Università degli studi di Milano-Bicocca

Data Science Lab

Final Essay

Exploring Poverty in Belize with Alkire-Foster Methodology and Self-Organizing Maps

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Abstract

This project explores poverty in Belize through a multidimensional perspective, challenging conventional measurement approaches. Traditionally, poverty is assessed using composed indicators, but such methods often fall short in capturing the complexity of social structures. I adopt the Oxford Poverty and Human Development Initiative (OPHI) methodology, based on Alkire and Foster's framework, which, while widely used, has limitations in representing societal complexity. To address these limitations, I introduce a different approach based non-aggregative algorithms, particularly Self-Organizing Maps (SOMs). This approach allows for a more detailed and dynamic understanding of poverty in Belize, moving beyond traditional aggregation constraints. The research focuses on evaluating the effectiveness of the Alkire and Foster methodology in capturing the intricate dimensions of poverty and how SOMs can enhance the analysis. Beyond academic insights, the practical implications of my study are significant. By shedding light on Belize's poverty landscape, I aim to contribute to a better understanding of poverty's dimensions. My ultimate goal is to provide actionable insights for the Belize government, empowering them to develop targeted strategies. Despite limitations related to binary data and the unavailability of social-demographic and economic information, my study strives to refine poverty analysis in Belize and offer methodologies with broader implications for global multidimensional poverty research. The code associated with this study is available at the following GitHub repository[1].

Contents

1 Belize

Belize is a small Central American country located on the eastern coast of the Caribbean Sea, see Figure 1. It shares borders with Mexico to the north and Guatemala to the west and south. With a population of approximately 400,000 people [1], Belize boasts diverse cultures and languages, including English as the official language. Known for its stunning natural beauty, Belize is home to tropical rainforests, rich biodiversity, the second-largest barrier reef in the world, and a mix of vibrant marine and terrestrial ecosystems. Tourism, agriculture (including citrus and sugar production), and services contribute significantly to its economy. While Belize's natural beauty and cultural diversity are prominent, the country also faces challenges related to poverty and inequality.

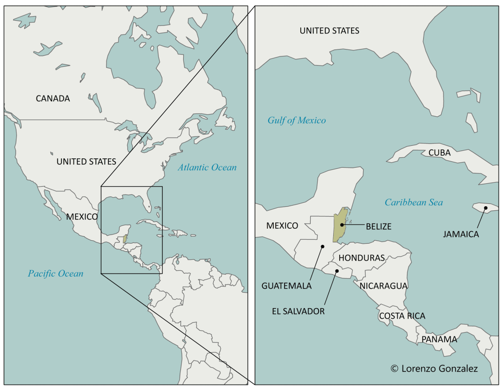

Figure 1: Where is Belize on the map

2 Poverty in Belize

Poverty in Belize is multidimensional, encompassing various dimensions of well-being beyond just income. The population faces disparities in access to basic services, education, healthcare, housing, and employment opportunities. Children, in particular, face high rates of poverty, lacking essentials such as nutrition and education. Despite efforts by the Belizean government and organizations like UNICEF and OPHI, significant gaps remain, limiting children's access to

[1] https://github.com/veronicamorelli/Belize-Multidimensional-Poverty

social protection [2]. UNICEF emphasizes the need for additional funding to close these gaps, enhance existing programs, and establish a universal child benefits system. Their support aligns with global goals to reduce overall poverty in Belize and improve the effectiveness of social protection systems. Key initiatives like BOOST (Building Opportunities for Our Social Transformation) provide cash transfers to families, addressing immediate needs. UNICEF's focus on child-sensitive social protection recognizes the importance of childhood in shaping long-term development. Their efforts include data generation, evaluations, and conferences, contributing to better policymaking for poverty reduction in Belize. OPHI measures poverty in Belize using a multidimensional approach that considers various dimensions such as health, education, living standards, and social inclusion. This approach offers a comprehensive understanding of the challenges faced by individuals and families. To overcome this situation, the Belizean government and international organizations are engaged in efforts to address poverty through targeted policies, poverty measurement, and interventions.

3 Multidimensional Poverty

3.1 Oxford Poverty and Human Development Initiative (OPHI)

The OPHI is a research center based at the University of Oxford in the United Kingdom. Established in 2007, OPHI focuses on advancing the understanding of poverty and human development through rigorous research, measurement methodologies, and policy analysis. Led by its founder, Sabina Alkire, OPHI plays a significant role in shaping the discourse on multidimensional poverty measurement and policy formulation globally.

The OPHI focuses on several key objectives. Firstly, OPHI is widely recognized for its contributions to multidimensional poverty measurement through the development of the Alkire-Foster Methodology. This approach, which extends beyond traditional income-based measures, takes into account various dimensions of poverty, including education, health, and living standards. Secondly, OPHI engages in comprehensive data collection and analysis from diverse countries, providing valuable insights into the prevalence of multidimensional poverty and uncovering patterns, disparities, and trends. Thirdly, OPHI actively collaborates with governments, international organizations, and policymakers to integrate multidimensional poverty measures into policy frameworks. By offering evidence-based insights, OPHI contributes to the formulation of effective poverty reduction strategies and development agendas. Lastly, OPHI plays a crucial role in capacity building by offering training programs. These initiatives aim to enhance the skills of researchers, policymakers, and practitioners, enabling them to effectively measure and address multidimensional poverty challenges.

OPHI's work has had a significant impact on global poverty measurement and policy. It aligns with the United Nations' Sustainable Development Goals (SDGs) by providing tools and insights for tracking progress on ending poverty in all its forms and dimensions. In particular, goal 1 of the Sustainable Development Goals (SDGs) proposes an end to poverty in all its forms everywhere, and Target 1.2 sets an aim for countries to reduce at least by half the proportion of men, women, and children of all ages living in poverty in all its dimensions according to national definitions by 2030. Recognizing the importance of such inequalities not only between but also within countries, the 2030 Sustainable Development Agenda pledged to ensure 'no one will be left behind' in the process of poverty reduction [3].

