Mapping Energy Poverty in Lombardy Using a Fuzzy Multidimensional Index

Extended Abstract

Raffaele Miniaci[a,b], Alessio Pirola[a,b], Nicola Pontarollo[a,b], Massimiliano Rizzati[a,b]

[a]*Department of Economics and Management, Università degli Studi di Brescia, Via San Faustino 74/B, Brescia, 25122, BS, Italy*
[b]*Fondazione Eni Enrico Mattei, Corso Magenta 63, Milano, 20123, MI, Italy*

Keywords: Energy Poverty, Efficiency Performance Certificates, Fuzzy logic, Spatial indicators

---

1. Motivation

This work aims at the development of a sub-municipal Energy Poverty Risk Index. Energy poverty, defined as the inability of households to secure adequate and affordable energy services for basic needs such as heating, cooling, and lighting, has gained increasing prominence in academic and policy discourse due to its social, spatial, and environmental implications (Bouzarovski and Petrova, 2015). Despite substantial progress in understanding the drivers of energy deprivation, recent crises such as the COVID-19 pandemic and the energy price surge following the war in Ukraine have exposed the fragility of household energy security across Europe (Lavecchia et al., 2024). The urgency of addressing energy poverty is further amplified by the clean energy transition, which risks exacerbating socio-economic inequalities without targeted interventions (Pye et al., 2017; Thomson et al., 2017).

Energy poverty is now widely recognised as a multidimensional and spatially uneven phenomenon, rooted not only in low household income and high energy expenditures but also in building inefficiency, climatic exposure, and territorial disparities (Gouveia et al., 2019; Meyer et al., 2018). Traditional income- or expenditure-based indicators frequently underestimate the problem by overlooking "hidden energy poverty," where households suppress energy use to avoid unaffordable costs (Legendre and Ricci, 2015). Moreover, national indicators lack the spatial granularity needed to detect local pockets of vulnerability—especially in rural, mountainous, or deprived peri-urban areas—thereby limiting the effectiveness of policy design (Robinson et al., 2018).

Recent methodological advances demonstrate that fine-scale, place-based energy poverty metrics are essential for designing targeted interventions and for informing the "just transition" in energy policy (Bouzarovski and Petrova, 2015). Composite indices such as the Energy Poverty Risk Index (EPRI) in Italy (Lavecchia et al., 2024) and the Energy Poverty Vulnerability Index (EPVI) in Portugal (Gouveia et al., 2019) have begun to integrate physical and socio-economic dimensions of vulnerability. However, these efforts are typically limited to the municipal level due to data availability (Rizzati et al., 2022), overlooking intra-urban inequalities and sub-municipal heterogeneity, which are crucial for policy interventions at the scale where vulnerability is experienced—neighbourhoods and communities (Roberts et al., 2015; Sánchez et al., 2020).

To address this methodological and policy gap, the present work develops a sub-municipal energy poverty risk index using spatially disaggregated data integration and fuzzy logic. A fuzzy-based approach is particularly suited to capturing the uncertainty and linguistic vagueness inherent in social vulnerability assessments (Bollino and Botti, 2017; Benedetti et al., 2025). We leverage data availability for Energy Certificate Performance in the NUTS 2 region of Lombardy, Italy. By combining heterogeneous datasets, ranging from housing-level energy performance certificates and climatic exposure to socioeconomic fragility indicators this study responds to the call for high-resolution, multidimensional diagnostics capable of supporting place-sensitive policies. The proposed index provides an instrument to identify energy poverty hotspots below the municipal level and to not get lost in averages when performing energy poverty-related assessments.

2. Methodology

As is standard in the literature on composite indicator construction, this work identifies a set of analytically meaningful dimensions that capture the multifaceted nature of energy poverty. Following a review of the literature, we select the following six dimensions: i) housing energy efficiency and energy

Dimension	Sample variable	Source
Housing energy efficiency	Total Energy Performance Index	*CENED*
Housing energy consumption	Residential energy consumption	*JRC*
Financial capacity	Average income per capita	*MEF*
Climatic conditions	Heating Degree Days	*ERA5*
Energy-related needs	Excess winter deaths	*ISTAT*
Energy market accessibility	District heating availability	*A2A*

Table 1: Examples of variables for each of the index dimensions.

demand/expenditure, ii) household energy consumption and actual energy expenditure, iii) financial capacity and housing affordability, iv) climatic and weather conditions, v) energy-related needs and health vulnerabilities, vi) accessibility of energy markets and infrastructures.

