A New Multidimensional Energy Poverty Index for Mexico

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April 14, 2026

Abstract

This paper proposes a novel and time-comparable Multidimensional Energy Poverty Index (MEPI) for Mexico, spanning the period from 2016 to 2024. Utilizing the Alkire-Foster (AF) methodology and data from the National Household Income and Expenditure Survey (ENIGH). The study develops a dimensionally-flexible framework that incorporates eight empirical dimensions: electricity access, water heating, communication, entertainment, refrigeration, cooking, thermal comfort, and energy affordability. A key contribution is the integration of an affordability dimension and a climate-sensitive thermal comfort metric that accounts for heterogeneous needs across warm, cold, and temperate municipalities. The results reveal a significant monotonic reduction in energy poverty, with the adjusted headcount ratio (M_0) falling from 7.098% in 2016 to 4.847% in 2024—a 31.7% relative decrease. During this period, approximately 6.1 million people escaped energy poverty. The most substantial improvements were observed in the affordability dimension, consistent with recent real-wage increases in Mexico. While overall incidence (H) and intensity (A) of poverty declined, the findings highlight persistent challenges: we identify and report substantial asymmetric energy poverty outcomes across sociodemographic groups, income levels and states.

Keywords: Multidimensional Energy Poverty, Alkire-Foster Method, Affordability, Thermal Comfort, Mexico.

*Major B: Macroeconomics, finance and the socioeconomic bifurcation. Minor B2: Socioeconomic and ecological economics. Associated to Università degli Studi Roma Tre, Sorbonne Université and Université de Technologie de Compiègne.

Contents

1 Introduction and Literature Review

As of 2025, 730 million people live without access to electricity, and around 2 billion people rely on cooking methods that are detrimental to human health (IEA, 2025). This implies that one quarter of the world population lies within the broad threshold of what could be considered *energy poverty* (Ritchie et al., 2019). For Reddy (2000, p. 44), energy poverty is defined as: "the absence of sufficient choice in accessing adequate, affordable, reliable, high-quality, safe and environmentally benign energy services to support economic and human development".[1]

Energy poverty has been proven to be a serious obstacle in the implementation of sustainable development and poverty reduction policies, particularly in the context of UN's millennium development goals (MDG's) (UN, 2015) and sustainable development goals (SDG's) (UN, 2025) (Groh, 2014; Jannuzzi & Goldemberg, 2012; Liu et al., 2022; McCollum et al., 2018; Modi et al., 2005; Pachauri et al., 2012; Santika et al., 2019). Furthermore, it has been observed that energy poverty has negative impacts on health, education, social mobility and economic growth (González-Eguino, 2015; Hernandez-Cortes et al., 2025; Nadimi & Tokimatsu, 2018; Nadimi et al., 2017). Precise estimations of energy poverty are essential in the articulation of evidence-based public policy destined towards improving access to modern energy services, and hence, reducing energy poverty (Nussbaumer et al., 2012; Pelz et al., 2018).

The characterization presented by Reddy (2000) gravitates closely around Sen's *capability approach* (see Sen 2000b; Sen 2000a; and Sen 2011). From this perspective, development has

[1] Bazilian et al. (2010), Bouzarovski and Petrova (2015) and Day et al. (2016) present overviews of the various definitions and measures of energy poverty.

to do with non-exclusion from accessing a set of options related to the realization of welfare (González-Eguino, 2015). Capabilities represent the "various combinations of functionings... that the person can achieve" (Sen, 1995, p. 40). In this framework functionings are the *beings* and *doings* that people value: let them be healthcare, education, nourishment, community engagement, etc (Sen, 2011).

This approach has been fundamental in the "reconsideration of the concepts of poverty" (Jenkins & Micklewright, 2007, p. 9) that, within economics, occurred in the space of utility maximization (Alkire, 2015, p. 5). Poverty in the space of capabilities is naturally multidimensional: "it is concerned with a plurality of different features of our lives and concerns" (Sen, 2011, p. 233). It is in this context that poverty measurement efforts started to evolve towards a multidimensional approach, now commonly known as the Alkire-Foster (AF) method (Alkire & Foster, 2011; Alkire & Santos, 2010). For our purposes, energy poverty can be understood as "only one dimension of deprivation and insufficient well-being" (Pelz et al., 2018, p. 1), i.e., another dimension of poverty.

In Mexico, was the recent fall in *multidimensional poverty*[2] accompanied by a fall in energy poverty? Between 2018 and 2024 the share of the Mexican population in multidimensional poverty fell from 41.9% to 29.6%, that implies a net difference of 13.4 million people (INEGI, 2025d). Moreover, between 2018 and 2024 the the federal minimum wage increased, in real terms, by 116.4pp, accounting for 49.2% of the total reduction in poverty (Munguía Corella & Gómez Lovera, 2025, p. 7).[3]

These recent events compel us to identify and include an affordability dimension into previous multidimensional energy poverty (MEP) measures estimated for Mexico (e.g., García-Ochoa and Graizbord Ed 2016; García-Ochoa et al. 2016; Santillán et al. 2020; Robles-Bonilla and Cedano 2021; Cedano et al. 2021; Soriano-Hernández et al. 2022; Jiménez Torres et al. 2026; and Canto-Franco et al. 2026). Within a country, as average household income rises, according to the "energy ladder" theory (Van Der Kroon et al., 2013; Waweru et al., 2022), there is a substitution process between *traditional* (biomass sources, primarily) non-monetary commercialized and *modern* (oil, gas, electricity) monetary commercialized fuel sources.

We can see this trend in Panels (a) and (b) presented of Figure 1. The former shows a na-

[2]For CONEVAL (2019b), an individual is considered to be multidimensionally poor if: (*i*) his *total current income per capita* (ICTPC, by its acronym in spanish) falls bellow a predefined welfare-income line (with a rural-urban distinction); (*ii*) and possesses one or more *social deprivations*: education, healthcare, social security, basic services, housing quality and food security.

[3]This increase in the minimum wage is reported utilizing the weighted average methodology in line with by CONASAMI (2023).

tionwide distributional shift, apparently symmetrical (with a constant standard deviation), the latter shows a multi-modal distribution where it is visually evident that the share of the population within the bottom 20% of the distribution with an energy expenditures above the national average increased dramatically from 2016 to 2024. We argue that the topic of affordability is then essential for the analysis of energy poverty in Mexican context.

The first systematic measurements of energy poverty date back to the 1980's in western Europe (particularly in the United Kingdom). These works where distinctively concerned with the dimension of *fuel poverty* (heating fuel) (Day et al., 2016; K. Li et al., 2014; Primc et al., 2021; Sovacool, 2015). These early studies emphasized the affordability aspect of energy services (see Bradshaw and Hutton 1983; Krugmann and Goldemberg 1983; Leach 1987; Goldemberg and Johansson 1995; and Boardman 1991).[4] In these approaches households are identified as poor if they spend more than a certain share of their income on fuel services or if that income falls below an specific consumption-based energy poverty line (see Thomson, Bouzarovski, and Snell 2017; Thomson, Snell, and Bouzarovski 2017; Awaworyi Churchill and Smyth 2020; and Awaworyi Churchill et al. 2020).