3.1.1 Alkire-Foster Methodology

The Alkire-Foster (AF) Methodology presented in [4] by Sabina Alkire and James Foster, is a versatile approach for measuring poverty or well-being. It allows the incorporation of various dimensions and indicators to create measures tailored to specific contexts, making it adaptable for different uses. One notable application is in creating national, regional, or international measures of poverty or well-being, such as the global Multidimensional Poverty Index (MPI) [5] featured in the United Nations Development Program's Human Development Reports. The AF method is also employed in monitoring and evaluating program effectiveness over time, as seen in the Women's Empowerment in Agriculture Index [6]. The benefits of the AF method for policymakers include effective resource allocation, informed policy design targeting specific needs, identification of interconnections among deprivations, and the ability to show impacts over time. The methodology is flexible, allowing the selection of dimensions, indicators, and cut-offs tailored to specific situations. It complements other metrics, providing a more comprehensive understanding of poverty and facilitating in-depth analyses of the situation of individuals and households. What sets the AF Method apart is its focus on people, mapping outcomes for each individual or household against measured criteria. This unique approach captures both the percentage of people facing multidimensional poverty and the overlapping deprivations each individual or household experiences. The method reflects the intensity of poverty and allows for disaggregation by region, social groups, and dimensions, providing valuable insights for policymakers striving to achieve the Sustainable Development Goals' promise to 'leave no one behind'.

3.1.2 Multi Dimensional Poverty Index (MPI)

As previously aforementioned, the global MPI was created using the multidimensional measurement method of AF. An early and prominent application was the global MPI [7] and [8]. Later, it was revised in different papers, for example [9] and [10]. The global MPI is an index of acute multidimensional poverty that covers over 100 countries. It is computed using data from the most recent Demographic and Health Surveys (DHS), Multiple Indicator Cluster Surveys (MICS), Pan Arab Project for Family Health (PAPFAM) and national surveys. The MPI has three dimensions and 10 indicators as illustrated in Figure 2. Each dimension is equally weighted, and each indicator within a dimension is also equally weighted. [2] Any person who fails to meet the deprivation cutoff is identified as deprived in that indicator. See Table 1 of the appendix for a definition of each deprivation indicator. In the global MPI, a person is identified as multidimensionally poor or MPI poor if they are deprived in at least one third of the weighted MPI indicators. In other words, a person is MPI poor if the person's weighted deprivation score is equal to or higher than the poverty cutoff of 33.33%. A person is identified as vulnerable to poverty if they are deprived in 20–33.33% of the weighted indicators. Concurrently, a person is identified as living in severe poverty if they are deprived in 50–100% of the weighted indicators.

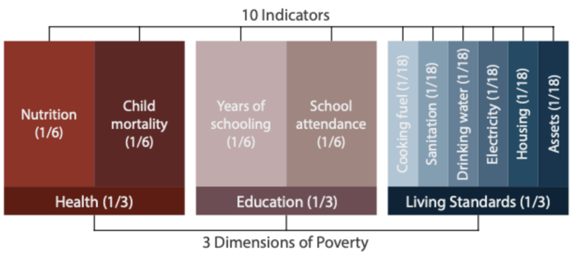

Figure 2: Structure of the Global MPI. Source [5]

The AF methodology has a property that makes the global MPI even more useful dimensional breakdown. This property makes it possible to compute the percentage of the population who are multidimensionally poor and simultaneously deprived in each indicator. This is known as the **censored headcount ratio** of an indicator. Poverty information, however, becomes even more valuable when it is disaggregated by urban and rural areas if data are available. In addition, the MPI can also be computed by subnational regions to show disparities in poverty within countries. This analysis shows the contribution of different indicators to poverty in different areas, which can reveal structural differences. This in turn could mean different policy responses in different areas, making the MPI useful for monitoring the effects of policy shifts and program changes. The censored headcount ratio shows the extent of deprivations among the poor but does not reflect the relative value of the indicators. Two indicators may have the same censored head-count ratios but different contributions to overall poverty, because the contribution depends both on the censored headcount ratio and on the weight assigned to each indicator. As such, a complementary analysis to the censored headcount ratio is the **percentage contribution** of each indicator to overall multidimensional poverty.

3.2 Limitations and Alternatives in Social Indicator Construction

The statistical construction of social indicators faces formidable challenges, as highlighted in the paper [11]. Traditional approaches either provide a plethora of elementary indicators or resort to hyper-aggregated global indicators, revealing fundamental flaws; these methods fail to offer precise structural representations of societal complexity. Challenges in social measurement, including definitional uncertainty and the nuanced nature of key concepts such as poverty and well-being, highlight the problem. A paradigm shift is needed; emphasizing the creation of structural depictions of social phenomena is crucial, steering away from the practice of condensing them into composite scores. This aligns with the goal of comprehensively analyzing multidimensional poverty, object of this project. To achieve this, the implementation of different algorithms is necessary and proposed, such as SOMs and partially order sets (Posets), often referred to as 'non-aggregative' to mark their differences from classical procedures employed in composite indicator construction, based on the aggregation of the input variables. In this project we will concentrate on SOMs algorithms.

