AppliedMath

Article

Monetary Poverty in Peru: Analysis and Measurement Using Fuzzy Set Theory

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Abstract

This paper applies the updated fuzzy model proposed by Belhadj and Bounani in 2023 to microdata from the National Household Survey (ENAHO) for the province of Trujillo, La Libertad, Peru, to measure monetary poverty. The study demonstrates that this framework offers a more detailed, continuous assessment of poverty levels than traditional binary classifications. By assigning degrees of deprivation to various poverty indicators, the fuzzy approach captures the full intensity of deprivation, uncovering intermediate socioeconomic states that conventional methods systematically overlook. While the official binary classification by INEI categorizes 94.62% of Trujillo's population as "non-poor," the fuzzy methodology reveals that only 22.18% experience complete non-deprivation. Crucially, it exposes that 49.94% of the population resides in a state of "mild poverty"—a highly vulnerable segment rendered invisible by standard metrics. District-level disaggregation highlights sharp territorial disparities, ranging from severe structural vulnerability in Florencia de Mora (Fuzzy Poverty Index = 0.428) to consolidated stability in Víctor Larco Herrera (0.288). Ultimately, the fuzzy approach provides a more nuanced and realistic representation of poverty dynamics. This offers crucial insights for policymakers designing targeted poverty-reduction interventions.

Keywords: monetary poverty; poverty measurement; fuzzy sets; public policies

1. Introduction

The standardization of multidimensional poverty measurement through the Multidimensional Poverty Index (Global MPI) in many countries around the world has led to the assumption that monetary poverty measurement is already well established [1].

However, income and assets sufficiency remain necessary condition for social participation and individual well-being; therefore, the importance of monetary poverty—or the monetary dimension of multidimensional poverty—remains relevant. Consequently, improving methods for understanding and measuring the monetary poverty experienced by people is crucial, as a broader understanding of this issue can directly contribute to designing effective public policies aimed at its eradication.

In most Latin American countries, monetary poverty is defined as the insufficiency of monetary resources to purchase a socially acceptable minimum consumption basket. To establish this insufficiency, a well-being indicator (per capita spending) and socially

Check for updates

Academic Editor: Takayuki Hibi

Received: 2 August 2026
Revised: 30 August 2026
Accepted: 31 August 2026
Published: 4 September 2026

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acceptable parameters are chosen: the total poverty line for total consumption, and the extreme poverty line for food. This is considered an "indirect method" [2], which is also applied in Peru. However, this classical approach is not without its limitations. It relies on dichotomous classification of households: extremely poor households (whose income does not allow them to purchase a basic food basket) versus non-extremely poor households (whose income allows them to cover food needs, but not necessarily others).

This dichotomous classification fails to adequately reflect the complex reality of poverty, as it overlooks the group of families that are borderline between extreme poverty, moderate poverty, and non-poverty. Hence, since the 1990s, alternative methodologies have been applied to poverty measurement, seeking to move beyond traditional methodologies, capturing the multiple situations and experiences of poverty beyond the poverty line. A prominent example is the use of fuzzy methodologies, based on the work of Zadeh [3] and further developed by Dubois and Prade [4] using set theory and fuzzy numbers.

The objective of this study is to propose an improved measurement of monetary poverty in Peru through the application of the fuzzy methodology, specifically the version developed by Belhadj and Bouanani [5]. To this end, we apply the model to a specific Peruvian population—the province of Trujillo, located in the Department of La Libertad—using empirical data from the 2022 National Household Survey (ENAHO) conducted by Peru's National Institute of Statistics and Informatics (INEI) [6].

The fuzzy model allows for a more precise quantification of monetary poverty levels and determines the extent to which it is experienced across specific indicators (in our study, net income, food expenditure, and state transfers as social support, as we will explain). Unlike the traditional poverty line method, it successfully captures intermediate stages or transition states between "poor" to "non-poor,". This improved perception of experienced monetary poverty has the distinct advantage of identifying individuals or families who are not in the groups of poor people yet experience a level of deprivation similar to those in poverty and, therefore, should be taken into account in public policies and/or social programs.

This paper is structured as follows: Section 1 introduces the subject, objectives and motivation for the study. Section 2 provides a brief literature review on monetary poverty measurement and recent fuzzy methods. Section 3 explains the methodology used to measure monetary poverty in Peru via the fuzzy model, based on national survey data. Section 4 presents the results, and Section 5 is devoted to their analysis, interpretation and discussion. Finally, Section 6 summarizes the main conclusions of the work.

2. Literature Review

The traditional method used to measure poverty has consisted—within technical and, more precisely, economic terminology—of establishing a poverty threshold, generally defined in monetary terms, and identifying those who fall below it. Thus, poor people are considered to be those whose income level is insufficient to ensure a minimally adequate diet in nutritional terms, as well as to meet essential non-food requirements.

The main problem arising from the application of this method lies in establishing a minimum threshold beyond which an individual is no longer considered poor. As André Corten notes in relation to banking discourse—although the idea can be extrapolated here—speaking of a "poverty threshold" rather than "poverty" also makes it possible to refer to the "number of poor people" rather than to "the poor". Moreover, the notion of a "poverty line" allows poverty to be considered eliminated as soon as the threshold is crossed [7]. Establishing such a poverty line or threshold results in a rigid dichotomous classification of households or individuals—poor versus non-poor (Figure 1)—which leads to the loss of information about families whose situation lies very close to the boundary separating the poor from the non-poor.

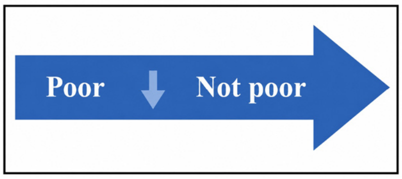

Figure 1. Poverty line and classical measurement. Source: Created by the authors.

Overcoming the rigid dichotomous classification of households or individuals experiencing poverty has been the objective since the 1990s, pursued through the application of fuzzy methodologies—that is, approaches based on fuzzy set theory—to poverty measurement and the identification of the poor, as in the pioneering work proposed by Cerioli and Zani [8]. These fuzzy methodologies seek to measure degrees or levels of individual poverty (across one or several indicators) as well as degrees of poverty for an entire group (or a poverty index). They also aim to represent the situation of individuals or families according to their degree of membership in specific poverty groups or categories.

