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Can Data Empower Indigenous People? Unveiling an Innovative Dataset for Quantitative Analysis, Replication Modeling, and Economic Development

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Abstract

Indigenous peoples are among the most vulnerable, ignored, and marginalized groups in society. Poverty is the oldest social problem and difficult to counter. The Indigenous people with which the authors live and work, the Agta Tabangnon, suffer from poverty and multidimensional socioeconomic deprivations. Indigenous peoples' studies are qualitative, while poverty studies are typically generic, exposed to large sampling errors, and intended for nationwide decisions. Therefore, measuring poverty for specific tribes through complete enumeration with multifaceted disaggregation is critical for economic development. There is no comprehensive census specifically designed for Indigenous peoples to encompass the multidimensional aspects of their way of life. Nonetheless, the authors are resourceful in generating useful datasets from their partners. The locale is situated in the poorest district of the poorest province in the poorest region of Luzon, Philippines. The datasets contain multidimensional

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poverty indicators that are readily usable, along with complementary analytics to visualize the data. They may serve to measure poverty in Indigenous communities across different regions and countries. By utilizing this data, further empirical analysis, regressions, machine learning, and econometric modeling can be conducted. It can be freely utilized to target policies that address the multifaceted poverty and promote economic development within tribal communities.

Keywords

indigenous people – multidimensional poverty – economic development – data analytics for humanities and social sciences – Philippines

– Related data set "Measuring the Unmeasurable Multidimensional Socio-Economic Deprivations and Poverty Predictions: Indigenous People Datasets for Econometrics, Machine Learning, and Quantitative Social Science Modeling" with DOI www.doi.org/10.7910/DVN/QSZKUP in repository "Harvard Dataverse"

1. Introduction

Poverty has perennially remained one of the most persistent social issues that has yet to be fully resolved. Haughton and Khandker (2009) argue that it exerts a negative impact on societal growth and economic prosperity, posing significant challenges to mitigation efforts. Despite numerous attempts by economists, social scientists, and humanitarians to explain the root causes of global poverty and advocate for necessary reforms, quantifying and predicting poverty at localized levels or within Indigenous communities presents a more difficult challenge, compounded by a scarcity of published literature on the topic.

Indigenous peoples have been an integral part of human civilization since its inception, with poverty intertwined in societal structures from the beginning. These communities, existing since time immemorial, hold a vital place in society. Alongside principles of self-governance, empowerment, social justice, human rights, and cultural integrity, they also possess rights to ancestral territories and lands (Andaya, 2023; Republic Act 8371). It is imperative that native communities are respected by the broader public and afforded official protection. As their rich culture and traditions endure, efforts must be made to address their poverty and foster sustainable growth (Onsay, 2022).

In order to quantify the multidimensional socio-economic deprivations and poverty conditions in their area and develop effective policy interventions that can reduce poverty and advance the economic development of our Indigenous people, researchers have been gathering the data and statistics they need from extensive community-based monitoring systems. The local government owns the community-based monitoring system (CBMS), a system for gathering and evaluating data at the community level. Policymaking, local planning, service delivery, and impact evaluation all make use of the CBMS's outputs (Reyes et al., 2014; Sobreviñas, 2017). There is no thorough census or study that is unique to the Indigenous population. Thus, to reduce poverty and advance economic development, we use, process, and produce crucial data on Indigenous people. Data from the social sciences and humanities are crucial for problem assessment and opportunity analysis in contemporary society, both historically and prospectively (Sawkins & Smith, 2023).

Numerous scholars have attempted to measure the unmeasurable in the field of natural sciences (Eid, 2008; Gruijters et al., 2018; Rabajante, 2020; Wu et al., 2022). However, social difficulties and economic problems are hard to measure, difficult to evaluate, and sometimes even considered unmeasurable (United Nations, 2012). A limited amount of research has been conducted on the complex aspects of poverty among Indigenous peoples in the Philippines. No research has been undertaken to quantify poverty using predictive analytics and advanced econometrics in the Bicol region.[1] Therefore, the dataset is crucial for addressing the root causes of multidimensional poverty and promoting economic growth among Indigenous peoples, not only in this locale but also around the world, by leveraging the models and indicators utilized in this study.