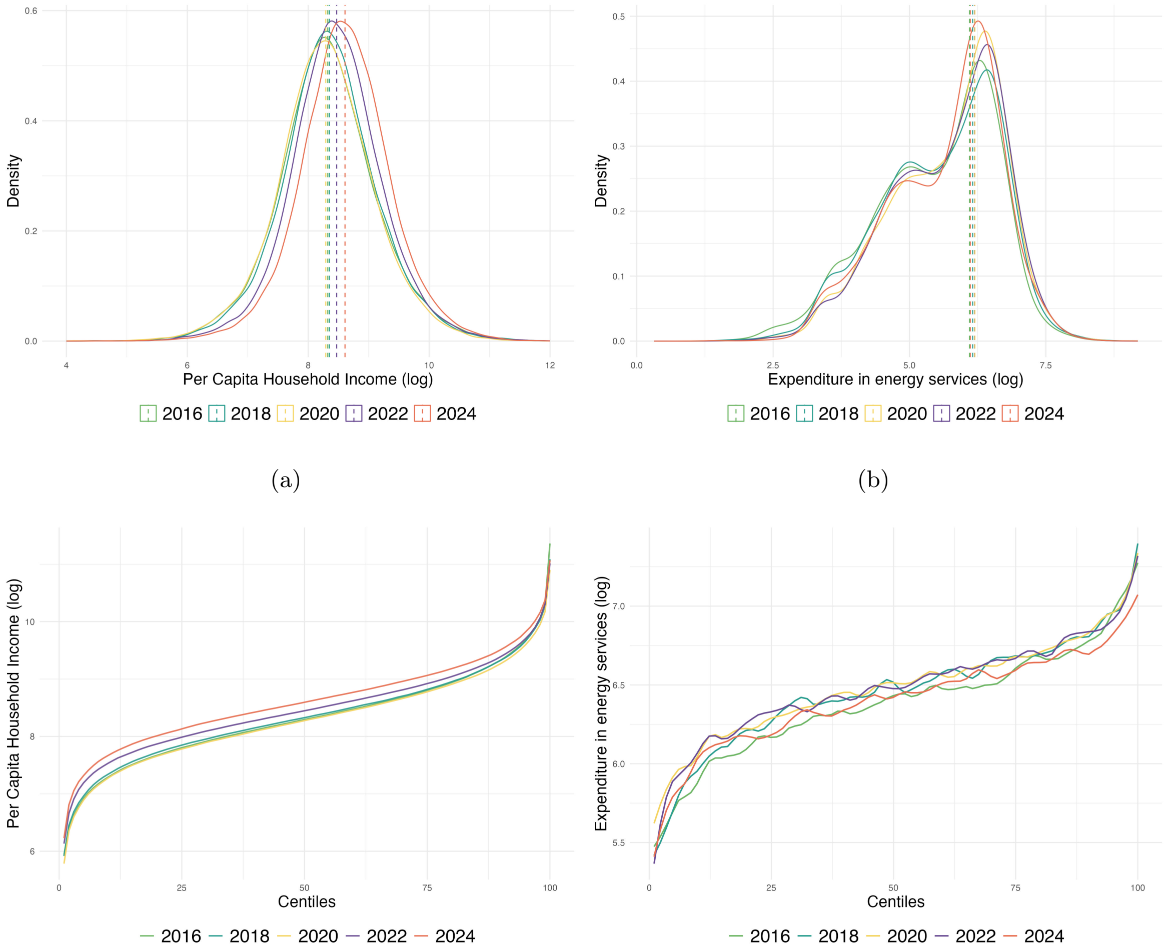
The limitations of this approach eventually fostered the development of the "low income high cost" approach (Hills, 2011, 2012), where a household is identified as poor if their income fails to be above the poverty line after deducting energy expenditures. These unidimensional consumption based measures are, nevertheless, not entirely appropriate and applicable to the realities of developing countries (K. Li et al., 2014; Rafi et al., 2021; Sy & Mokaddem, 2022): problems related to preferences, the availability and reliability of electricity, as well as the fact that vulnerabilities related to the inaccessibility of energy services might be spread across income groups serve as arguments (and limitations) against universal all encompassing energy poverty measures (Akpalu et al., 2011; Barnes et al., 2010, 2011; Hiemstra-van Der Horst & Hovorka, 2008; Leach, 1992).

A wide variety of empirical approaches have been put forward in order to monitor and asses energy poverty in developing countries, Sy and Mokaddem (2022, p. 6) outlines three big categories of indicators: (*i*) unidimensional; (*ii*) dashboard; and (*iii*) composite/multidimensional. Unidimensional measures can be consumption-based, focusing on minimum energy requirements, efficiency, etc. This is the so called *engineering approach*.[5] Another–already previously mentioned–set of unidimensional indicators are income based, this is the *economic approach*.[6]

[4] As noted by Soriano-Hernández et al. (2022), most of the studies utilizing this methodology are a popular proxies of energy poverty in the global north (see Balaskas et al. 2021; Tundys et al. 2021; and Das et al. 2022).

[5] Some examples of this approach are Goldemberg (1990), Johansson (2000), Krugmann and Goldemberg (1983), Pachauri et al. (2004), Parikh (1978), Reddy (1999), Swan and Ugursal (2009), and Ye and Koch (2021).

[6] See Barnes et al. (2010, 2011), Boardman (1991), Bradshaw and Hutton (1983), Hills (2011, 2012), Khundi-



(a) (b)

(c) (d)

Figure 1: Panels of shits in the distribution of income and energy expenditures (2016–2024). All variables are deflated to August 2024. All means where computed using ENIGH's stratified clustered design, with primary sampling units, sample design stratum, and individual expansion factors. (a) ICTPC kernel distributions. (b) Energy expenditure kernel distributions, bottom 20% of the ICTPC distribution. (c) Shifts in the distribution of income across ICTPC centiles. (d) Shifts in the distribution of energy expenditures across ICTPC centiles, lines smoothed with using Locally Estimated Scatterplot Smoothing (LOESS). Own estimations using data from INEGI (2017, 2019, 2021, 2023a, 2025a).

Dashboard indicators are non-aggregated estimates at the national and/or global level, they are "based on economic, environmental, social, technical and institutional sustainability" (Sy & Mokaddem, 2022, p. 8) (see Manning 2009; and Vera and Langlois 2007). These indicators aim to provide a broad picture of the energy system in place and its progress towards MDG's and SDI's (UN, 2015, 2025).

Finally, composite estimates can be *multifaceted*, *target-based*, or *binary* (Sy & Mokaddem, 2022). Multifaceted outlooks on energy poverty are household based measures characterized by employing a *fuzzy set* procedure of identification (rather than a *crisp set approach*, see Olsen and Nomura 2009): the elements (households) of a set (the energy poor), rather than just belonging, or not, to it, have "different degrees of membership" (Alkire, 2015, p. 102).[7] The target based approach is "designed to evaluate the progress towards achieving the sustainable development goals relating to the global energy sector" (Sy & Mokaddem, 2022, p. 11), hence, the backbone of these measures is the assessment of (on a national-based perspective) access to modern energy services, energy intensities, and the share of renewable sources in the energy mix without necessarily just focusing on the residential sector (Primc et al., 2019).[8]

The multidimensional binary approach of energy poverty belongs to the family of MEPI estimates first developed by Nussbaumer et al. (2012) under the AF framework (see Alkire and Santos 2010; Alkire and Foster 2011; and Alkire 2015). These measures have substantially grown in popularity over the last 15 years, being applied in a multiplicity of socioeconomic environments across many different countries (Pelz et al., 2018; Sy & Mokaddem, 2022).[9] In our view, this is because the family of MEPI indicators have certain attractive features for researchers: (*i*) low data requirements (i.e., can be computed with a regular household income-expenditure survey); (*ii*) high degree of normative customization-flexibility (in weighting and in deprivation and poverty cutoffs); and (*iii*) they hold all of the desirable common properties familiar to AF indexes (e.g., subgroup decomposability, dimensional breakdowns).