Official poverty measurement in Peru, based on INEI's traditional monetary threshold, employs a deterministic binary logic (poor/non-poor) that establishes a strict limit for economic sufficiency. While this headcount approach provides useful national benchmarks, it imposes rigid boundaries that fail to capture the socioeconomic vulnerability of households situated just above the poverty line. In order to overcome these analytical limitations, fuzzy set theory—introduced by Zadeh [3] and applied to poverty analysis by Cerioli and Zani [8], Dagum et al. [9] and Cheli et al. [10]—replaces dichotomous indicators with a continuous membership function ranging from 0 to 1. This mathematical framework models poverty as a continuous transition, effectively illustrating the stages of deprivation and economic risk. Thus, the fuzzy approach does not aim to replace the traditional method but rather to complement it, offering greater sensitivity to microdata fluctuations and superior precision for the accurate targeting of public policies.

To determine the degrees or levels of individual poverty, we begin with a value x that quantifies the situation of the individual or household. For each indicator, two thresholds are established: a lower threshold L, which represents the upper limit of the values associated with the extremely poor group, and an upper threshold U, which represents the lower limit of the values corresponding to the non-poor group. Thus, the situation of the individual or household varies according to its position relative to these two thresholds for each indicator.

In representing (or modeling) the situation of individuals or households, the fuzzy subset of poverty within the set of real numbers x—corresponding to indicator values—is defined using a continuous, non-increasing membership function μ. This function takes the value $\mu(x) = 1$ on the interval $[0, L]$, $\mu(x) = f(x)$ on $[L, U]$, and $\mu(x) = 0$ for all $x > U$. The value $\mu(x)$, generally referred to as the "degree of membership in the poverty set," is in fact the level or degree of poverty of the individual whose indicator takes the value x. The function f defined on $[L, U]$ is continuous and decreasing (Figure 2).

Authors such as Cerioli and Zani [8], in Italy, employed a linear membership function, a choice subsequently adopted by several authors applying fuzzy poverty measurement in different countries. Examples include Dagum et al. [9] and Cheli et al. [10] for Poland, Miceli [11] for Switzerland, Bazán et al. [12] for Paraguay, Vero [13] for France, Appiah-Kubi et al. [14] for Ghana, Belhadj and Matoussi [15], Belhadj [16], Kacem and Kacem [17] and Belhadj and Bouanani [5] for Tunisia, Todeschini and Bezerra-Baco [18] for Brazil, Costa and De Angelis [19] for Italy, Morales-Ramos and Morales-Ramos [20] for Mexico, Chacón et al. [21] for Venezuela, Gao and Sun [22] for China, Bedoya and Galvis [23] for Colombia and García-Vélez and Núnez [24] for Ecuador, among others.

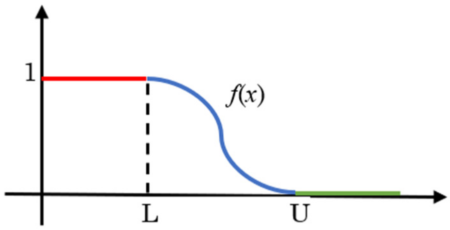

Figure 2. Membership function of the fuzzy set poverty. Source: Created by the authors.

Other authors have employed more general nonlinear membership functions, such as Chakravarty [25], Zheng [26], and Belhadj and Bouanani [5], who adopt a convex nonlinear specification whose particular case reduces to the linear form.

To obtain the degree of individual poverty across multiple criteria, fuzzy methodologies aggregate the individual membership degrees using a specific rule. One common choice is the weighted average, where the smallest membership value receives the highest weight. This aggregation rule, originally proposed by Cerioli and Zani [8], has been widely used in empirical studies, such as in [16,18]. Miceli [11], in turn, proposes the use of a generalized mean, which includes as special cases the arithmetic, geometric, harmonic and weighted means.

Regarding the degree of poverty at the aggregate level—or the computation of the poverty index—the individual poverty degrees are combined through the most commonly employed aggregation rule: the arithmetic mean [8,11,21]. Todeschini and Bezerra-Baco [18] use a weighted mean, while Belhadj and Matoussi [15] and Gao and Sun [22] propose alternative aggregation schemes such as entropy-based measures from information theory as a generalization of the Watts index [27].

These fuzzy methodologies have been applied either to measure monetary poverty exclusively, or to measure monetary poverty within broader multidimensional poverty analysis. Monetary-only fuzzy measurement is examined in [28] by using the generalized membership function from [8] and the monetary poverty index similar to the headcount ratio (HCI), which is called the Foster–Greer–Thorbecke fuzzy poverty index (FGT). Other authors have measured monetary poverty as a part of their study of multidimensional poverty. The same membership function is used in [5] as in [28] with a small variation. On the other hand, Betti and Verma [29] and Pham [30] applied the generalized membership function obtained by combining the distribution function and the Lorenz curve proposed by Betti et al. [31]; the former applied it in Italy and the latter to the study of poverty in Vietnam.

Fuzzy Set Theory

The notion of a fuzzy set was first proposed by Zadeh [3]. The concept of a fuzzy set, as used in fuzzy theory, assumes that an element's membership in a set is not restricted to belonging or not belonging, but rather is expressed on a scale from 0 to 1. In this way, unlike classical set theory—where an individual either belongs or does not belong to a set—fuzzy logic avoids the traditional dichotomous division between membership and non-membership by introducing a gradation indicating the degree to which an element belongs to a set.

Given a set X and an element $x \in X$, a fuzzy subset A of X is characterized by a membership function, $\mu\colon A \to [0, 1]$ which associates each point $x \in X$ with a real number $\mu_A(x) \in [0, 1]$ referred to as the degree of membership of x in A. If A is a classical crisp set, this function is called a characteristic function and takes only the values 0 and 1.

From this definition, we can consider a fuzzy set A as an ordered pair (X, $\mu_A(x)$), therefore it is characterized by the set of ordered pairs A = {(x, $\mu_A(x)$)/x ∈ X}.

Fuzzy numbers, defined on the foundation of fuzzy set theory, provide a formal framework for quantifying subjective or imprecise information. Figure 2 illustrates a representative fuzzy set that also constitutes a fuzzy number, specifically termed a Z-type fuzzy number. In applied contexts, triangular (Figure 3) and trapezoidal (Figure 4) fuzzy numbers are more commonly employed. Standard arithmetic operations from classical mathematics—such as addition, multiplication, and division—are extended to these fuzzy numbers. Consequently, combining fuzzy numbers with their associated operational rules enables the formulation of mathematical models capable of handling subjective evaluations and inherently imprecise data [4,32].

The utility of fuzzy sets and fuzzy numbers primarily stems from the specification of their membership functions, which explicitly capture the continuous, gradual nature of real-world phenomena. In this study, the proposed membership function (Figure 2) models the deprivation gradient in poverty assessment, reflecting how individuals incrementally transition out of deprivation as their income rises. Specifically, an individual with an income level L experiences maximum deprivation; as income increases, the degree of deprivation systematically declines until reaching income threshold U, at which point deprivation vanishes and the individual is classified as non-poor. This continuous socioeconomic transition is rigorously represented by the membership function of the fuzzy set.