3.2.1 Self-Organizing Maps (SOM)

SOM is an unsupervised machine learning algorithm introduced by Teuvo Kohonen in the 1980s [12], that is why sometimes SOMs SOM is called Kohonen map. As the name suggests, the map organises itself without any instruction from others. SOM is a simple kind of neural network. At its core, the SOM operates by facilitating a form of self-recognition among data points within a dataset. Each data point competes for representation, initiating a dynamic process. The SOM mapping begins with the initialization of weight vectors. Later, a sample vector is randomly selected, and the map of weight vectors is traversed to identify the weight that best represents the chosen sample, usually known as the Best Matching Unit (BMU). Notably,

[2] It should be noted that the AF method can be used with different indicators, weights and cutoffs to develop national MPIs that reflect the priorities of individual countries. National MPIs are more tailored to the context but cannot be compared.

each weight vector has neighboring weights in proximity. The selected weight is then rewarded by adjusting its attributes to resemble the randomly chosen sample vector. Additionally, the neighboring weights receive rewards, allowing them to adapt to resemble the chosen sample vector. This iterative process fosters the growth and formation of diverse shapes within the map. In two-dimensional feature space, these shapes commonly manifest as square, rectangular, hexagonal, or L-shaped formations [13]. SOMs are usually used in non-linear dimensionality reduction, which can be seen as an enhancement of the principal component approach, where the approximating linear subspace is substituted with a topological manifold. SOMs are often used for their ability to unveil the complex structure of the data, focusing on the identification of patterns, rather than on the quantification of the underlying latent trait. SOMs are quite an old algorithm, and there is a very huge body of theoretical and applied research on them; nevertheless, they are not often employed in the social sciences, where dimensional reduction is usually achieved through SVD-based algorithms or factor analysis procedures, with the possible drawbacks highlighted above. In this paper [14], SOMs and Posets are used for the study of multidimensional deprivation in Milan. I will draw inspiration from this paper for our analysis.

3.3 Handling Missing Values

Missing values, often due to survey non-response, pose challenges in poverty estimates [15]. Two common approaches are dropping units with missing information, risking bias, or defining criteria to mitigate missing data impact. When missing values exceed 10%, a bias analysis is recommended to assess differences between observations with and without missing values. If significantly different, resulting estimates may be biased, and it's essential to clarify whether they represent lower or upper bounds. If missing information leads to a substantial sample reduction (above 15%), considering alternative indicators with less missing data is advisable. An alternative approach involves defining criteria to reduce missing data impact, especially in transforming individual to household indicators. For example, in the global MPI, households are classified as non-deprived if at least one member aged 10 or older has five or more years of education. If information on at least two-thirds of household members is available, each with less than five years of education, the household is classified as deprived; otherwise, it is dropped. Care must be taken in computing missing values, checking if questions were specific or filtered at the individual and household levels. In income poverty estimates, common imputation techniques are used, but these are yet to be adapted for multidimensional cases due to model accuracy dependencies and challenges in handling multiple indicators.

4 Analysis

4.1 Dataset Overview

The dataset includes information on 19,257 individuals across 4,636 households. Following the AF methodology, a total of 10 indicators, representing the well-being and deprivation conditions of each individual, have been measured. The dimensions of poverty indicators and deprivation criteria are shown in Table 1 of Appendix A. The dataset includes the following variables: `hh_id` and `ind_id`, uniquely identifying households and individuals, respectively. `d_cm` denotes child mortality, where 0 indicates no under-18 child mortality in the last 5 years, and 1 signals the opposite. `d_nutr` flags malnourished individuals, `d_satt` reflects school attendance, and `d_educ` marks households with at least one member having 6 years of education. `d_elect` identifies households with electricity, `d_wtr` indicates access to drinking water meeting MDG standards, and `d_sani` flags improved sanitation. `d_hsg` highlights housing conditions meeting quality standards, `d_cklf` denotes cooking fuel meeting MDG standards, and `d_asst` indicates ownership of assets. `miss` identifies individuals with at least one missing indicator, `weighted_sum` represents the sum of weighted indicators, with the weights shown in Table 1, and `multi_deprived` flags multidimensional poverty. The cut-off is set following the AF methodology at 0.3333. For binary variables, 1 signifies the presence of the deprivation condition, while 0 indicates its absence. These variables encompass the three poverty dimensions of health, education, and living standard conditions, providing a nuanced understanding for targeted interventions in Belize.

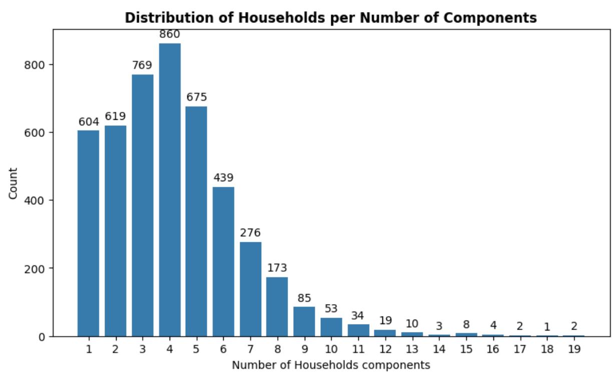

Figure 3: Distribution of Households per Number of Components

4.2 Data Pre-processing

The dataset contains information regarding the household and the individuals comprising each household. The data related to each individual within a household is identical to each other. I decided to create a new dataset in which there is information only related to the households (one row for each household). To incorporate information related to individuals, I counted how many individuals are in each household and added this information to the resulting dataset; the new variable is called `ind_id_count`.

Figure 3 represents a bar plot showing the distribution of households in Belize based on the number of individuals in each household. The x-ax represents the count of individuals in a household, ranging from 1 to 19. The y-ax indicates the count of households that have the corresponding number of individuals. For example, there are 604 households with only 1 individual, 619 households with 2 individuals, 769 households with 3 individuals, and so on. In general, this plot shows that there are more households with smaller sizes (1 to 5 individuals), and the number of households decreases as the size of the household increases. From a policy and planning perspective, such insights into the distribution of household sizes can be instrumental. By understanding this distribution, authorities can make informed decisions about the size and type of houses to build. For instance, a higher number of smaller households might suggest a need for more compact living spaces, while households with a larger number of individuals may indicate a demand for larger homes or multiple-bedroom accommodations. This knowledge is crucial for effectively addressing housing needs and ensuring that housing developments align with the diverse requirements of the population.