To effectively monitor progress towards UN Sustainable Development Goal No. 1 (No poverty) and related objectives, it is crucial to ensure the disaggregation of national poverty measures by subpopulation groups, including Indigenous and non-indigenous communities, ethnicities, and other relevant categories. Therefore, the utilization of community-focused datasets highlighted in this article becomes imperative and valuable (Allen et al., 2018; Onsay & Rabajante, 2024b). This article, along with its associated Indigenous People datasets, enables the extension of previous empirical work and facilitates advanced quantitative analyses, such as econometrics,

1 This work was conducted in the Bicol Region, Philippines. Notably, this region stands as the poorest among Luzon's provinces, and within it, Camarines Sur, home to Mount Isarog, emerges as the region's most impoverished province, with a poverty incidence of 38.7% (Philippine Statistics Authority, 2022). The slopes of Mount Isarog are home to 12 predominantly Agta villages, all comprehensively captured by the dataset through complete enumerations.

machine learning, and quantitative social science modeling, for both local and international Indigenous communities.

2. Problem

Poverty among Indigenous peoples varies greatly around the globe, so poverty reduction efforts must be tailored accordingly (Hall & Patrinos, 2012). Currently, there is a lack of research focusing on quantifying multidimensional poverty among Indigenous populations in the Philippines. In contrast, studies in developed nations like Australia have highlighted significant economic development challenges faced by Indigenous peoples (Fuller et al., 2007). Similarly, research has shown that a large proportion of Latin American Indigenous communities live in extreme poverty (Psacharopoulos & Patrinos., 1994). However, existing studies often operate at a macroeconomic level, are susceptible to sampling errors, and primarily inform broad national policies. In the Philippines, research on Indigenous communities is limited and primarily qualitative in nature. For instance, Tindowen (2016) conducted research on 25 Aeta families in the northern Philippines, revealing distinct socio-economic characteristics and limited technological access compared to rural and urban populations. In Southern Luzon, there is a notable absence of comprehensive quantitative assessments for the Agta Tabangnon[2] indigenous group, who have peacefully inhabited the region since the pre-colonial era, due to data scarcity. Given these gaps, the datasets emphasized in this research are crucial for the socioeconomic advancement of Indigenous communities and can serve as a blueprint for replication by various Indigenous societies in the Philippines and beyond.

While Indigenous people are represented in Philippine national living standards surveys such as The Family Income and Expenditure Survey (FIES), they are underrepresented due to reliance on sample selection. Additionally, these surveys lack comprehensive information about the standard of living

2 Agta Tabangnon, or Inagta Partido, is the tribe residing on the slopes of Mount Isarog, the tallest forested peak in southern Luzon, Philippines. This stratovolcano rises to 1,966 meters above sea level and was designated a Natural Park by Proclamation No. 214 from the Philippine Malacañang Palace in 2002. This region boasts a diverse array of endemic and endangered flora and fauna and serves as the ancestral home of the Indigenous People, known locally as Agta Tabangnon. Meanwhile, Northern Luzon encompasses Ilocos, Cagayan, and the Cordillera Administrative Region, areas that also host a variety of Indigenous communities known as the Aetas. In contrast, Southern Luzon specifically refers to the Bicol Region, the focus of this study. This work not only explores sampled Indigenous families but also examines entire households and populations of the native communities through a complete enumeration of disaggregated data illustrations.