The contribution to the literature of this essay is threefold. Firstly, it proposes an updated,

Mkomba et al. (2021), Leach (1987), and Phoumin and Kimura (2019)

[7] For examples, consult Bhatia and Angelou (2015), Gupta et al. (2020), Nathan and Hari (2020), Olang et al. (2018), and Seuret-Jimenez et al. (2020).

[8] See Banerjee et al. (2021), Bonatz et al. (2019), Che et al. (2021), Khanna et al. (2019), W. Li et al. (2021), and B. Wang et al. (2017).

[9] The literature is extensive: Abbas et al. (2020), Bersisa (2017), Bollino and Botti (2017), Canto-Franco et al. (2026), Cedano et al. (2021), Crentsil et al. (2019), Jayasinghe et al. (2021), Jiménez Torres et al. (2026), Kryk and Guzowska (2023), Mendoza et al. (2019), Nussbaumer et al. (2013), Ogwumike and Ozughalu (2016), Okushima (2017), Qurat-ul-Ann and Mirza (2021), Rizal et al. (2024), Robles-Bonilla and Cedano (2021), Sadath and Acharya (2017), Santillán et al. (2020), Sokołowski et al. (2020), Ssennono et al. (2021), Tovar Reaños et al. (2025), and Y. Wang and Boqiang Lin (2022).

novel, time comparable national, subnational and decomposable (through dimensions, population subgroups and income brackets) MEPI measure, relevant for analyzing recent trends in multidimensional poverty, sustainable development and income distribution in Mexico. Secondly, it develops an axiomatic and analytical presentation of a dimensionally-flexible MEPI indicator to address heterogeneous needs across subsets of the population. And, finally, it incorporates (for the first into a national measure): (*i*) the traditional MEPI dimensions (cooking, lighting, refrigeration, entertainment, communication) (Nussbaumer et al., 2012); (*ii*) the nationally relevant dimension of thermal comfort (see Canto-Franco et al. 2026; Cedano et al. 2021; Jiménez Torres et al. 2026; Robles-Bonilla and Cedano 2021); (*iii*) the water heating dimension of the Meeting of Absolute Energy Needs method (MAEN) (see García-Ochoa 2014; García-Ochoa and Graizbord Ed 2016; and García-Ochoa et al. 2016); (*iv*) and the affordability dimension *à la* Hills (2011, 2012). The structure of the essay is the following: Section 2 introduces the dataset we used and the axiomatic approach *à la* Alkire (2015) for our proposed MEPI; section 3 presents our national, subnational and subgroup estimations for the incidence (H), the intensity (A) and the adjusted headcount ratio (M_0) of energy poverty; and, finally Section 4 draws on some conclusions and discusses the potential limitations of the proposed MEPI.

2 Data and Methodology

2.1 Data

We use the *new series* (2016-2024, biennially) National Household Income and Expenditure Survey (ENIGH, by its acronym in spanish), made available by INEGI (2017, 2019, 2021, 2023a, 2025a), that is the Mexican National Institute of Geography and Statistics (INEGI being its acronym in Spanish): this is a repeated cross-section. As stated by CONEVAL (2019b), the ENIGH dataset is the only legal and necessary input for the calculation of the official multidimensional poverty measure made by the Mexican government. We complement the information provided by the ENIGH new series (see INEGI 2023b) with the multidimensional poverty datasets (2016-2022) elaborated by the National Council for the Evaluation of Social Development Policy (CONEVAL, by its acronym in spanish) (CONEVAL, 2023) and by the 2024 dataset now calculated by INEGI (2025c).

For the identification of households living in warm, cold or temperate municipalities we spatially joined isoline maps and weather station information (1,494 stations across 1902–2012) of average, maximum and minumum yearly temperatures (INEGI, 2007, 2023c) with the geostatistical framework (municipal projections) produced by INEGI (2025b). The information provided by the weather stations was spatially interpolated into the municipal projections using Inverse Distance Weighting (IDW) (Cressie, 1993; Gräler et al., 2016; Pebesma, 2004). See the panels in Figure 2.

2.2 Methods

The following presentation follows directly from Alkire (2015, pp. 24-50). Let $X \in \mathbb{R}_+^{n \times d}$ be the achievement matrix. Such that there are $n \in \mathbb{N}$ with $N = \{1, 2, ..., n\}$ individuals across $d \in \mathbb{N}$ with $D = \{1, 2, ..., d\}$ dimensions. Hence $X = \{x_{ij}\}$ is the matrix containing as entries the j-th achievement of the i-th individual $\forall i = 1, 2, ..., n$ and $\forall j = 1, 2, ..., d$.[10] Let $z = (z_1, z_2, ..., z_d) \in \mathbb{R}_{++}^d$ be the deprivation cutoff vector, such that matrix $G \in \{0, 1\}^{n \times d}$ is the deprivation matrix where each g_{ij} is defined as:

$$g_{ij}(x_{ij}; z_j) = \begin{cases} 1 \text{ if } x_{ij} < z_j \\ 0 \text{ if } x_{ij} \geq z_j \end{cases} \tag{1}$$

If we assume that not all dimensions are relevant for all individuals, then: for each j-th dimension $\exists J_j \subseteq N$ such that $N = \bigcup_{j=1}^d J_j$. Let $\mathcal{A} \in \{1, 0\}^{n \times d}$ be the *availability matrix*, with each a_{ij} defined as:

$$a_{ij} = \begin{cases} 1 \text{ if } i \in J_j \\ 0 \text{ if } i \in J_j^c = N \setminus J_j \end{cases} \tag{2}$$

In the original Alkire (2015, p. 30) method each dimension j has a relative weight $w_j > 0 \, \forall j$, thus $w = (w_1, w_2, ..., w_d) \in \mathbb{R}_{++}^d$ where $\sum_{j=1}^d w_j = 1$. In our proposed framework, for i-th individual we have:

$$\tilde{w}_i = \left(\frac{w_1 a_{i1}}{\sum_{j=1}^d w_j a_{ij}}, ..., \frac{w_d a_{id}}{\sum_{j=1}^d w_j a_{ij}} \right) \in \mathbb{R}_+^d \iff \sum_{j=1}^d w_j a_{ij} > 0 \, \forall i \tag{3}$$

$$\Rightarrow c_i = \sum_{j=1}^d \tilde{w}_{ij} \cdot g_{ij} \in [0, 1] \tag{4}$$

The i-th row of $\mathcal{A}$, is given by $a_i \in \{1, 0\}^d$, and its defined as the *dimension availability vector* of i across all d. Hence, in equation (3), the condition $\sum_{j=1}^d w_j a_{ij} > 0 \, \forall i$ means that $a_i \neq 0 \, \forall i$ (at least one dimension is relevant for each individual i). Equation (4) defines the deprivation score of each individual i, where $c_i \in [0, 1]$ by construction: $\sum_{j=1}^d \tilde{w}_{ij} = 1$ by

[10] Note that the i-th row $x_i \in \mathbb{R}_+^d$ represents the achievements of i across all d $\forall i$, similarly the j-th column $x_j \in \mathbb{R}_+^n$ represents the achievements of dimension j across all i $\forall j$.