4.3 Exploratory Data Analysis (EDA)

4.3.1 Missing Values

Regarding missing values in the household-aggregated dataset, it is noted that `hh_id` exhibits no missing values, ensuring a robust foundation for household identification. However, dimension `d_nutr` (Nutrition) show relatively higher percentages of missing values equal to 3.67%. This indicates potential gaps in data related to this critical dimension of well-being. Additionally, variables like `weighted_sum` and `multi_poor` exhibit 4.85% missing values, emphasizing the need for careful consideration when interpreting aggregated and multidimensional poverty measures. Overall, while the dataset generally maintains low levels of missing information, attention to specific dimensions with higher percentages is crucial for a comprehensive analysis. Considering that the percentage of missing values per variable is lower that 5-10% it is decided not to eliminate any column. In addition, less than 5% of rows regarding household information contained missing values, which were handled by dropping those rows. The final dataset is constituted by 4411 observation related to households.

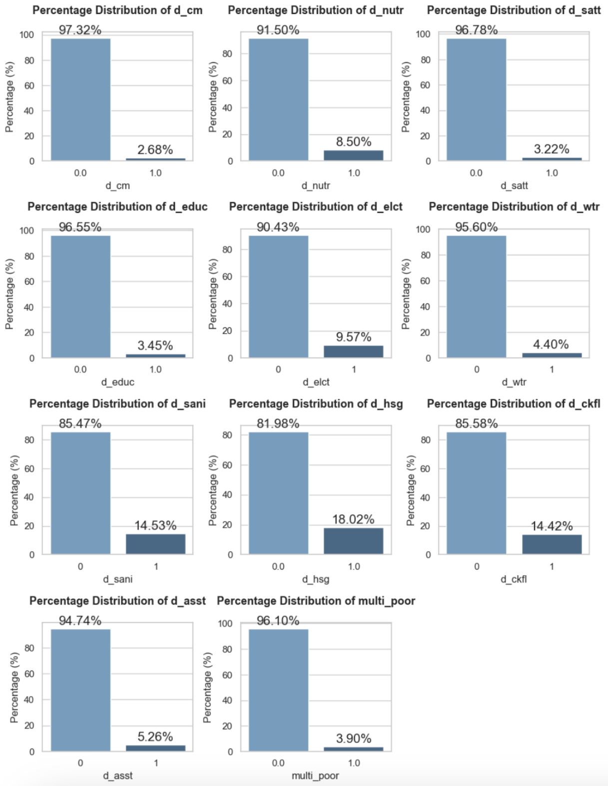

Figure 4: Percentage Distribution Binary Variables

4.3.2 Descriptive analysis

Figure 4 illustrates the distribution of binary values per variable, providing insights into critical dimensions for poverty analysis in Belize. Child Mortality (`d_cm`) predominantly indicates the absence of a child under 18 dying in the household during the five years preceding the survey, with a percentage of 97.32%, suggesting relatively low occurrences. Conversely, Nutrition (`d_nutr`) highlights a concerning 8.50% incidence, indicating at least one undernourished person in the household and emphasizing the need for targeted interventions to address malnutrition. School attendance (`d_satt`) reveals a specific concern, with approximately 3.22% of households reporting that any school-aged child is not attending school up to the age at which they would complete class 8. Understanding the reasons for nonattendance becomes crucial in addressing this issue. Education (`d_educ`) and Asset Ownership (`d_asst`) exhibit occurrences of 3.45% and 5.26%, respectively. The ownership of fewer than one asset (example assets described in Table 1) could be critical, potentially influencing other poverty dimensions. For instance, a household without essential items like a radio, TV, computer, or telephone might impact the education dimension of children. Housing (`d_hsg`), Sanitation (`d_sani`) and Cooking fuel (`d_ckfl`) show the highest presence proportions at 18.02%, 14.53% and 14.42%, respectively, signaling potential areas of vulnerability. These dimensions are crucial for maintaining a correct and healthy lifestyle;

for example, having an unsafe source of drinking water could influence all other dimensions. The government should ensure safe access to clean drinking water. Another important aspect regards electricity, showing that almost 10% of households have no electricity. This lack of access to a basic utility raises concerns about the overall living standards and potential challenges in daily activities. The absence of electricity can impact various dimensions, including education (limited study hours), health (access to medical services and refrigeration), and overall well-being. Policymakers can utilize these proportions to tailor interventions, emphasizing preventative measures for dimensions with higher presence rates.

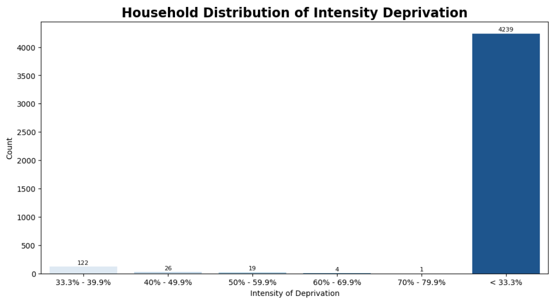

Figure 5: Household Distribution of Intensity Deprivation

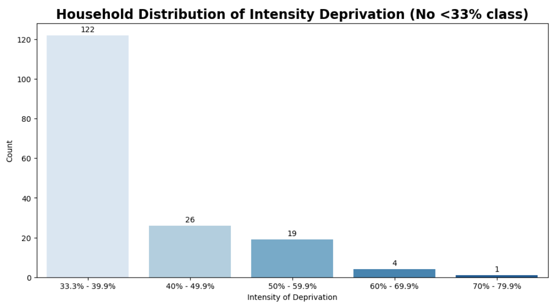

Figure 6: Household Distribution of Intensity Deprivation only on deprived households (without considering $< 33\%$ group.