of Indigenous communities. The Annual Poverty Indicator Survey (APIS) includes some information about Indigenous communities using a sampling design, but it lacks comprehensive health information. The Labor Force Survey (LFS) also suffers from underrepresentation and focuses solely on labor-related data. The current surveys in the Philippines are not very useful for Indigenous communities. More often, Indigenous communities are underrepresented, and they lack economic, demographic, and social data. The current surveys conducted by the National Statistics Agency are not designed to cater specifically to Indigenous communities. In fact, there is no survey specifically designed to capture the overall conditions of Indigenous people (Onsay & Rabajante, 2024a). The current census conducted by the Indigenous People Office is carried out manually, with information written on bond paper using a pen. These records are susceptible to fading, loss, and damage from moisture, and can be easily overlooked or misrepresented. This survey only captures the name of the household head and their members, the age of each member, and their address. It does not include data pertaining to sex, income, and other vital social and economic statistics. Thus, this dataset cannot be used for modeling, inferential analysis, or advanced analysis. However, the datasets we present here are unique, highly reliable, and relevant. Obtaining data for Indigenous communities is particularly difficult, especially in mountainous or remote areas. Nevertheless, the authors have displayed innovation and resourcefulness by filtering, cleaning, and transforming the extensive community-based monitoring system to generate data exclusively for Indigenous communities. The data we provide here are comparable to other datasets in the Philippines as the Community-Based Monitoring System (CBMS) is being implemented nationwide (Republic Act 11315 [2018]). Furthermore, the CBMS network is implemented in more than 20 countries worldwide, allowing for the generation of similar datasets by other researchers (CBMS Network, 2020). These datasets are valuable for achieving the UN Sustainable Development Goals (SDGs) by 2030 and can be used in conjunction with other datasets to assess progress towards those goals. The data we produce and the work we put forth can be utilized by other researchers and replicated in different regions that have Indigenous communities.

3. Data

- **Measuring the Unmeasurable Multidimensional Socio-Economic Deprivations and Poverty Predictions deposited at Harvard Dataverse** – **DOI:** www.doi.org/10.7910/DVN/QSZKUP
- **Temporal coverage:** 2018–2020

The datasets in the repository contain 8 components, namely: the multidimensional poverty-comprehensive data; the population dynamics; the Indigenous people analytics; the poverty computational data; the data dictionary; the graph of poverty results; the table of poverty indices; and the prescriptive policy analytics. The multidimensional poverty variables are contained in an Excel file with 64 indicators from 1,660 Households of Indigenous People and 8,022 Individuals from 12 tribes of the 3 sectors (Isarog, Ranggas, and Salog). The application of indicator deprivation cutoffs and poverty cutoffs will facilitate the assessment of multidimensional socio-economic deprivations and poverty predictions. The CBMS Simple Composite Indicator (SCI) can be adopted (Sobreviñas, 2017). The SCI consists of four clusters: Severely poor (out of 15 indicators, deprived in at least 7 basic needs); Poor (deprived in at least 4 basic needs); Near Poor (deprived in 1–3 basic needs); and Not Poor (not deprived in any of the basic needs). Income poverty and food poverty, as measured by income and expenses, are based on the country (province) poverty line (threshold), usually determined by the governing national statistics agency of a country. It is important to remember that different countries have different poverty lines. Thus, when applying the models and utilizing the data, it is vital to establish the poverty line. Moreover, other deprivation cut-offs can be applied. Localized multidimensional composite cut-offs, as developed by the authors, have five groups: Extremely poor (deprived of 13–15 basic needs); Very Poor/Not well-off enough standard of living (deprived of 10–12 basic needs); Poor/barely enough standard of living (deprived of 7–9 basic needs); Moderately Poor/A not well-to-do standard of living (deprived of 4–6 basic needs); Slightly poor/A well-to-do standard of living (deprived of 1–3 basic needs); and Not Poor or a Wealthy Life (not deprived of any basic needs) (Onsay & Rabajante, 2024b).