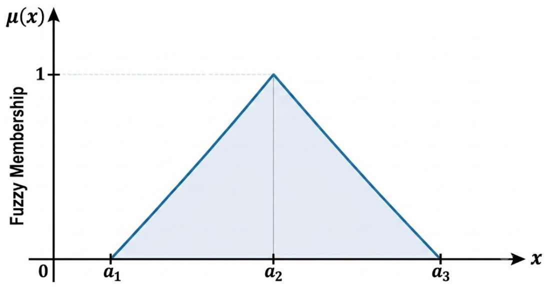

Figure 3. Triangular fuzzy number. Source: Created by the authors.

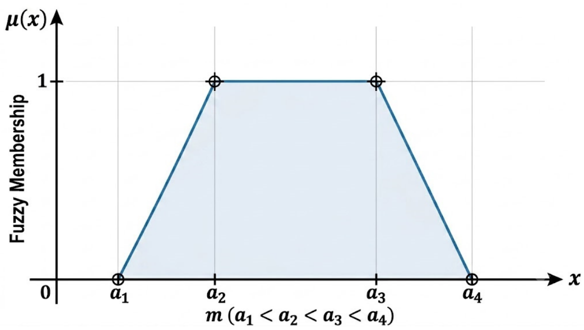

Figure 4. Trapezoidal fuzzy number. Source: Created by the authors.

3. Materials and Methods

In this study, to apply the fuzzy methodology to the measurement of monetary poverty, we used data from the 2022 National Household Survey (ENAHO), conducted by the National Institute of Statistics and Informatics (INEI) of Peru [6].

The 2022 ENAHO sample comprises 36,848 households, 24,256 located in urban areas and 12,592 in rural areas. ENAHO provides information on a wide range of dimensions, including housing and household characteristics, individual demographic attributes, education, health, employment and income, household expenditures, participation in social programs, self-employment or employer income, agricultural producers' income, and the governance, democracy, and transparency module.

3.1. Population

The selected population corresponds to the province of Trujillo, in the Department of La Libertad (Peru). The province consists of eleven districts; each district has its corresponding population and location presented in Table 1.

Table 1. The districts of Trujillo with their location and population.

Nº	District	Location Code	Population	Households Surveyed	Population Surveyed
1	Trujillo	130101	329,127	235	759
2	El Porvenir	130102	196,333	150	544
3	Florencia de Mora	130103	42,978	36	157
4	Huanchaco	130104	72,237	57	214
5	La Esperanza	130105	190,881	149	543
6	Laredo	130106	36,353	30	105
7	Moche	130107	35,945	34	137
8	Poroto	130108	3127	0	0
9	Salaverry	130109	19,095	17	69
10	Simbal	130110	4433	0	0
11	Víctor Larco Herrera	130111	66,607	59	182
		TOTAL	997,116	767	2710

Source: Prepared by the authors using data from ENAHO.

3.2. Variables and Data

Monetary poverty is, above all, an insufficiency of monetary resources and goods. This concept of monetary poverty is already well established in the literature and among international organizations and essentially defines monetary poverty in terms of the indicators used to measure it, which is debatable. However, we chose this concept as our starting point in order to improve its measurement, thereby redefining the specific indicators used for its calculation.

Since average income (per consumption unit) has traditionally been the indicator of the general standard of living, in this study we use "income"—understood as income from work—as the main instrument enabling the individual to achieve self-reliance, provided that labor is remunerated with a decent minimum wage or generates sufficient income for a dignified life.

Given the importance of work as a means of earning an effective income, we treat income as an indicator of monetary poverty independent of the transfers made by the State, especially monetary transfers provided as social support to disadvantaged groups. The rationale is that government social (monetary) support does not carry the same implications for all households; that is, identical cash transfers—although of equal value to all beneficiary families—do not produce uniform effect, enabling some families to escape poverty while leaving others below the threshold.

Likewise, family food expenditure varies across households, regardless of size and income. For this reason, food expenditure must also be assessed independently.

Consequently, our study uses three variables or indicators to measure monetary poverty: net income, food expenditure, and government transfers as social support. The latter distinguishes our approach from that of INEI, which incorporates social support directly into net income in its monetary poverty assessment.

From the 2022 ENAHO (survey code 784–Module 34, "summary-2022"), we extracted net household income, total government transfers from social programs, and food expenditure. Food expenditure was computed by aggregating all survey items associated with household food consumption.

We also incorporated the poverty line (code LINEA) and the extreme poverty line (code LINPE). The module reports the number of surveyed households and the number of surveyed individuals in each district (columns 5 and 6 of Table 1); however, no households are reported in two districts—Poroto and Simbal.

Because the income reported for households in ENAHO Module 34 includes government transfers from social support programs, we subtracted these amounts so that the net income variable differs from that reported in the 2022 ENAHO. Moreover, while survey values correspond to annual household aggregates, the poverty line is defined on an individual, monthly basis.

To standardize all data on an individual, monthly basis, the amounts corresponding to food expenditures, income, and social support were divided by the number of household members resident in the dwelling and subsequently by twelve months. Thus, income, food expenditures, and government social support are expressed as average monthly values per person within each household. Our underlying assumption is that all household members experience monetary poverty equally; that is, poverty—expressed through these specific indicators—equally affects the rights and dignity of every individual in the household.

3.3. Thresholds

For each selected indicator, we established two thresholds—one lower and one upper—as required by the fuzzy methodology, in order to measure the condition of each family or individual.

In the case of net income, the lower threshold corresponds to the poverty line established by the National Institute of Statistics and Informatics (INEI) (414.87 soles), while the upper threshold corresponds to the minimum legal wage (1025 soles). The choice of the latter is grounded in the original purpose of the minimum wage as conceived by the International Labour Office (ILO), which sought to protect low-income workers through the establishment of a fair and effective wage floor that would enable income redistribution toward lower-wage groups and thereby contribute to mitigating poverty [33].

To our knowledge, no study on poverty measurement explicitly incorporates this important benchmark, but we consider it valid and widely accepted worldwide that an individual may be regarded as non-poor if their monthly income is equal to or greater than the minimum wage. The minimum wage does not constitute an amount that allows a worker to live an affluent life; rather, it represents a moderate, baseline level of income.

For the food expenditure indicator, the lower threshold corresponds to the extreme poverty line established by INEI (214.74 soles), while the upper threshold is an amount proportional to the minimum wage (530.55 soles).