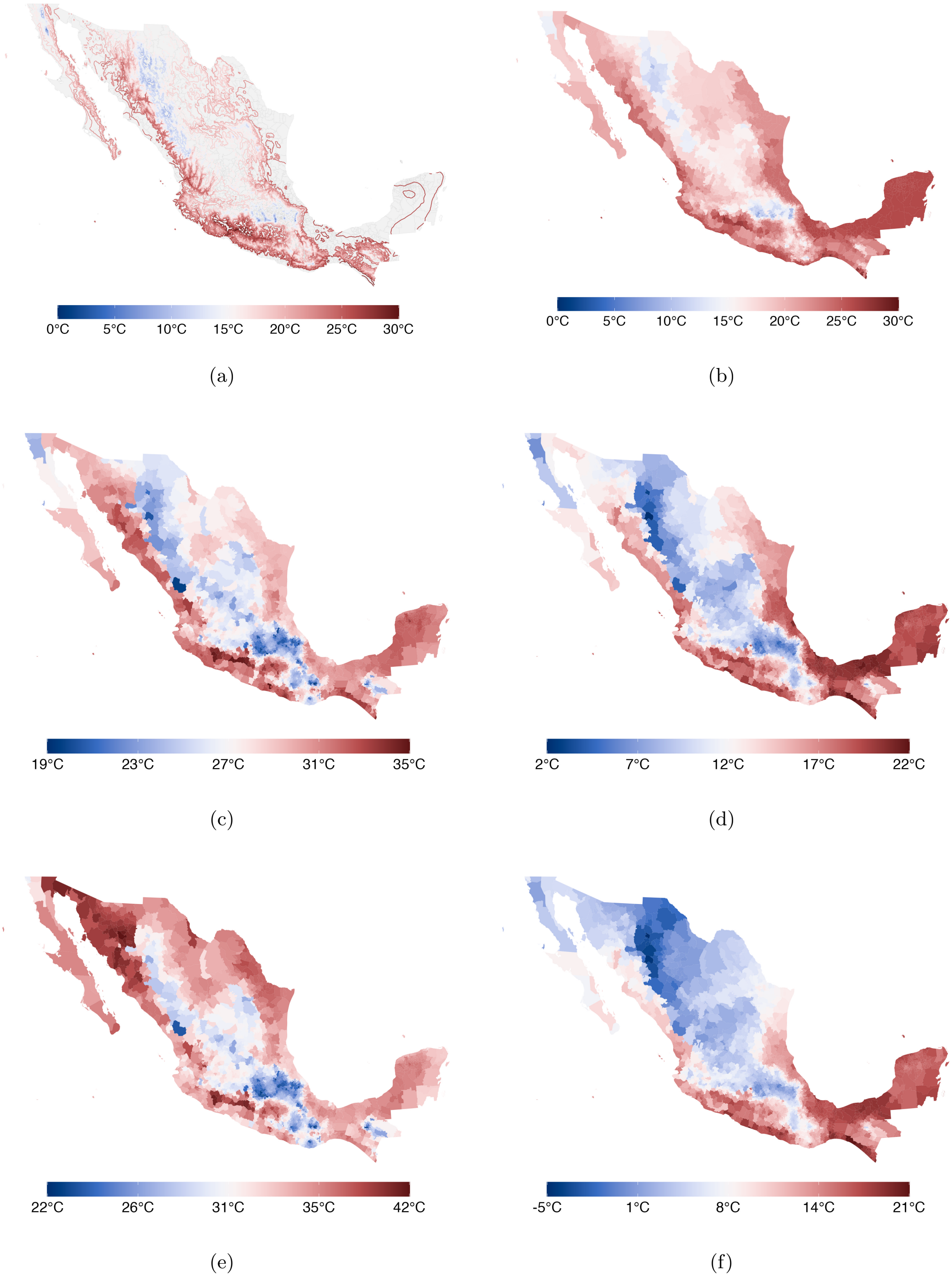


Figure 2: Temperature Maps. (a) Isoline map (average yearly temperature); (b) Municipality spatial join; (c) average yearly maximum temperature; (d) average yearly minimum temperature; (e) maximum yearly temperature; (f) minimum yearly temperature. Own elaboration with data from INEGI (2007, 2023c, 2025b).

(3) and $g_{ij} \in \{0,1\}$ by (1). As stated by the dual-cutoff approach (Alkire, 2015, pp. 148-156), we define the poverty cutoff $k \in (0,1]$ as the determination of the minimum deprivation score required for an individual to be identified as multidimensionally poor. We can define the function $\rho_k : [0,1] \to \{0,1\}$:

$$\rho_k(x_i; z) = \begin{cases} 1 \text{ if } c_i \geq k \\ 0 \text{ if } c_i < k \end{cases} \tag{5}$$

This approach encompasses the union and intersection criteria as special cases. Given the specification of $\mathcal{A}$ outlined in equation (2), we have that $\tilde{w}_i$ varies across individuals, however the union and intersection cutoff's must hold universally across all availability subsets of N. The censored deprivation score is then:

$$c_i(k) = c_i \cdot \rho_k(x_i; z) = \begin{cases} c_i & \text{if } c_i \geq k \\ 0 & \text{if } c_i < k \end{cases} \tag{6}$$

Let $q = \sum_{i=1}^{n} \rho_k(x_i; z) \in \mathbb{N}$ denote the number of poor individuals, such that $Z = \{i \in N : \rho_k(x_i; z) = 1\}$ is the set of poor individuals, and let $D_i = \{j : a_{ij} = 1\}$ be the set of dimensions available to individual i. Then, the three identification cutoffs are: (i) $k = \min_{i \in N} \min_{j \in D_i}\{\tilde{w}_{ij}\}$ (union); (ii) $k \in (\min_{i \in N} \min_{j \in D_i}\{\tilde{w}_{ij}\}, 1)$ (middle-ground); and (iii) $k = 1$ (intersection). From here we can define the incidence (H, share of the population in multidimensional poverty), intensity (A) and the adjusted headcount ratio (M_0) of poverty:[11]

$$H = \frac{q}{n} = \frac{1}{n}\sum_{i=1}^{n} \rho_k(x_i; z) \in [0,1] \tag{7}$$

$$A = \frac{\sum_{i=1}^{n} c_i(k)}{q} = \frac{\sum_{i=1}^{n} c_i(k)}{\sum_{i=1}^{n} \rho_k(x_i; z)} \in [0,1] \tag{8}$$

$$M_0 = H \cdot A = \frac{q}{n} \cdot \frac{\sum_{i=1}^{n} c_i(k)}{q} = \frac{1}{n}\sum_{i=1}^{n} c_i(k) \tag{9}$$

For dimensional contributions, note that by (4) and (6) we have that $c_i(k) = \sum_{j=1}^{d} \tilde{w}_{ij} \cdot g_{ij} \cdot \rho_k(x_i; z)$, such that we can write (9) as:

$$M_0 = \frac{1}{n}\sum_{i=1}^{n} c_i(k) = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{d} \tilde{w}_{ij} \cdot g_{ij} \cdot \rho_k(x_i; z)$$

$$\Rightarrow M_0 = \sum_{j=1}^{d} \frac{1}{n}\sum_{i=1}^{n} \tilde{w}_{ij} \cdot g_{ij} \cdot \rho_k(x_i; z) = \sum_{j=1}^{d} \delta_j \tag{10}$$

$$\Rightarrow \delta_j^{(r)} = \frac{\delta_j}{M_0} \in [0,1] \tag{11}$$

[11] In the empirical application, all estimates are computed using ENIGH's stratified clustered design, with primary sampling units, design strata, and individual expansion factors f_i. The population share $\frac{n_l}{n}$ in the subgroup decomposition is replaced by the weighted share $\hat{\pi}_l = \frac{\sum_{i \in N_l} f_i}{\sum_{i \in N} f_i}$.