The bar charts in Figure 5 and Figure 6 depict the distribution of household intensity of deprivation, as measured by the Alkire-Foster method, across various ranges. The intensity of deprivation is categorized into six intervals: less than 33.3%, 33.3% - 39.9%, 40% - 49.9%, 50% - 59.9%, 60% - 69.9%, and 70% - 79.9%. The most striking observation from this chart is the significant number of households (4,239) that fall below the 33.3% intensity of deprivation threshold, indicating that the majority of households in the dataset are not considered multidimensionally poor according to the AF method's cutoff point. This could be interpreted as a positive sign, suggesting that most households have a level of well-being above the poverty threshold set by the AF methodology. On the other end of the spectrum, there are very few households in the higher intensity brackets (70% - 79.9% and 60% - 69.9%), with only 1 and 4 households respectively, showing that extreme deprivation is quite rare within this dataset. For the remaining categories, the numbers are relatively low, with 19 households in the 50% - 59.9% range, 26 households in the 40% - 49.9% range, and 122 households in the 33.3% - 39.9% range. These figures suggest that there is a small proportion of households that experience moderate levels of deprivation. This plot sets the stage for a deeper analysis to understand the characteristics of households in each intensity bracket, which could inform targeted poverty alleviation policies.

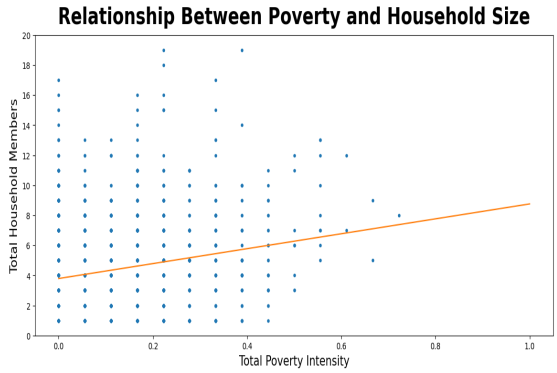

Figure 7: Relationship between Poverty and Household Size

Figure 7 shows a scatter plot illustrating the relationship between total poverty intensity and household size in Belize. The positive but weak correlation (0.2116) suggests that, on average, larger households experience slightly higher poverty intensity. However, other factors contribute to poverty dynamics. To address poverty, policies should adopt a comprehensive approach considering diverse household compositions. Interventions must encompass factors like employment, education, and healthcare. Housing policies should be flexible, accommodating the needs of households of varying sizes. A holistic strategy, addressing social and economic aspects, is crucial for effective anti-poverty measures tailored to Belizean households.

Figure 8 shows the Phi correlation plot. The plot above unveils the relationships between various binary variables, providing a comprehensive view of the associations among different dimensions of household well-being in Belize. The values represent the Phi correlation coefficients, ranging from 0 to 1, with higher values indicating stronger associations. Notably, some variables exhibit significant correlations, such as `d_cm` (child mortality) and `multi_poor` (multidimensional poverty), with a Phi correlation of 0.195. This suggests that households experiencing child mortality are more likely to face a range of deprivations across various dimensions. Similar correlations can be observed between other variables, unveiling patterns of interdependence among dimensions like nutrition, sanitation, education, and overall poverty. From a policy and planning perspective, these insights can inform targeted interventions. For instance, recognizing the correlation between education (`d_educ`) and poverty (`multi_poor`) implies that improving educational access and quality may be an effective strategy in alleviating multidimensional poverty.

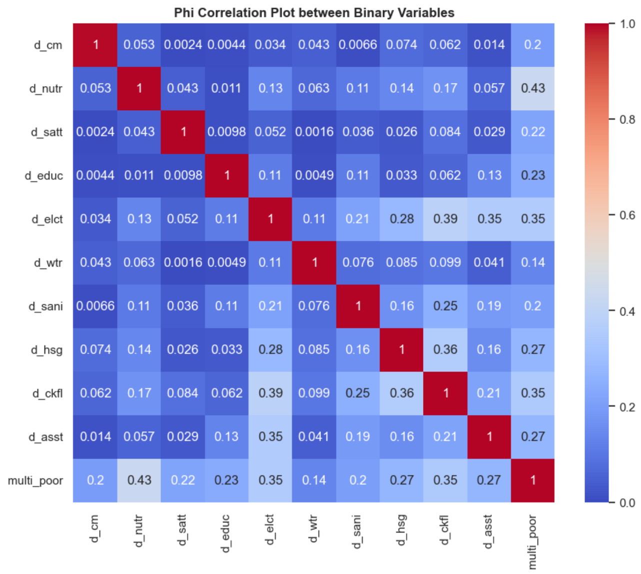

Figure 8: Correlation Binary Variables

4.4 Alkire-Foster Methodology Analysis

The bar chart shown in Figure 9 displays the censored headcount ratio for each of the indicators used in the Alkire-Foster Methodology to compute the MPI. The indicators are categorized under three dimensions of poverty: health, education, and living standards. Each bar represents the percentage of multidimensionally poor individuals who are deprived in each specific indicator. From a policy-making perspective, this chart is particularly useful. It shows which deprivations are most and least common among the multidimensionally poor population, thereby guiding targeted interventions. For instance, the indicators with the highest censored headcount ratios, such as improved housing conditions (`d_hsg`) and asset ownership (`d_asst`), which both stand at over 14%, indicate areas where a significant portion of the poor population faces challenges. Consequently, these areas might be prioritized for policy intervention. On the other hand, child mortality (`d_cm`) and malnutrition (`d_nutr`) have lower censored headcount ratios, suggesting that fewer poor individuals are affected by these issues or that interventions in these areas have been more effective. However, it's important to note that the severity and impact of each type of deprivation can vary; for instance, child mortality, although less frequent, has a profound impact on the affected households. The policy implication here is to not only focus on the indicators with the highest ratios but also to consider the weight and impact of each deprivation. For example, while improving housing conditions and asset ownership can significantly reduce the headcount ratio, improving nutrition and reducing child mortality can have a transformative effect on the quality of life. Disaggregating this data by urban and rural areas, or by regions, would be an excellent next step, as it could highlight specific local needs and lead to more effective, tailored policy responses. Such disaggregation might reveal, for instance, that rural areas have a higher deprivation in access to clean water (`d_wtr`), while urban areas might struggle more with housing conditions (`d_hsg`), thus requiring different policy actions. Overall, this chart provides a clear visualization of where policy interventions can be most impactful, illustrating the importance of a multifaceted approach to poverty alleviation that takes into account the multidimensional nature of poverty. It underscores the necessity for nuanced policies that address the specific deprivations of the multidimensionally poor, rather than adopting a one-size-fits-all solution.