Consequently, by establishing these thresholds for the income and food expenditure indicators, we infer that, for the income indicator, a family experiences extreme poverty if its income is below 414.87 soles, and is considered non-poor if its income is equal to or greater than 1025 soles. Likewise, for the food expenditure indicator, a family experiences extreme poverty if its per capita average food expenditure falls below 214.74 soles, and is considered non-poor if its food expenditure is equal to or greater than 530.55 soles.

Regarding social support, its effect has been evaluated in relation to the poverty lines using the following scoring system: the assessment of social support is established on a scale from 1 to 5 according to its effectiveness in overcoming poverty thresholds. If social support added to income reaches or exceeds 1025 soles, the value assigned to social support is 5 (indicating it is sufficient to surpass general poverty). If social support plus income is less than 1025 soles but the sum of social support and food expenditure is not below

530.55 soles, social support is assigned a value of 4. If the sum of social support and food expenditure is below 530.55 soles but not below 414.87 soles, social support is scored as 3. If the sum of social support and food expenditure lies between 214.74 and 414.87 soles, social support is scored as 2. Finally, if the sum of social support and food expenditure is less than or equal to 214.74 soles, social support is scored as 1. Thus, the assessment of social support takes values from a finite set {1, 2, 3, 4, 5}, and we consider L = 1.5 as the lower threshold and U = 3.5 as the upper threshold.

This implies that if, after receiving social support, the family or individual remains at the level of extreme poverty, such support is deemed extremely insufficient, whereas if the social support enables the family or individual to rise above the poverty threshold in food expenditure, the support deemed sufficient.

The thresholds for the three indicators in our study are presented in Table 2.

Table 2. Thresholds for monetary poverty indicators.

Indicators	Rating	Lower Threshold	Upper Threshold
Net income	In soles	414.87	1025
Food expenses	In soles	214.74	530.55
Social support	{1, 2, 3, 4, 5}	1.5	3.5

3.4. Models

The Belhadj and Bounani model [5] represents the most generalized version of the membership functions used by several authors in applications of the fuzzy method to poverty measurement across various countries [8–28]. Therefore, this model, represented by Equation (1), is used here.

$$\mu(x) = \begin{cases} 1, & \text{if } x < L \\ \left(\frac{U-x}{U-L}\right)^{\delta}, & \text{if } L \leq x < U \\ 0, & \text{if } x \geq U \end{cases} \tag{1}$$

where $\delta > 0$, L is the lower threshold, U is the upper threshold, and x is the value of the indicators. When $\delta = 1$, Equation (1) reduces to the linear membership function used in [8].

To obtain the individual poverty index or degree across k indicators we use Formula (2), which is the weighted mean employed in [8]:

$$\mu_p(i) = \sum_{j=1}^{k} \omega_j \mu_j(i) \tag{2}$$

where $\mu_j(i)$ is the degree or level of poverty of individual i for indicator j, and the weight ω_j is given by Formula (3).

$$\omega_j = \frac{\ln\left(\frac{1}{\overline{\mu_j}}\right)}{\sum_{j=1}^{k} \ln\left(\frac{1}{\overline{\mu_j}}\right)} \tag{3}$$

Here $\overline{\mu_j} = \frac{1}{n}\left(\sum_{i=1}^{n} \mu_j(i)\right)$, represents the average degree of poverty for indicator j, where n is the total number of individual or households in the study population.

To obtain the overall poverty index for the entire group of n units, we apply the arithmetic mean in Formula (4).

$$I_{PM} = \frac{1}{n} \sum_{i=1}^{n} \mu_p(i) \tag{4}$$

Finally, to consolidate the poverty index for G groups with $n_1, n_2, \ldots, n_G$ members, we use Formula (5).

$$I_T = \frac{\sum_{g=1}^{G} n_g I_{PM}(g)}{\sum_{g=1}^{G} n_g} \tag{5}$$

The indices given in Equations (4) and (5) are of the same type as those addressed by [25], who demonstrates that that both the unidimensional and multidimensional fuzzy indices satisfy the axioms of poverty measurement.

3.5. Application of Fuzzy Models to the Data

By applying the membership function (1) to each indicator using the corresponding thresholds, the membership function to poverty within that indicator is obtained. After evaluating this function for each family, we determine the degree to which each family belongs to poverty in the given indicator. If the membership degree is 1, the family is in a situation of extreme poverty, whereas if the value is 0, the family is non-poor; in all other cases, the family experiences poverty with a membership degree of $\mu(x)$.

By combining the three membership degrees corresponding to each of the indicators using Equation (2), we obtain the overall degree of membership in monetary poverty for each family. If the membership degree is 1, the family is in extreme poverty; if it is 0, the family is non-poor. In all other cases, that is, if $0 < \mu(x) < 1$, families experience different intermediate levels of poverty.

By counting the families in situations of extreme poverty, poverty, and non-poverty, and comparing these with the total number of families studied, the percentages of families at each poverty level are obtained.

Up to this point, as can be seen, we rely on the same poverty categories used by INEI—extreme poverty, poverty, and non-poverty—although the methodology differs due to the fuzzy model adopted and the indicators and thresholds established to operationalize it.

Finally, we calculate the poverty index for each district using Equation (4), combining the poverty level or degree of each surveyed family. This index allows us to compare poverty levels among districts within the same province, with the district exhibiting the highest index reflecting the greatest degree of poverty. The overall fuzzy monetary poverty index for the province of Trujillo is calculated using Equation (5) and, analogously to the individual cases, reflects a predominance of poverty if the index is close to 1, or a predominance of non-poverty if its value is close to 0.

4. Results

4.1. Membership Function and Poverty Levels for Each Indicator

By substituting the parameters from Table 2 into Equation (1), the membership function for each indicator is obtained, as shown in the second column of Table 3. Additionally, the third column presents the weights obtained using Equation (3).

Table 3. Indicators with membership functions and weights.

Indicator	Membership Function	Weight
Net Income	$\mu(x) = \begin{cases} 1, & x < 414.87 \\ \frac{1025-x}{610.13}, & 414.87 \leq x < 1025 \\ 0, & x \geq 1025 \end{cases}$	0.45312849
Food Expenses	$\mu(x) = \begin{cases} 1, & x < 214.74 \\ \frac{530.55-x}{315.81}, & 214.74 \leq x < 530.55 \\ 0, & x \geq 530.55 \end{cases}$	0.17792382

Table 3. *Cont.*

Indicator	Membership Function	Weight
Social Support	$\mu(x) = \begin{cases} 1, & x < 2 \\ \frac{3.5-x}{2}, & 1.5 \leq x < 3.5 \\ 0, & x \geq 3.5 \end{cases}$	0.36894769

The respective graphics of these membership functions are shown in Figures 5–7.