Where δ_j is the dimensional contribution of j to M_0, hence $\delta_j^{(r)}$ is the relative contribution of j to M_0, which implies that $\sum_{j=1}^{d} \delta_j^r = 1$. Finally, for subgroup decomposition, we have that if N is partitioned in $L \in \mathbb{N}$ mutually exclusive and exhaustive subsets, such that $N = \bigcup_{l=1}^{L} N_l$ and if $i \neq j \Rightarrow N_i \bigcap N_j = \emptyset$, with $n_l = |N_l| \ \forall l$ (which implies that $\sum_{l=1}^{L} n_l = n$). Then:

$$M_0 = \frac{1}{n}\sum_{i=1}^{n} c_i(k) = \frac{1}{n}\sum_{l=1}^{L}\sum_{i\in N_l} c_i(k) = \sum_{l=1}^{L}\frac{n_l}{n}\cdot\frac{1}{n_l}\sum_{i\in N_l} c_i(k) = \sum_{l=1}^{L}\frac{n_l}{n}\cdot M_0^{(l)} \tag{12}$$

Therefore $M_0^{(l)} = H^{(l)} \cdot A^{(l)}$ is the adjusted headcount ratio withi subgroup l, and $\frac{n_l}{n}$ is the share of the population n within subgroup l. This additive decomposition holds for any partition (e.g., urban/rural, federal entity, sex, ethnicity, income brackets). Our empirical approximation for determining dimensions, cutoffs and weights is is summarized in Tables 1 and 2. Note that, by construction $z_j = 1 \ \forall j = 1, ..., 8$.

Table 1: Empirical Dimensions, Deprivation Cutoffs, and Weights

j	Dimension	Deprivation cutoff z_j	w_j
1	Electricity Access (Ea)	Has access to electricity	0.3102
2	Water Heating (Wt)	Has gas, electric, or solar water heater or stove	0.1476
3	Communication (Cm)	Has access to a cellphone or a landline at home	0.1434
4	Entertainment (Et)	Has television, radio, or computer with internet access	0.1229
5	Refrigeration (Rf)	Has refrigerator	0.1145
6	Cooking (Ck)	Uses gas, electric, or solar stove; chimney required if biomass fuel is used (CONEVAL, 2019b)	0.1005
7	Affordability* (Af)	ICTPC exceeds poverty line after subtracting energy expenditures (Hills, 2011, 2012)	0.0312
8	Thermal Comfort** (Tc)	Hot climate: air conditioning or $\geq$1 fan per 2 members (García-Ochoa & Graizbord Ed, 2016); Cold climate: heating system	0.0293

Notes: Weights w_j are estimated via Multiple Correspondence Analysis (MCA) on the pooled 2016–2024 cross-sections (Asselin & Anh, 2008; Dhongde & Haveman, 2017; Noglo, 2017): this avoids violating the AF properties of *monotonicity* and *subgroup consistency* (as noted by Dutta et al. 2021). * Following INEGI (2023b) expenditure codes, the goods and services taken into account are: electricity, natural gas, oil, diesel, stationary and non-stationary LP gas, liquid fuels, coal-charcoal, wood-based fuels, candles, and "other biomass fuels". ** Indoor climate applies only in hot ($> 30°$C) or cold ($< 10°$C) municipalities (as in Cedano et al. 2021; and Robles-Bonilla and Cedano 2021), weights are re-normalized over the remaining 7 dimensions in temperate zones (10–30°C) via the availability matrix $\mathcal{A}$ (equation 2). Source: table adapted from García-Ochoa and Graizbord Ed (2016) and Nussbaumer et al. (2012) using microdata from INEGI (2017, 2019, 2021, 2023a, 2025a).

Table 2: Empirical Construction of the Achievement Matrix X

d_j	ENIGH Variables	x_{ij}
Ea	$ea \in \{1, ..., 5\}$	$x_{i1} = \mathbf{1}(ea \leq 4)$
Wt	$sh, gh \in \{0, 1\}$; $st \in \mathbb{N}$	$x_{i2} = \mathbf{1}(sh = 1 \vee gh = 1 \vee st \geq 1)$
Cm	$cl, tl \in \{0, 1\}$	$x_{i3} = \mathbf{1}(cl = 1 \vee tl = 1)$
Et	$tv, rd, cm \in \mathbb{N}$; $ic \in \{0, 1\}$	$x_{i4} = \mathbf{1}[tv \geq 1 \vee rd \geq 1 \vee (cm \geq \wedge ic = 1)]$
Rf	$fr \in \mathbb{N}$	$x_{i5} = \mathbf{1}(fr \geq 1)$
Ck	$fu \in \{1, ..., 7\}; ch \in \{0, 1\}$	$x_{i6} = \mathbf{1}[cm \geq 3 \vee (cm < 3 \wedge ch = 1)]$
Af	$ict, ee, hs^e \in \mathbb{R}_+$; $ru \in \{0, 1\}$	$x_{i7} = \mathbf{1}(\frac{ICT - ee}{hs^e} \geq \ell_{ru})$
Tc	$ac, ht \in \{0, 1\}$; $wt \in \{1, 2, 3\}$ $hs, fn \in \mathbb{N}$	$x_{i8} = \begin{cases} \mathbf{1}(ac = 1 \vee \frac{fn}{hs} > \frac{1}{2}) \text{ if } wt = 1 \\ \mathbf{1}(ht = 1) \text{ if } wt = 3 \end{cases}$

Notes: Where $\mathbf{1}(\cdot)$ is the *indicator function*. ea =electricity access (1=private, 2=public, 3=solar, 4=other, 5=no access); sh =solar heating; gh =gas heating; st =number of stoves; cl =cellphone; tllandline telephone; tv =number of televisions; rd =number of radios; cm =number of computers; ic =internet access; fr =number of refrigerators; fu=type of fuel in use (1=wood, 2=coal, 3=gas by tank, 4=gas by pipe, 5=electricity, 6=other, 7=household doesn't cook); ch =chimney; ict =total current income; ee =sum of energy expenditures; hs^e =scaled household size (see CONEVAL 2019b); ru =rural household; ac =air conditioning; ht =heating; wt =type of weather (1=hot, 2=temperate, 3=cold); hs =household size; fn =number of fans. Source: Own elaboration using microdata from INEGI (2017, 2019, 2021, 2023a, 2025a).

3 Results

Our results reveal a significant, however asymmetric, reduction in the incidence and intensity of energy poverty and its dimensional components. According to the estimated MEPI (see Table 3 and A1) we can obverse that the share of the population living in energy poverty (H) fell from 26.13% (31.5 million people) in 2016 to 19.51% (25.3 million people) in 2024: this is a reduction of 6.6pp. According to our proposed measure 6.1 million people escaped energy poverty between 2016 and 2024. The average intensity of poverty (A) also decreased, albeit modestly, with a 2.31pp reduction: those remaining in poverty still face a dense cluster of deprivations (those remaining in poverty experience on average 24.9% of all weighted deprivations).