Each dimension is populated by a set of variables collected from heterogeneous data sources and harmonised to the OMI zone resolution. Data harmonisation is achieved by rescaling spatial datasets using population-weighted grids, or by intersecting more granular geospatial information such as the variables coming from single Energy Performance Certificates (EPCs) and aggregating values at the zonal level (typically using the median). Table 1 provides examples of variables selected for each dimension.

Following Benedetti et al. (2025), we compute a normalized relative deprivation score for each variable j in each OMI zone i:

$$s_{ij} = 1 - \frac{1 - F(c_{ij})}{1 - F(1)} \tag{1}$$

where $F(c_{ij})$ is the cumulative distribution function at the variable value c and $F(1)$ corresponds to the most deprived observed value. The score s_{ij} therefore represents the relative position of zone i in the deprivation distribution for variable j, with higher values indicating greater disadvantage.

Each variable within a dimension is then weighted using a two-step weighting scheme designed to consider variability while penalizing redundancy. The weight $\omega_{d,j}$ assigned to variable j within dimension d is defined as:

$$\omega_{d,j} = \omega^a_{d,j} \times \omega^b_{d,j} \tag{2}$$

where

$$\omega^a_{d,j} \propto \frac{\sigma_{s_{d,j}}}{1 - \bar{s}_{d,j}} \tag{3}$$

is the variability-targeting weight, with $\sigma_{s_{d,j}}$ denoting the standard deviation of s_{ij} and $\bar{s}_{d,j}$ the mean deprivation score of variable j, while

$$\omega^b_{d,j} \propto \left(\frac{1}{1 + \sum |\rho_{d,j,d,j^*}| < r^*} \right) \times \left(\frac{1}{1 + \sum |\rho_{d,j,d,j^*}| \geq r^*} \right) \quad (4)$$

is the redundancy penalty component, with ρ_{d,j,d,j^*} being the Kendall correlation between variables j and j^* within dimension d, and r^* a critical redundancy threshold based on the largest correlation gap.

Dimension scores are then aggregated into a composite Energy Poverty Risk Index for each OMI zone i, assuming equal weighting across dimensions[1].

Finally, to capture the degree of belonging of each zone to the latent condition of energy poverty, we define a fuzzy membership function:

$$\mu_i = (1 - F_S(s_i))^{\alpha - 1} (1 - L_S(s_i)) \quad (5)$$

where $\mu_i \in [0, 1]$ denotes the fuzzy membership value of zone i, $F_S(s_i)$ is the cumulative distribution function of the composite score s_i, $L_S(s_i)$ is the associated Lorenz curve, and α is an inequality sensitivity parameter.

Fuzzy logic is particularly relevant in the context of energy poverty measurement because the phenomenon lacks a clear binary threshold and involves gradual transitions between non-poor and energy-poor conditions. Unlike crisp classification approaches, fuzzy membership functions allow us to model intermediate states of vulnerability.

3. Expected results

We expect to generate an Energy Poverty Index at the OMI zone level, expressed as a single composite score. This will be complemented by a fuzzy membership function for each of the selected vulnerability dimensions. The indicator is designed as a policy-oriented tool capable of simulating the propagation of energy poverty under changes in its underlying determinants.

For example, being this work a part of the wider research program Cost Effective Building Emission Reduction Scenarios (CEBERS), by integrating a companion, engineered energy performance simulation tool, we will be able to assess the impact of different building renovation strategies and compare

[1] Alternative inter-dimensional weighting schemes will also be explored in future extensions of this work.