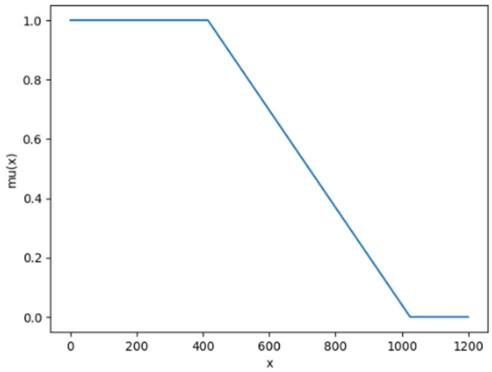

Figure 5. Membership function of net income. Source: Created by the authors.

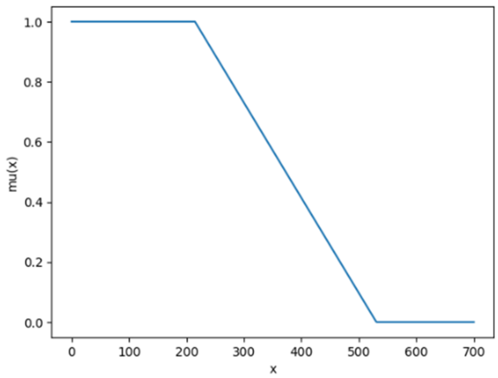

Figure 6. Membership function of food expenses. Source: Created by the authors.

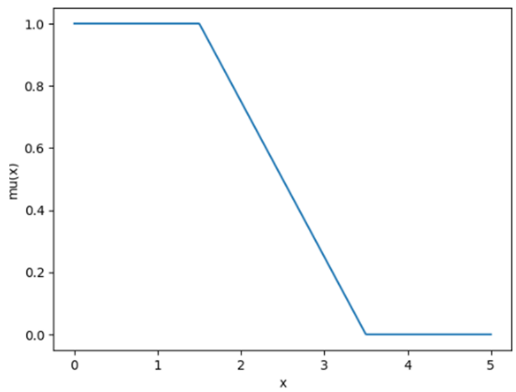

Figure 7. Membership function of social support. Source: Created by the authors.

The membership functions illustrate the gradual transition between extreme poverty and non-poverty, avoiding abrupt classifications. This allows individuals near the poverty thresholds to be represented more realistically, capturing intermediate deprivation levels that are ignored in classical approaches.

https://doi.org/10.3390/appliedmath6090146

The percentage of families by poverty category, according to our study using the fuzzy methodology, for each indicator is presented in the Table 4.

Table 4. Family poverty classification in Trujillo Province according to fuzzy measurement.

Districts	Fuzzy Measurement								
	Net Income			Food Expenditure			Social Support		
	Extremely Poor	Poor	Non-Poor	Extremely Poor	Poor	Non-Poor	Very Insufficient	Insufficient	Sufficient
Trujillo	8.51	28.94	62.55	24.25	55.32	20.43	13.19	20	66.81
El Porvenir	23.33	51.33	25.34	41.33	53.33	5.34	30.66	42.67	26.67
Florencia de Mora	25	44.44	30.56	52.78	47.22	0	38.9	30.55	30.55
Huanchaco	15.78	42.11	42.11	31.58	54.38	14.04	22.81	31.58	45.61
La Esperanza	11.41	51.68	36.91	27.52	63.09	9.39	18.79	36.24	44.97
Laredo	13.33	50	36.67	23.33	73.33	3.34	16.67	46.66	36.67
Moche	8.82	55.88	35.30	32.35	55.88	11.77	26.47	35.29	38.24
Poroto	---	---	---	---	---	---	---	---	---
Salaverry	11.76	58.82	29.41	41.18	52.94	5.88	35.29	35.29	29.42
Simbal	---	---	---	---	---	---	---	---	---
Víctor Larco Herrera	5.09	28.81	66.10	20.34	67.8	11.86	16.95	13.56	69.49
Overall Province	13.33	42.11	44.59	30.51	57.63	11.86	21.12	30.51	48.37

4.2. Calculation of Individual and Group Poverty Levels by Districts

Using Equation (2) with the weights shown in the third column of Table 3 and the membership degrees for each of the three indicators, we obtain the individual monetary poverty degree. Once the individual poverty index or degree is obtained, we can determine the percentages of families in each poverty category or situation.

If we perform this calculation according to the three categories considered by INEI—extreme poverty, poverty and non-poverty—in each district, the results appear in Tables 5 and 6.

Table 5 presents the percentage of families in each category, allowing for a comparison between the results obtained by INEI using the classical methodology and those obtained using the fuzzy methodology.

Figure 8 illustrates the poverty levels based on the results obtained for each poverty category.

Table 5. Percentage of families in poverty categories in the province of Trujillo.

Districts	Classical Measurement (INEI)			Fuzzy Measurement		
	Extremely Poor	Poor	Non-Poor	Extremely Poor	Poor	Non-Poor
Trujillo	0	3.4	96.6	5.11	74.89	20
El Porvenir	1.33	23.33	75.34	16.67	78	5.33
Florencia de Mora	0	33.33	66.67	13.89	86.11	0
Huanchaco	1.76	8.77	89.47	5.26	82.46	12.28
La Esperanza	0	13.42	86.58	6.04	86.58	7.38
Laredo	0	6.67	93.33	3.33	93.34	3.33
Moche	2.94	23.53	73.53	8.82	82.36	8.82
Poroto	---	---	---	---	---	---
Salaverry	0	17.65	82.35	11.76	82.36	5.88
Simbal	---	---	---	---	---	---
Víctor Larco Herrera	0	10.17	89.83	5.09	83.05	11.86
Overall Province	0.52	12.91	86.57	8.22	80.7	11.08

Table 6. Percentage of families by poverty categories and levels.