Also between 2016–2024, we can report a reduction in incidence through all dimensions but one: entertainment (which grew by 1.67pp). In relative terms, the biggest improvements where made in the following dimensions: affordability (−18.09pp), thermal comfort (−11.16pp) and

Table 3: Multidimensional Energy Poverty Index: National Estimates (means-shares, %), 2016–2024

	2016	2018	2020	2022	2024	Δ (pp)
MEP Index components						
H^*	26.129	25.975	22.566	22.399	19.505	−6.625
A^{**}	27.165	27.215	25.882	25.574	24.851	−2.314
$M_0{}^{***}$	7.098	7.069	5.841	5.728	4.847	−2.251
Dimensional deprivation rates						
Ea	0.409	0.395	0.222	0.321	0.242	−0.166
Wt	9.741	9.753	8.486	8.490	7.342	−2.399
Et	3.918	4.913	4.510	6.112	5.593	+1.676
Cm	9.196	7.879	4.904	3.887	2.582	−6.614
Rf	13.758	13.159	11.003	10.274	9.209	−4.549
Ck	11.635	12.589	11.697	11.311	9.698	−1.936
Af	55.430	56.378	55.216	45.845	37.333	−18.098
Tc	61.746	61.259	57.850	55.828	50.577	−11.169

Note: All estimates computed using ENIGH's stratified clustered design with individual expansion factors (INEGI, 2023b). Δ (2016–2024) expressed in percentage points (pp). * The poverty cutoff is set at $k = 0.15$. ** Share (%) of deprivations experienced by the poor. ** Share (%) of all possible deprivations experienced by the population through the poor. Source: Own estimations using data from INEGI (2017, 2019, 2021, 2023a, 2025a).

communication (-6.61pp). In totals, the picture changes slightly, the largest improvemenst where made in: affordability (−18.3 million), communication (−7.7 million) and refrigeration (−4.6 million). The large improvements made in the affordability dimension are consistent with the literature on the recent trends in wages and multidimensional poverty in Mexico (see Campos-Vázquez and Rodas Milián 2020; Campos-Vazquez and Esquivel 2021; Campos-Vazquez and Esquivel 2023; Munguía Corella and Gómez Lovera 2023; and Munguía Corella and Gómez Lovera 2025).

With respect to M_0–see Table A2–we observe that the adjusted headcount ratio decreases monotonically (even with the COVID-19 pandemic shock) from 7.098% (2016) to 4.847% (2024). This represents a substantial 31.7% relative reduction in the breadth and depth of energy poverty over the eight-year period. This is a generalized reduction in censored deprivations across most dimensions, as seen in the decline of their absolute contributions δ_j. However, note that this improvement is not *neutral*: there is a clear reconfiguration of its internal structure. Relative contractions in $\delta_j^{(r)}$ are noticed in communication (−11.19pp), affordability (−1.38), refrigeration (-0.49pp), electricity access (-0.28pp), and thermal confort (-0.14pp). Expansions are detected in entertainment ($+7.57$pp), cooking ($+3.725$) and water heating ($+2.16$pp): this trends are observable in Figure 3.

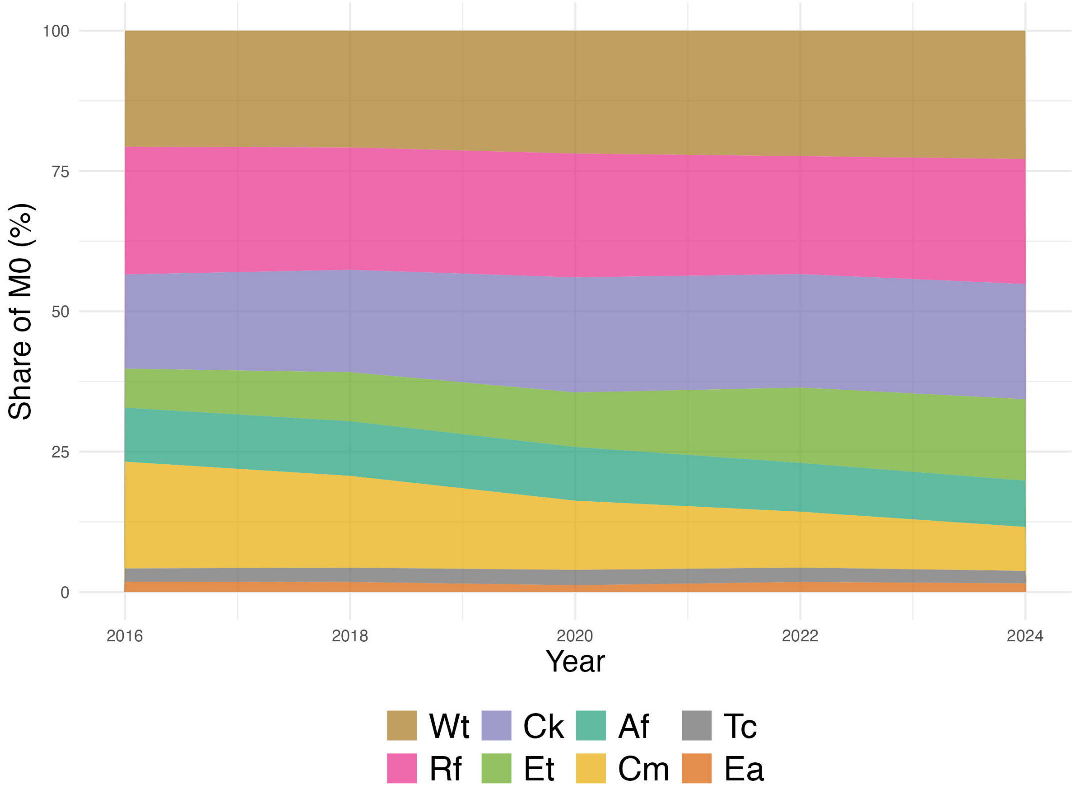


Figure 3: Dimensional contributions to M_0 (2016-2024). Own elaboration with data from INEGI (2007, 2017, 2019, 2021, 2023a, 2025a, 2025b).

The disaggregated data by sociodemographic subgroups compiled in Table 4 stresses the structural character of vulnerabilities in Mexico (see CONEVAL 2019a, for example). As of 2024, rural, indigenous, poor, children and uneducated individuals continue to endure, disproportional rates of MEP: with gaps (and factors) amounting to 36.47pp ($\times 4.16$), 56.85pp ($\times 4.62$), 29.11pp ($\times 3.67$), 4.73pp ($\times 1.26$) and 23.69pp ($\times 2.57$) accordingly. Note that the indigenous/non-indigenous MEP gap is the only one that increased across our period of study ($+2.04$pp). The most notable convergence was in the elderly/non-elderly gap, which nearly closed: from 2.07pp in 2016 to 0.34pp in 2024. Across the income distribution (ICTPC centiles), as expected, we can observe an steady quasi-monotonically decreasing trend regarding H and A, as income increases. Moreover, we observe a positive correlation between ΔH and ICTPC centiles: higher incomes imply slower reductions in H, which implies–although at this stage only visual–a convergence process in energy poverty levels across income levels (see the panels of Figure A1).