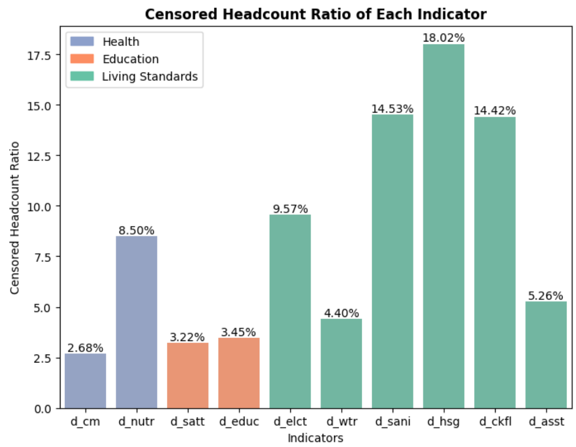

Figure 9: Censored Headcount Ratio of Each Indicator

4.5 Self-Organizing Maps (SOM)

Unsupervised SOMs were implemented in R using the `kohonen` package [16]. In this analysis I used the dataset aggregated per household without missing values. Only binary variables were used. This approach has the aim to provide a comprehensive exploration of poverty in Belize combining SOMs with household-level data.

4.5.1 Tanimoto Distance

The Tanimoto distance is often used for binary or categorical data. It's a similarity metric that measures the dissimilarity between two sets. In the context of binary data, it is commonly employed to assess the dissimilarity or distance between binary vectors.

The Tanimoto distance (or Tanimoto coefficient) is calculated as the ratio of the intersection of the sets to the union of the sets. For two binary vectors A and B, the Tanimoto coefficient (T) is defined as:

$$T(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

The Tanimoto distance can be obtained by subtracting the Tanimoto coefficient from 1:

$$\text{Tanimoto Distance} = 1 - T(A, B)$$

It ranges from 0 (for identical sets) to 1 (for completely dissimilar sets). Tanimoto distance is available as distance metric to use in the `som` function when working with the `kohonen` package in R. It has been used in this analysis considering that all variables are binary.

4.5.2 SOM Analysis

After applying the SOM algorithm, I generated various plots. The initial plot, referred to as the '**mapping plot**,' is presented in Figure 10. Although this map does not directly illustrate the patterns of poverty, it effectively demonstrates how households are clustered based on multidimensional poverty indicators. Each hexagon on the map corresponds to a neuron. The black and white segments within each hexagon may represent the presence or absence of specific poverty attributes in the households associated with that neuron. Subsequent plots will further delineate these neurons with colors corresponding to the values of different variables.

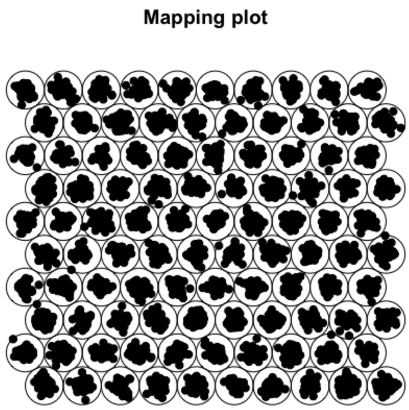

Figure 10: Mapping Plot

The "**Codes Plot**" in Figure 11 shows how each neuron's pie chart provides a visual summary of the prototype or average characteristic of the households associated with that neuron. The variation in pie chart sizes across the map suggests a diversity of deprivation profiles within the dataset. Some neurons show large pie sections for certain deprivations, indicating clusters of households that are particularly affected by specific indicators. For example, larger pie slices for housing (`d_hsg`) or assets (`d_asst`) suggest that these are areas of widespread need and could guide targeted housing policies and asset-building programs. Conversely, nodes with significant sections for critical indicators like child mortality (`d_cm`) or malnutrition (`d_nutr`) indicate clusters where urgent health interventions could be lifesaving.

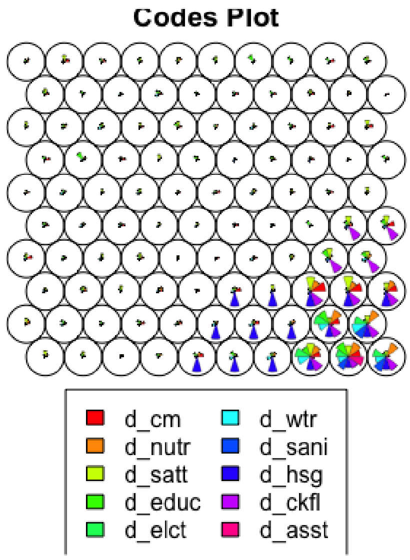

Figure 11: Codes Plot

The SOM analysis also allows for precision in policy targeting. Nodes with multiple deprivations, such as those lacking both water (`d_wtr`) and sanitation (`d_sani`), call for integrated approaches, such as Water, Sanitation, and Hygiene (WASH) programs. Furthermore, clusters with pronounced educational (`d_educ`) and health deprivations may benefit from coordinated investments in school infrastructure and local healthcare services, while economic interventions could strategically focus on nodes with substantial asset ownership deprivations.

The "**Neighbour Distance Plot**" and the "**Counts Plot**", depicted in Figures 12 and 13, are critical outputs from the SOM analysis that provide a multidimensional perspective on poverty within Belize. These tools are instrumental for policymakers in devising targeted poverty alleviation strategies. The "Neighbour Distance Plot," or U-matrix, reveals the dissimilarities between clusters of households as indicated by the gradient from red to yellow. Yellow regions, representing closer distances, identify clusters of households with similar deprivation profiles, suggesting a commonality in their experience of poverty. These clusters enable policymakers to target interventions more precisely. Conversely, red areas signify the boundaries between clusters, which are crucial in recognizing where stark transitions between poverty profiles occur. This understanding is vital for identifying the areas that are distinctly different in terms of poverty characteristics and may require unique policy responses.