Districts	Extreme Poverty	Severe Poverty	Medium Poverty	Moderate Poverty	Mild Poverty	Non-Poverty
Trujillo	5.11	11.06	12.34	6.38	45.11	20
El Porvenir	16.67	22	25.34	9.33	21.33	5.33
Florencia de Mora	13.89	36.11	11.11	8.33	30.56	0
Huanchaco	5.26	24.56	15.79	10.53	31.58	12.28
La Esperanza	6.04	18.79	21.48	12.75	33.56	7.38
Laredo	3.33	33.34	23.33	3.33	33.34	3.33
Moche	8.82	29.41	11.77	8.82	32.36	8.82
Poroto	----	----	----	----	----	----
Salaverry	11.76	17.65	23.53	11.77	29.41	5.88
Simbal	----	----	----	----	----	----
Víctor Larco Herrera	5.09	15.25	6.78	3.39	57.63	11.86
Overall Province	8.22	19.03	17.08	8.47	36.12	11.08

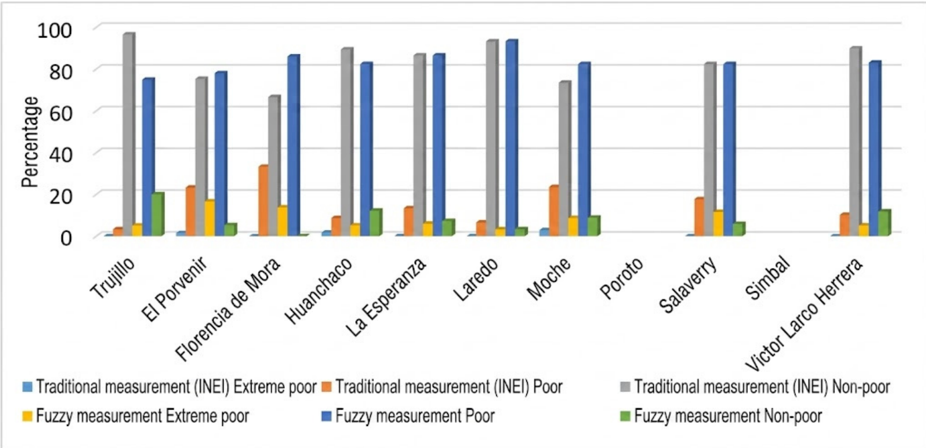

Figure 8. Poverty levels in Trujillo according to INEI and fuzzy measurement. Source: Created by the authors.

Another important aspect of fuzzy measurement is the improved identification of the experience of poverty. It allows family groups to be classified according to their poverty situation, thus overcoming the sharp divisions imposed by classical methodologies between poor and non-poor, or between extreme poverty, poverty, and non-poverty—the typical categorization in monetary poverty measurement.

In this study, we defined four subgroups, which we label as "severe poverty" ($0.75 \leq \mu < 1$), "medium poverty" ($0.5 \leq \mu < 0.75$), "moderate poverty" ($0.25 \leq \mu < 0.5$), and "mild poverty" ($0 \leq \mu < 0.25$). Table 6 provides the percentage of the population in extreme poverty, along with the non-poor population, and specifically presents the population in poverty divided into the four aforementioned subgroups.

4.3. Calculation of Fuzzy Poverty Indices by District

Using the fuzzy methodology, we calculated the fuzzy poverty index for each district using Equation (4). This result is reported in the fuzzy poverty map shown in Figure 9.

Finally, by applying Equation (5), the overall fuzzy poverty index for the province of Trujillo is obtained, which equals 0.42965189.

The map in Figure 9 shows that the district with the highest fuzzy poverty index is Florencia de Mora, followed by the district of El Porvenir, whereas the district with the lowest fuzzy poverty index is Víctor Larco Herrera.

The districts of Simbal and Poroto, shown in white, lack data because they were not selected by INEI to be part of the survey sample.

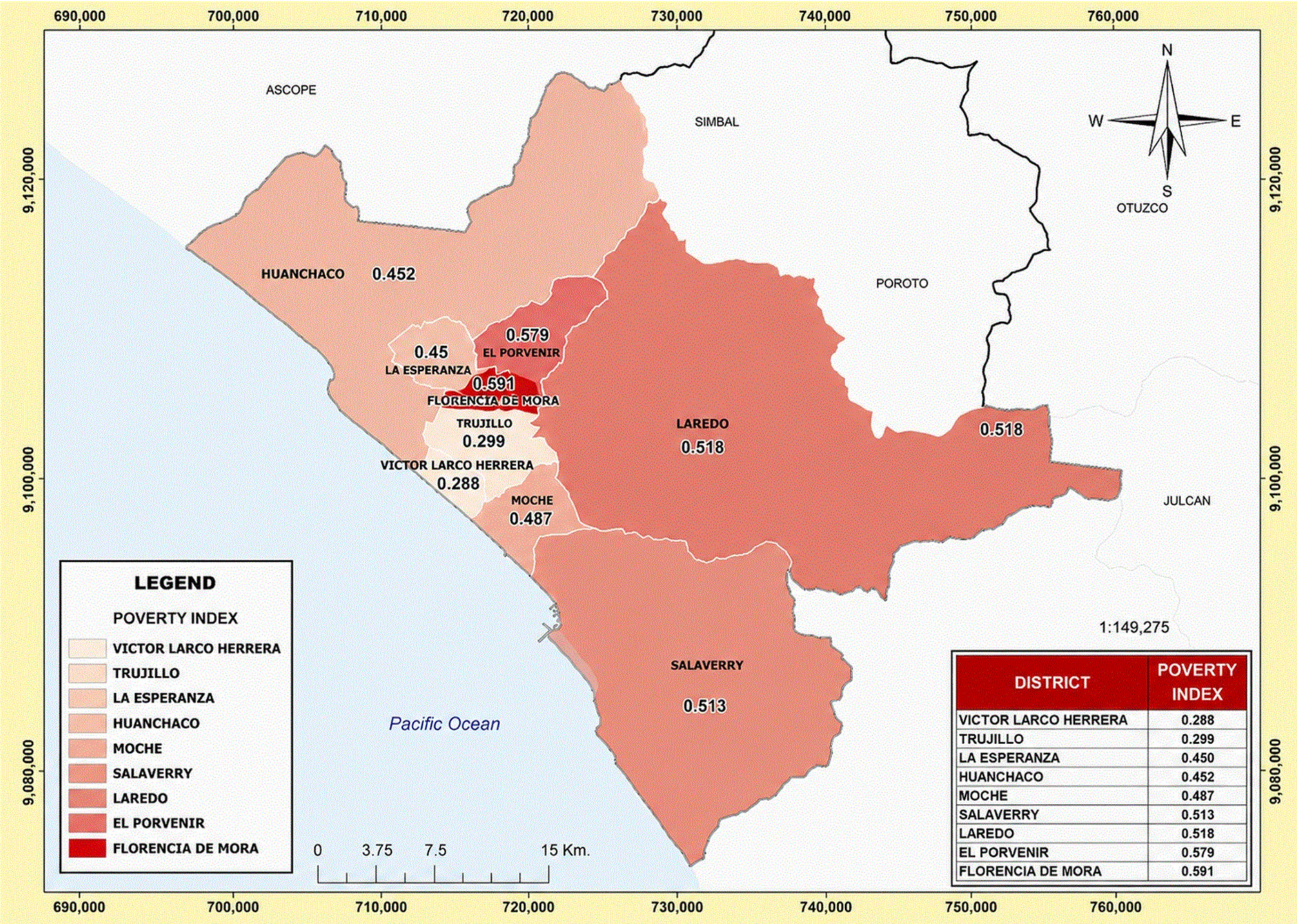

Figure 9. Map of the province of Trujillo with the fuzzy poverty rates by district. Source: Created by the authors.