The observed spatial distribution of energy poverty (as a proxy of general vulnerabilities) goes in line with previous findings, both in multidimensional poverty (CONEVAL, 2019a; INEGI, 2025d) and energy poverty (García-Ochoa et al., 2016; Jiménez Torres et al., 2026): regional disparities are outstanding. These results are presented in the panels of Figure 4. The southeastern states of Mexico (Campeche, Chiapas, Guerrero, Oaxaca, Tabasco, Quintana Roo, Yucatán) display higher rates of MEP incidence (H) and intensity (A). Lower average per capita incomes in comparison to other parts of the country are also visible in this region, especially with comparison to northern states (e.g., Coahuila, Durango, Nuevo León, Sonora, Tamaulipas). Nonetheless, MEP incidence is decreasing across the country with one exception: the northern state of Durango. Shifts in A across Mexican states follow a similar trend: the average share of deprivations experienced by the poor is decreasing, with the exception of Chihuahua and, again, Durango. Finally, in panel (f) we believe that there is an open question regarding income convergence and its role in reducing MEP.

Table 4: Multidimensional Energy Poverty Incidence (H) and Intensity (A) by Sociodemographic Subgroup (means-share, %), 2016 and 2024

		H		A		Δ (pp)	
Category	Subgroup	2016	2024	2016	2024	H	A
Rural	Urban	16.833	11.531	22.348	20.427	−5.301	−1.921
	Rural	57.173	48.008	31.666	28.567	−9.165	−3.099
Indigenous	Non-indigenous	22.622	15.698	24.472	21.454	−6.924	−3.018
	Indigenous	77.433	72.556	38.383	35.234	−4.876	−3.150
Poverty	Non-poor	11.992	10.909	20.120	18.889	−1.083	−1.231
	Poor	44.712	40.014	29.488	28.656	−4.698	−0.832
Children	Adults	24.391	18.191	26.526	24.118	−6.200	−2.408
	Children	29.669	22.925	27.919	26.229	−6.744	−1.690
Elderly	Non-elderly	25.967	19.469	26.895	24.724	−6.498	−2.171
	Elderly	28.036	19.809	28.706	25.510	−8.227	−3.195
Educ. lag	No educ. lag	21.400	15.091	25.277	22.897	−6.310	−2.379
	Educ. lag	47.009	38.790	30.605	28.052	−8.219	−2.553

Note: All estimates computed using ENIGH's stratified clustered design with individual expansion factors (INEGI, 2023b). Children = individuals aged ≤ 17. Elderly = individuals aged ≥ 65. Indigenous = Indigenous language speaker. Poverty = CONEVAL (2019b) multidimensional poverty classification. Educ. lag = household with educational (see CONEVAL 2019b). Source: Own estimations using data from INEGI (2017, 2019, 2021, 2023a, 2025a).

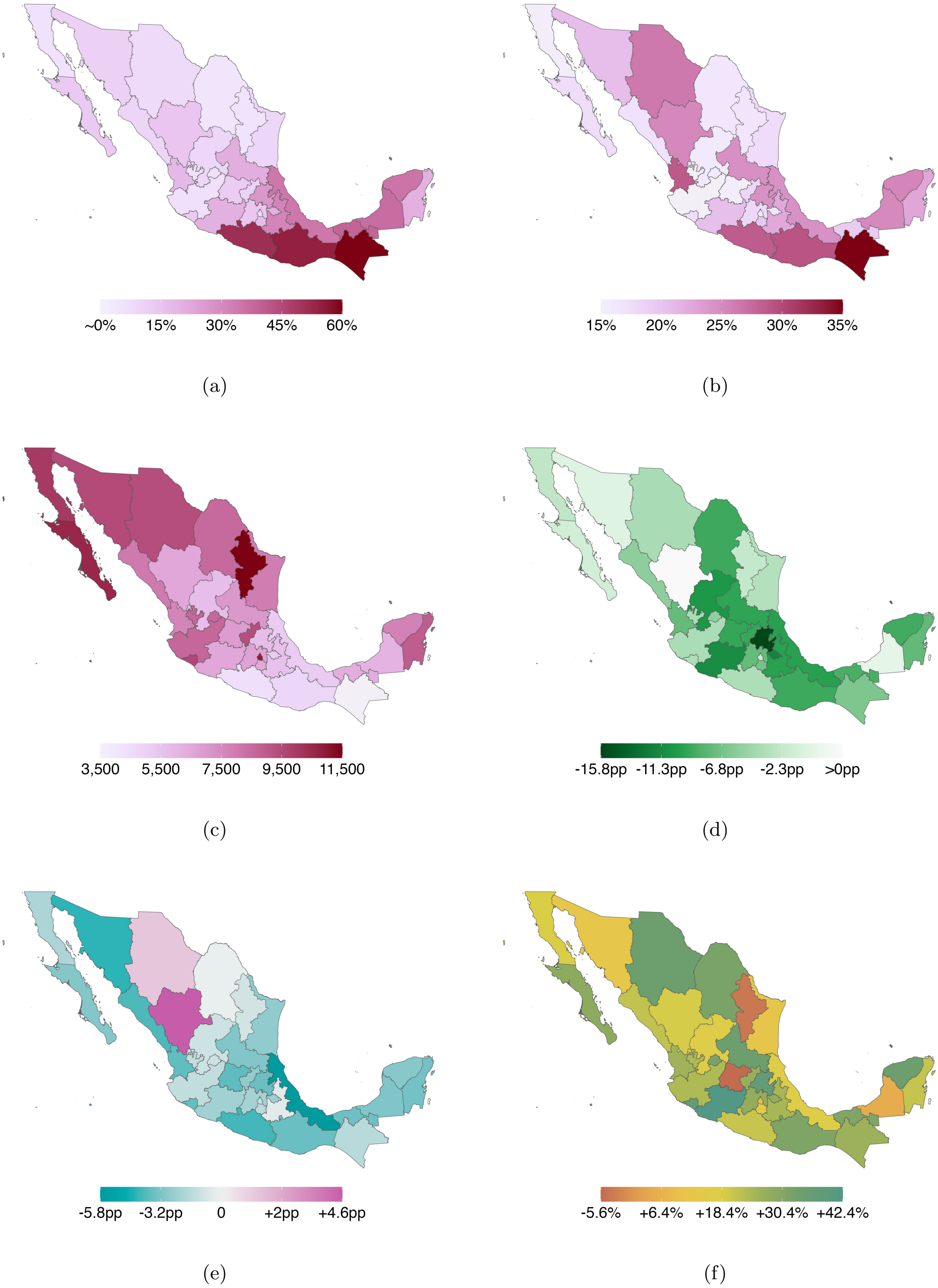


Figure 4: MEPI and income Maps. (a) Incidence (H), 2024; (b) Intensity (A), 2024; (c) ICTPC, 2024; (d) ΔH, in percentage points (2016-2024); (e) ΔA (2016-2024); (f) Real growth rate of the ICTPC, (2016-2024, prices deflated to August 2024). Own elaboration with data from INEGI (2007, 2017, 2019, 2021, 2023a, 2025a, 2025b).

