relevant policy concern. However, to obtain a comprehensive picture of the phenomenon, the information conveyed by this multidimensional index should be complemented by an assessment of its overall prevalence. For example, in Lombardy, Osservatorio Italiano sulla Povertà Energetica (OIPE) (2024) uses household budget survey data to compute a unidimensional expenditure-based indicator, estimating that 7.2% of households are energy poor. While this estimate cannot be replicated at smaller spatial scales, our multidimensional index can identify areas where energy-poor households are most likely to reside.

Under a methodological perspective, the transformation step to construct the fuzzy index is such that the information on the absolute values of the original variables is lost. The original variables $x_{i,dk}$ are transformed in equation (1) into a-dimensional scores. By design, any ranking-preserving transformation of the original variables does not affect the corresponding scores or the composite indices. Consequently, any event or policy intervention that changes the value of a variable $x_{i,dk}$, without altering the relative ranking of areas for that variable will have no impact on fMEPI. For example, a generalised, uniform decrease in per capita taxable income could increase the overall prevalence of energy poverty, yet it would not modify its spatial distribution as captured by our index. This apparent limitation of fMEPI is actually consistent with its purpose, that is, to provide information on the ranking of areas based on the risk of energy poverty, and not an estimate of the risk itself.

Defining the fuzzy multidimensional energy poverty index involves several methodological choices, including the transformation and membership functions as well as the weighting scheme. Each of these choices entails trade-offs. For example, scores can be anchored to relevant thresholds of the original variables, following an approach similar to Alkire and Foster (2011). Membership functions may place different emphasis on relative position versus inequality concerns, while weights could be derived through principal component analysis or consensus-based methods. A comprehensive sensitivity analysis of these design choices is beyond the scope of this paper and is left for future research.

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