5. Discussion

As detailed in Section 3, the three monetary poverty indicators we established is this study are net income, food expenditure, and government social support, each defined by a lower and an upper threshold. However, our study differs from the approach of the National Institute of Statistics and Informatics (INEI), which incorporates government social support directly into household net income and uses food expenditure exclusively as the extreme poverty line. Specifically, for 2022, INEI considers the extreme poverty line (214.74 soles) as the lower threshold and the general poverty line (414.87 soles) as the upper threshold.

5.1. Thresholds Established in the Indicators: Interpretation and Differences from INEI Standars

For the net income indicator, we adopt the general poverty line established by INEI (414.87 soles) as our lower threshold. In other words, we define the boundary between extreme poverty and poverty at the level that INEI uses to separate poverty from non-poverty. We argue that INEI's framework underestimates the sensitivity of poverty measurement.

For the upper threshold of net income, we adopt the minimum legal wage (1025 soles) as the threshold separating poor from non-poor individuals. This choice is based on three points: (1) it represents the legally established minimum income to ensure decent living conditions under Peruvian labor law; (2) it is a widely accepted benchmark for measuring basic purchasing capacity; and (3) it enables comparability with similar regional studies. In our framework, an individual is classified as non-poor when their income is equal to or greater than the minimum legal wage, as this amount represents the baseline compensation for an eight-hour workday that provides access to a dignified standard of living. Earnings below this floor imply an inability to fully exercise the right to a decent life, placing the individual in a condition of poverty.

For the food expenditure indicator, we use INEI's lower threshold (214.74 soles), and calculate the upper threshold by maintaining the same proportional ratio used in the income thresholds (530.55 soles). Consequently, the upper thresholds that distinguish poor from non-poor categories mark another key difference between our fuzzy approach and INEI's methodology.

Regarding government social support, our evaluation isolates its specific effectiveness in enabling households to surpass poverty lines across our four defined subgroups: severe, medium, moderate, and mild poverty. Thus, the lower threshold (L = 1.5) corresponds to social support received under extreme poverty conditions that fails to elevate the recipient above the poverty line, whereas the upper threshold (U = 3.5) represents social support sufficient to transition the beneficiary from poor to non-poor status in terms of food expenditure.

5.2. Comparison of Poverty Levels by Indicator in Families (Using INEI's Fuzzy Methodology)

These differences in population percentages, based on income, are reasonable for two main reasons. First, income includes only the family's own earnings and not social assistance, so what is reflected here is the poverty situation without the State's support. Second, we consider as the dividing line between extreme poverty and poverty what INEI considers the line between poverty and non-poverty; in other words, from our perspective, the population group that INEI classifies between extreme poverty and poverty is considered to be in extreme poverty. Theoretically, the percentage of families in extreme poverty in our study (Table 4, column 2) should be equal to or greater than the sum of the extreme poor and poor reported by INEI (Table 5, columns 2 and 3); however, the results show variations explained by methodological differences in the measurement of each indicator. For instance, in the district of Trujillo, INEI reports a combined poverty rate of 3.4%, whereas our fuzzy assessment yields an extreme poverty rate of 8.51%. Conversely, in Moche, INEI's combined poverty rate reaches 26.47%, compared to our extreme poverty rate of 8.82%.

Regarding food expenditure, although our lower threshold matches INEI's extreme poverty line, substantial divergence occurs. Under our model, a family is classified as extremely poor in this indicator if per capita food expenditure falls below 214.74 soles, regardless of total household income. In contrast, INEI classifies a family as extremely poor if its income is below 214.74 soles, without considering food expenditure. Consequently, our approach identifies families with inadequate dietary investment as deprived in this dimension, even when their overall income exceeds the minimum wage.

The high percentage of families in extreme poverty according to the food expenditure indicator shows that, across all districts of Trujillo—even among the non-poor population—food-consumption habits are inadequate. Consequently, alongside social support, the population needs education on healthy eating habits. The very small percentage of families classified as 'non-poor' in this indicator also reveals that few households maintain adequate dietary practices.

Regarding social support, our assessment differs from that of INEI. We evaluate social support based on its impact on income or food expenditure, as previously explained. In terms of population percentages under this indicator, there is a very high share of households in the 'very insufficient' support category. This is because this group includes those who receive social support but, even when combined with their food expenditure, still cannot rise above extreme poverty (which is classified as poverty, according to INEI), and also those who receive no support and whose food expenditure is below INEI's poverty line.

5.3. District-Level Comparison Between INEI and Fuzzy Methodologies

A comparative analysis of district-level monetary poverty between INEI's official reports and our fuzzy model reveal significant discrepancies (Table 5).

According to INEI (Table 5, column 2), six districts—Trujillo, Florencia de Mora, La Esperanza, Laredo, Salaverry, and Víctor Larco Herrera—report no households in extreme poverty. In contrast, our study (Table 5, column 5) identifies substantial population in extreme poverty across all these districts, with El Porvenir having the highest percentage (16.67%) and Víctor Larco Herrera the lowest (5.09%).

Furthermore, INEI reports very high percentages of people classified as non-poor (Table 5, column 4), the highest being 96.6% in the district of Trujillo, followed by Laredo (93.33%), then Víctor Larco Herrera and Huanchaco, and the lowest in Florencia de Mora (66.67%). In contrast, according to our results (Table 5, columns 5 and 6), most of the population falls within the poverty level, with the districts of Laredo, La Esperanza, and Florencia de Mora exceeding 85%. The highest percentage of non-poor households in our study appears in Trujillo (20%), while in the remaining districts the percentage is below 13%, reaching the lowest point in Florencia de Mora, where no non-poor households are recorded.

In line with Table 4—where the percentage of non-poor in the food expenditure indicator is very low—combining this with the other indicators increases the overall poverty level. A household can only be classified as non-poor if it is non-poor in all indicators; therefore, in Florencia de Mora, where no household is non-poor in the food expenditure indicator, there are no households classified as non-poor across the three indicators.

In the last row of Table 5, in the column corresponding to the 'poor' category, INEI reports 25.95% for the entire province of Trujillo, a percentage lower than what INEI reports for the Department of La Libertad in its poverty evolution study for 2014–2023 [34]. Meanwhile, the extreme poverty rate for the province of Trujillo reported by INEI is 0.52%, much lower than the 3.3% indicated by INEI for the Department of La Libertad [34]. However, regarding extreme poverty, our study reports 8.22% for the province of Trujillo, much higher than what INEI records in Table 5 and in its 2024 report.