4 Conclusion-Discussion

Our MEPI measure suggests that energy poverty in Mexico is in retreat (Tables 3 and A1). In this process we perceive shifts in the dimensional composition of MEP (Figure 3 Table A2) and structural and persistent socioeconomic and spatial inequalities (see Table 4, and Figures 4 and A1). To conclude, we believe that the present work needs further improvement and discussion in the following areas: (*i*) robustness tests with varying weighting approximations (exogenous and endogenous alike, see Dutta et al. 2021) and with contrasting poverty cutoffs (Chan & Wong, 2025); (*ii*) further work in formalizing our analytical proposal (i.e., mathematically prove that our MEPI holds the AF properties of *symmetry*, *monotonicity*; *transfer*, *subgroup decomposability*, etc); (*iii*) additional analysis regarding the positive trends the incidence of entertainment deprivation; and (*iv*) a critical assessment of the limitations attached to the conclusions that the researcher can derive from MEPI estimates.

Declaration of Artificial Intelligence (AI) use

Claude (Sonnet 4.6) was extensively used for debugging and optimizing R scripts.

Appendix

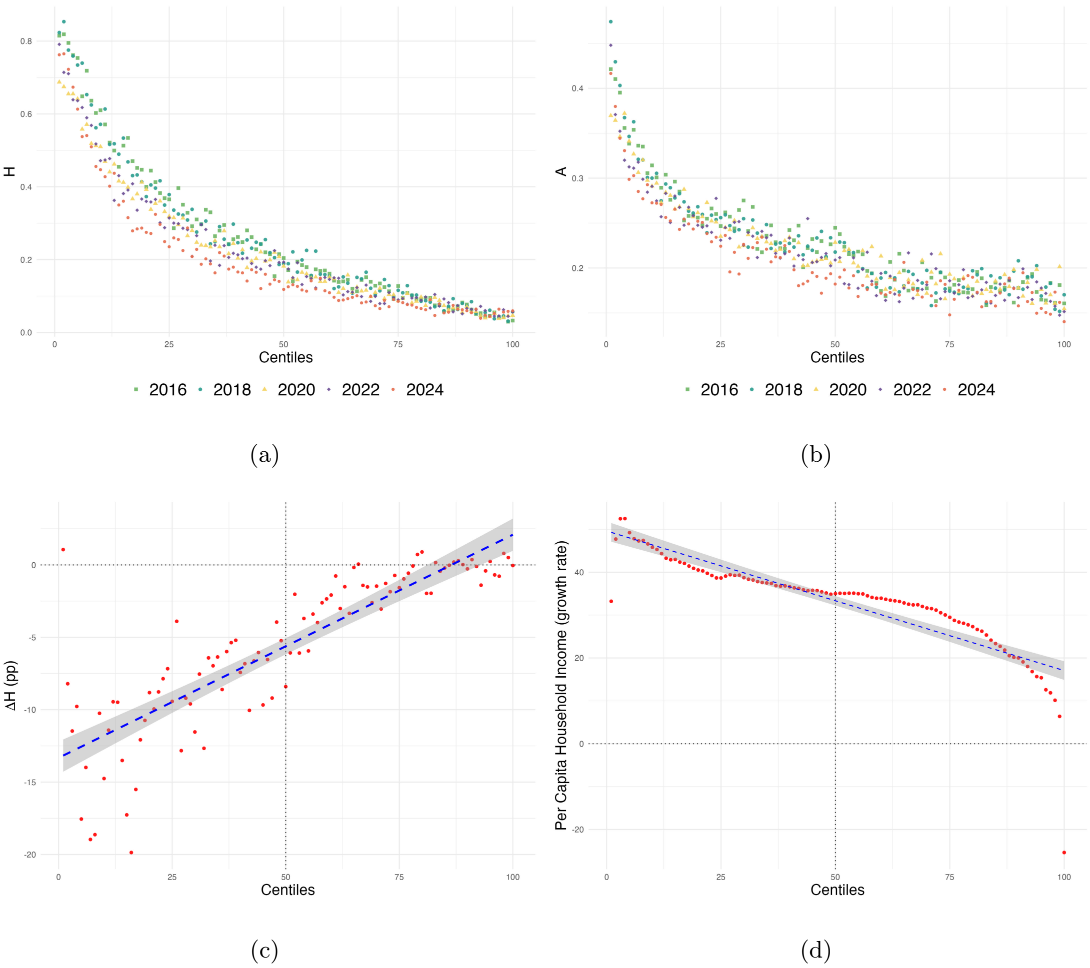


Figure A1: ICTPC centiles (2016–2024). All variables are deflated to August 2024. All variables are deflated to August 2024. All means where computed using ENIGH's stratified clustered design, with primary sampling units, sample design stratum, and individual expansion factors. (a) H; (b) A; (c) ΔH; (d) ICTPC growth rate. Ordinary Least Squares where used for the tendency lines (blue+dashed) in plots (c) and (d), shading=SE's. Own estimations using data from INEGI (2017, 2019, 2021, 2023a, 2025a).

Table A1: Multidimensional Energy Poverty Index: National Estimates (totals, millions of people), 2016–2024

	2016	2018	2020	2022	2024	Δ
MEP						
H	31.549	32.153	28.578	28.858	25.385	−6.164
Dimensional deprivation						
Ea	0.494	0.489	0.281	0.413	0.316	−0.17
Wt	11.762	12.072	10.747	10.938	9.557	−2.205
Et	4.730	6.082	5.712	7.874	7.280	+2.550
Cm	11.103	9.753	6.210	5.008	3.361	−7.742
Rf	16.611	16.289	13.935	13.236	11.986	−4.625
Ck	14.048	15.584	14.813	14.572	12.622	−1.426
Af	66.928	69.787	69.927	59.064	48.592	−18.336
Tc	15.466	16.249	16.263	15.909	13.504	−1.962

Note: All estimates computed using ENIGH's stratified clustered design with individual expansion factors (INEGI, 2023b). Source: Own estimations using data from INEGI (2017, 2019, 2021, 2023a, 2025a).

Table A2: Dimensional Contributions to M_0 (absolute and relative shares), 2016–2024

	2016		2018		2020		2022		2024	
d_j	δ_j	$\delta_j^{(r)}$	δ_j	$\delta_j^{(r)}$	δ_j	$\delta_j^{(r)}$	δ_j	$\delta_j^{(r)}$	δ_j	$\delta_j^{(r)}$
Ea	0.130	1.826	0.126	1.776	0.070	1.205	0.102	1.777	0.075	1.540
Wt	1.469	20.702	1.471	20.803	1.279	21.899	1.281	22.354	1.109	22.869
Cm	1.350	19.014	1.156	16.356	0.719	12.319	0.570	9.951	0.379	7.815
Et	0.493	6.947	0.618	8.735	0.567	9.701	0.768	13.404	0.703	14.511
Rf	1.613	22.727	1.542	21.806	1.288	22.059	1.204	21.014	1.080	22.278
Ck	1.192	16.789	1.289	18.237	1.197	20.496	1.158	20.220	0.994	20.514
Af	0.683	9.625	0.688	9.739	0.560	9.580	0.499	8.708	0.400	8.244
Tc	0.168	2.370	0.180	2.549	0.160	2.742	0.147	2.572	0.108	2.229
Total	7.098	100	7.069	100	5.841	100	5.728	100	4.847	100

Notes: All estimates computed using ENIGH's stratified clustered design with individual expansion factors (INEGI, 2023b). δ_j denotes the censored dimensional contribution, and $\delta_j^{(r)}$ its percentage contribution to total M_0, see equation (10) and (11). Source: Own estimations using data from INEGI (2017, 2019, 2021, 2023a, 2025a).

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