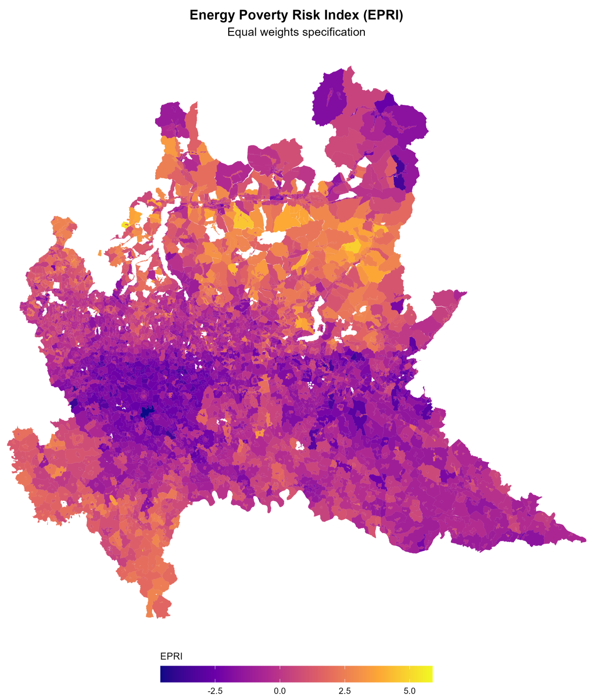

Figure 1: Replication of an Energy Poverty Risk index for Lombardy based on four sub-components, equal weights: Energy Expenditure, Building Quality, Climate and Income-Education.

policy alternatives in terms of their spatial effects on energy poverty and overall implementation costs. Additionally, the framework will allow us to evaluate how variations in fuel and electricity prices affect energy poverty levels across territories.

In Figure 1, to illustrate the expected spatial granularity of the final index, we present a replication of the Spatial Energy Index by Lavecchia et al. (2024), which we developed as an intermediate methodological step.

References

Benedetti, I., Crescenzi, F., Laureti, T., and Salvini, N. (2025). Business digitalization in italy: A comprehensive analysis using supplementary fuzzy set approach. *Big Data Research*, page 100538.

Bollino, C. A. and Botti, F. (2017). Energy poverty in europe: A multidimensional approach. *PSL Quarterly Review*, 70(283):473–507.

Bouzarovski, S. and Petrova, S. (2015). A global perspective on domestic energy deprivation: Overcoming the energy poverty–fuel poverty binary. *Energy Research & Social Science*, 10:31–40.

Gouveia, J. P., Palma, P., and Simoes, S. G. (2019). Energy poverty vulnerability index: A multidimensional tool to identify hotspots for local action. *Energy Reports*, 5:187–201.

Lavecchia, L., Miniaci, R., Valbonesi, P., and Venkateswaran, G. (2024). Energy poverty risk: a spatial index based on energy efficiency. *Bank of Italy Occasional Paper*, (864).

Legendre, B. and Ricci, O. (2015). Measuring fuel poverty in france: Which households are the most fuel vulnerable? *Energy Economics*, 49:620–628.

Meyer, S., Laurence, H., Bart, D., Middlemiss, L., and Maréchal, K. (2018). Capturing the multifaceted nature of energy poverty: Lessons from belgium. *Energy research & social science*, 40:273–283.

Pye, S., Dobbins, A., Baffert, C., Brajković, J., Deane, P., and De Miglio, R. (2017). Energy poverty across the eu: Analysis of policies and measures. In *Europe's Energy Transition*, pages 261–280. Elsevier.

Rizzati, M., De Cian, E., Guastella, G., Mistry, M. N., and Pareglio, S. (2022). Residential electricity demand projections for italy: A spatial downscaling approach. *Energy Policy*, 160:112639.

Roberts, D., Vera-Toscano, E., and Phimister, E. (2015). Fuel poverty in the uk: Is there a difference between rural and urban areas? *Energy policy*, 87:216–223.

Robinson, C., Bouzarovski, S., and Lindley, S. (2018). 'getting the measure of fuel poverty': the geography of fuel poverty indicators in england. *Energy research & social science*, 36:79–93.

Sánchez, C. S.-G., Fernández, A. S., Peiró, M. N., and Muñoz, G. G. (2020). Energy poverty in madrid: Data exploitation at the city and district level. *Energy Policy*, 144:111653.

Thomson, H., Bouzarovski, S., and Snell, C. (2017). Rethinking the measurement of energy poverty in europe: A critical analysis of indicators and data. *Indoor and built environment*, 26(7):879–901.