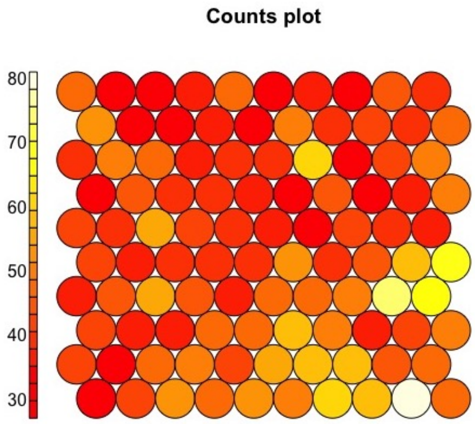

Figure 12: Counts Plot

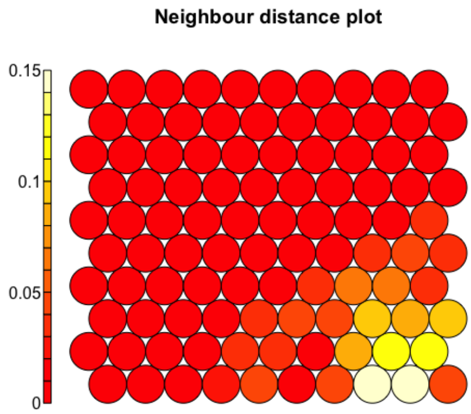

Figure 13: Neighbour Distance

The "Counts Plot" complements this by quantifying the prevalence of each cluster's characteristics, with warmer colors signifying a higher density of households. Areas highlighted in yellow or orange on this plot represent higher commonality in household characteristics, indicating potential priority areas for poverty alleviation initiatives. Such nodes can direct large-scale interventions where the impact could be maximized, addressing the needs of a substantial segment of the population. Integrating the insights from these plots, policymakers can discern not only the common deprivations affecting the population but also the specific areas where these deprivations are most intense. By targeting the yellow regions on the "Counts Plot" that correspond to the yellow clusters on the "Neighbour Distance Plot," interventions can be both broad-reaching and focused, ensuring that resources are deployed where they are needed most and can do the most good.

The **heatmaps** showed in Figure 14 provided delineate the varying levels of deprivation across multiple indicators within the Self-Organizing Map (SOM) framework, as part of the multidimensional poverty analysis in Belize. These indicators are grouped by the dimensions of Health, Education, and Living Standards, offering a structured approach to understanding the distinct aspects of poverty.

(a) `d_cm` (Child Mortality): The heatmap reveals nodes with higher child mortality rates, necessitating targeted health interventions in these critical areas.

(b) `d_nutr` (Nutrition): The heatmap displays a range of deprivation levels, with certain nodes indicating significant nutritional deprivation. This highlights potential areas for intervention in nutrition programs.

(c) `d_satt` (School Attendance): While overall school attendance appears sufficient, certain nodes demonstrate a lack, highlighting the need for targeted educational outreach.

(d) `d_educ` (Education): Varying levels of educational attainment across nodes can inform potential policy enhancements and educational resource allocation.

(e) `d_ckfl` (Cooking Fuel): Significant deprivation in access to clean cooking fuel in specific nodes suggests a broad area for clean cooking initiatives.

(f) `d_sani` (Sanitation): There is a more pronounced spread in sanitation deprivation, with some nodes showing moderate to high deprivation levels. This suggests a need for targeted sanitation infrastructure improvements.

(g) `d_wtr` (Drinking Water): Most nodes show adequate water access, with a few highlighted for potential water access interventions.

(h) `d_elect` (Electricity): General access to electricity is indicated, yet select nodes may require focused efforts to achieve universal access.

(i) `d_hsg` (Housing): The diverse range of housing quality suggests the necessity for targeted housing improvement programs.

(l) `d_asst` (Assets): Asset ownership is least deprived overall; however, economic development programs could further support the identified nodes in need.