All these differences in population percentages across the typical poverty categories (extreme poverty, poverty, non-poverty) reported by INEI and by our study are partly due, as already noted, to the different initial research assumptions and decisions (regarding indicators and thresholds). However, we also believe that they reveal that the fuzzy methodology makes it possible to perceive—and therefore visualize—higher levels of experienced poverty among households or individuals, which is crucial for effectively addressing and eradicating poverty.

5.4. Fuzzy Poverty Categories and Transition Between Categories

With the fuzzy methodology, it is possible to distinguish the difference in the experience of poverty. It allows for a classification of families within the poverty category itself. In our study, we classified them into four subgroups: severe poverty, medium poverty, moderate poverty, and mild poverty, as shown in Table 6.

The severe-poverty subgroup comprises families with a high degree of poverty whose situation is very close to that of families in extreme poverty, placing them at high risk of falling into extreme poverty. The percentage of these families ranges from 11.06% in the district of Trujillo, which has the lowest proportion of its population in this condition, to 36.11% in the district of Florencia de Mora, which has the highest proportion.

The medium-poverty subgroup includes families with a lower degree of poverty than the previous group. They face a lower risk of falling into extreme poverty but may still fall into severe poverty. The percentage of families in this subgroup ranges from 6.78% to 25.34%, with the lowest percentages in the districts of Víctor Larco Herrera, Moche, Florencia de Mora, and Trujillo, and the highest in El Porvenir, Laredo, Salaverry, and La Esperanza.

The so-called moderate-poverty group includes those in a better situation than those in median poverty. In this regard, the percentage of the population by district ranges from 3.39% in the district of Víctor Larco Herrera to 12.75% in La Esperanza, with the districts of La Esperanza, Huanchaco, and Salaverry having the highest percentages.

The families in the best situation within the poor category make up the mild-poverty group, whose situation is similar to that of the non-poor. In this group, we find the highest percentages in several districts such as Víctor Larco Herrera, with 57.63%, and Trujillo with 45.11%, while the districts with the lowest percentages are El Porvenir, with 21.33%, and Salaverry with 29.41%.

At the provincial level (Table 6, bottom row), the combined prevalence of extreme and severe poverty reaches 27.25%, exceeding INEI's official regional estimates for La Libertad in 2022 [34].

5.5. Comparison of Fuzzy Poverty Rates Across Districts (Spatial Analysis)

As an additional contribution of our study, and distinguishing it from the methodology used by INEI, we have calculated the fuzzy poverty indices for each district, as shown in Figure 9.

The calculation of these indices is important because it allows for comparisons within a geographic area—in our case, a spatial analysis of poverty across the entire province of Trujillo. It can be seen that Florencia de Mora has the highest poverty index, followed closely by El Porvenir. They are followed, in descending order, by Laredo, Salaverry, Moche, Huanchaco, and La Esperanza, all with values above the provincial poverty index. Finally, the districts of Trujillo and Víctor Larco Herrera show values well below the provincial average, with Víctor Larco Herrera having the lowest index in the entire province, including the capital district of Trujillo.

The results provided by spatial analysis can be important for the design and implementation of policies and programs aimed at combating poverty, prioritizing the group of districts with high poverty rates that are made up of El Porvenir, Florencia de Mora and Laredo, which not only have the highest poverty rates, but also present high percentages of poverty in the indicators.

6. Conclusions

This study introduced applied fuzzy set methodology to evaluate monetary poverty as a continuous gradient in the province of Trujillo, Peru, using microdata from the 2022 National Household Survey (ENAHO). The central contribution lies in the assessment of three independent indicators: net primary income, food expenditure, and government social support. This methodology prevents the artificial dilution of deprivation inherent in traditional income-aggregating approaches.

Our results reveal substantial divergences from official statistics reported by the National Institute of Statistics and Informatics (INEI). At the provincial level, the model identifies an extreme poverty rate of 8.22%, compared to the official figure of 0.52%. When accounting for severe poverty ($0.75 \leq \mu < 1.00$, 19.03%), the combined prevalence reaches

27.25%—exceeding INEI's aggregate estimate for the entire La Libertad region (25.95%). Across all three indicators, only 3.85% of households are classified as strictly non-poor ($\mu = 0$), underscoring widespread latent vulnerability.

Spatial disaggregation yields an overall provincial fuzzy poverty index of $\mu = 0.4297$ and uncovers significant intra-provincial disparities. Florencia de Mora ($\mu = 0.5843$) and El Porvenir ($\mu = 0.5281$) exhibit the highest poverty levels, with El Porvenir recording the highest extreme poverty rate (16.67%). Seven of the eleven districts registered indices above the provincial average. Meanwhile, although official records report zero extreme poverty across six districts, the proposed fuzzy model detects extreme poverty rates ranging from 5.09% in Víctor Larco Herrera ($\mu = 0.2468$) to 13.89% in Florencia de Mora.

These findings carry key policy implications. High deficits in food expenditure across the analyzed districts demonstrate that income enhancement alone is insufficient without targeted nutritional interventions. Moreover, persistent deprivation among public transfer recipients highlights structural gaps in social support effectiveness. District-level fuzzy indices offer local authorities a high-resolution tool for targeted municipal resource allocation across the evaluated territories.

Limitations and Future Work

The findings depend on the selected thresholds (L, U) and equal-weight aggregation assumptions. Future research should test index sensitivity under dynamic or subjective poverty lines, extend the framework to longitudinal datasets to analyze temporal poverty mobility, and integrate non-monetary multidimensional metrics (housing, basic services, and education) to support broader regional planning in Peru.

Author Contributions: Conceptualization, E.R.V.M. and J.M.G.M.; methodology, E.R.V.M.; validation, E.R.V.M., R.M.A.U., J.C.P.B. and Y.M.V.S.; formal analysis, E.R.V.M., R.M.A.U., J.C.P.B. and Y.M.V.S.; investigation, E.R.V.M., R.M.A.U., J.C.P.B. and Y.M.V.S.; writing—original draft, E.R.V.M.; writing—review and editing, J.M.G.M.; visualization, J.M.G.M.; supervision, E.R.V.M. and J.M.G.M.; project administration, E.R.V.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Universidad Nacional de Trujillo, grant number PIC-2-MOD1-2023-Ext, through the Canon Project (VII Call for Science and Technology Projects).

Data Availability Statement: The data presented in this studio are openly available from INEI at [https://www.inei.gob.pe] (accessed on 27 June 2026).

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ENAHO	National Household Survey
INEI	National Institute of Statistics and Informatics
LINEA	Total poverty line
LINPE	Extreme poverty line

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