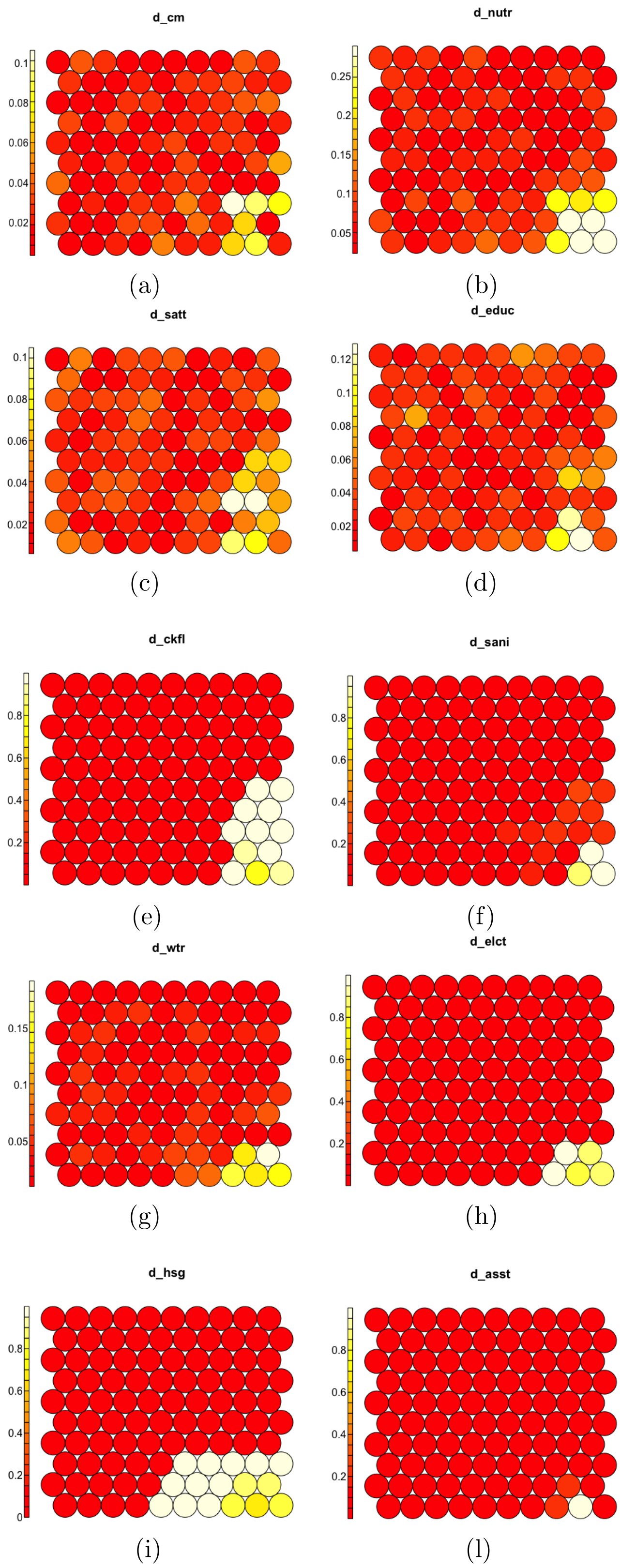

Figure 14: Indicators: (a) `d_cm` (Child Mortality); (b) `d_nutr` (Nutrition); (c) `d_satt` (School Attendance); (d) `d_educ` (Education); (e) `d_ckfl` (Cooking Fuel); (f) `d_sani` (Sanitation); (g) `d_wtr` (Drinking Water); (h) `d_elect` (Electricity); (i) `d_hsg` (Housing) and (l) `d_asst` (Assets).

These heatmaps can be instrumental in visualizing the specific geographic or demographic areas where interventions could be most impactful. They allow for the identification of both widespread issues that require broad policy measures and localized problems that need targeted interventions.

5 Conclusions and Future Developments

This study has provided a comprehensive analysis of multidimensional poverty in Belize utilizing both the Alkire-Foster method and SOM. The Alkire-Foster method offered an aggregated perspective on poverty, highlighting the prevalence and intensity of deprivations across households. In contrast, SOM revealed complex patterns and clusters in the data, affording a nuanced understanding of the multidimensional poverty landscape.

5.1 Conclusions

Our findings suggest that while a significant proportion of the population experiences multidimensional poverty, there are distinct clusters of households that share common deprivation characteristics. The SOM analysis, in particular, enable the identification of these clusters, allowing for the visualization of poverty in a way that is not immediately apparent through traditional aggregate measures. The clusters identified suggest that interventions can be more targeted, focusing on the specific needs of different household groups. Policymakers should consider leveraging the insights gained from the SOM analysis to design and implement poverty alleviation programs that address the distinct needs of each cluster. This approach can lead to more effective and efficient use of resources, ensuring that interventions are not only well-informed but also appropriately scaled to the magnitude of the deprivations faced by different household segments.

5.2 Future Developments

Looking ahead, there are several avenues for further research and development:

- **Data Enhancement**: Acquiring more comprehensive socio-demographic and economic data on households and individuals will enable a deeper understanding of the underlying factors contributing to poverty.
- **Variable Diversification**: Expanding the dataset beyond binary variables to include continuous and ordinal variables will enrich the analysis, potentially revealing additional layers of complexity within the poverty dynamics.
- **Poset Implementation**: Employing Partially Ordered Sets (Posets) could offer a more flexible analytical framework, accommodating the multidimensionality of poverty more effectively than traditional scalar approaches.
- **Area Disaggregation**: Disaggregating data by urban and rural areas could uncover spatial disparities in poverty, guiding region-specific policies and interventions.

These developments would not only enhance the granularity of my understanding but also provide a more robust foundation for crafting policies tailored to the challenges of Belize's diverse population. As such, the government is encouraged to invest in data collection and analytical methodologies that can drive more nuanced and impactful poverty reduction strategies.

In conclusion, my study underscores the complexity of poverty and the importance of using multidimensional analysis tools to capture this complexity. By adopting a multifaceted approach to data analysis and policy formulation, it is possible to make significant strides in alleviating poverty and improving the well-being of all Belizeans.

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A Data

Dimension	Indicator	Deprived if living in a household where...	Weight	SDG Area
Health (1/3)	Nutrition	Any person under 70 years of age for whom there is nutritional information is **undernourished**.	1/6	SDG 2: Zero Hunger
	Child mortality	A child **under 18** has **died** in the household in the five-year period preceding the survey.	1/6	SDG 3: Health and Well-being
Education (1/3)	Years of schooling	**No** eligible household member has completed **six years of schooling**.	1/6	SDG 4: Quality Education
	School atten-dance	Any school-aged child is **not attending** school **up tp** the age at which he/she would complete **class 8**.	1/6	SDG 4: Quality Education
Living Standards (1/3)	Cooking fuel	A household cooks using **solid fuel**, such as dung, agricultural crop, shrubs, wood, charcoal, or coal.	1/18	SDG 7: Affordable and Clean Energy
	Sanitation	The household has **unimproved** or **no** sanitation **facility** or it is improved but **shared** with other households.	1/18	SDG 6: Clean Water and Sanitation
	Drinking water	The household's source of **drinking water** is **not safe** or safe drinking water is a **30-minute** or **longer walk** from home, roundtrip.	1/18	SDG 6: Clean Water and Sanitation
	Electricity	The household has **no electricity**.	1/18	SDG 7: Affordable and Clean Energy
	Housing	The household has **inadequate** housing materials in **any** of the three components: **floor**, **roof**, or **walls**.	1/18	SDG 11: Sustainable Cities and Communities
	Assets	The household does **not own more than one** of these **assets**: radio, TV, telephone, computer, animal cart, bicycle, motorbike, or refrigerator, and does not own a car or truck.	1/18	SDG 1: No Poverty

Table 1: Dimensions of Poverty Indicators and Deprivation Criteria