A multidimensional poverty index (MPI) can be computed using various approaches, such as via theoretical frameworks or modifications (Alkire & Foster, 2011; Foster et al., 1984; Sen, 2006; Onsay, 2022; Sobreviñas, 2017). This index encompasses three key dimensions at the household level: health, education, and standard of living. To identify individuals living in poverty, a dual cutoff method is employed, involving cutoff levels within each dimension and a cutoff based on the number of dimensions in which a person must be deprived to be considered multidimensionally poor. Assigning weights to indicators is a viable option (Alkire & Foster, 2011). In this approach, each dimension—health, education, and standard of living—is assigned an equal weight of 1/3. Individuals are classified as multidimensionally poor when their family experiences a weighted sum of 0.3 or more in terms of deprivation across the dimensions. It is worth noting that these cutoffs and the index itself can be adapted and modified when applied to other local contexts or marginalized groups, such as Indigenous populations. In this study, the deprivation indicators are confined to widely used metrics found in global and national Multidimensional Poverty Indices (MPIs). This decision stems from the similarities observed between the situations of Indigenous communities and the broader population in the Philippines. Despite their distinct cultures, Indigenous groups are integrated into the same societal framework, subjected to comparable policies, encountering similar economic hardships, and engaging in political processes akin to other households. Therefore, certain critical indicators unique to Indigenous communities, such as land area, ancestral domains, clothing design, and arts, have been omitted from the analysis. This exclusion is influenced by their shared land ownership, particularly evident in the Mount Isarog barangays and Natural Park. The primary focus of the analysis revolves around economic and social science aspects, deliberately sidelining cultural and artistic considerations due to their more abstract and subjective nature. This decision has been made to uphold the precision and integrity of future modeling and analytical endeavors. Furthermore, the datasets also included Indigenous people analytics, both descriptive and diagnostic, covering 12 tribes with measurements of magnitude and proportion. These datasets were curated, mined, cleaned, filtered, transformed, coded, analyzed, and processed by researchers within the extensive community-based monitoring system. The dataset contained numerous variables that were not pertinent to Indigenous policy-making. Thus, researchers utilized various software tools such as R, STATA, Python, SPSS, and MS Excel to efficiently generate the required data for economic development. Additionally, they employed descriptive, diagnostic, predictive, and prescriptive models to extract and analyze data, providing valuable insights for economic advancement.

The Philippines is home to hundreds of distinct Indigenous groups. However, it is crucial to note that the data presented in this article focuses specifically on the population and households of Agta Tabangnon residing in Mount Isarog, Bicol Region. The dataset comprises 66 columns and 1,279 rows (66 × 1,279), which have been coded and transformed into easily comprehensible cross-sectional data by referring to the data dictionary. Through the codes prepared by the researchers, data analytics and econometric modeling can be easily conducted. The dataset is hosted in the Harvard Dataverse Repository (https://dataverse.harvard.edu) under the reference www.doi.org/10.7910/DVN/QSZKUP, Harvard Dataverse, V2. The data included in this database were collected between 2018 and 2020 through the Community-Based Monitoring System, conducted once every three years. This system, under the ownership of the Local Government Unit of Goa, Camarines Sur, Philippines, is publicly accessible, particularly for academia, which has been instrumental in data analysis and policy formulation. Data collection and analysis in social sciences and economics are often resource-intensive and challenging endeavors. Public enumerators, supervised by the local government, are responsible for collecting this data. While the basic analysis and processing are overseen by the planning office, the more advanced analyses are entrusted to academia, specifically researchers, to extract valuable insights from the vast dataset. The CBMS serves as a valuable instrument for assessing local poverty levels, promoting transparency, accountability, and efficient resource allocation by providing essential data for research purposes. Aligned with the guidelines of Republic Act 11315 (2018), the CBMS acts as a blueprint for crafting impactful policies and programs that bolster community progress, alleviate poverty, and identify its underlying causes. While the survey is mandatory for all residents, the primary focus is not on Indigenous populations. However, researchers have demonstrated innovation, creativity, and resourcefulness in generating data that benefit Indigenous communities. Consequently, we selectively identified Indigenous individuals from 12 distinct tribes by filtering through extensive datasets. The evaluation encompasses 14,021 households comprising 63,749 members to ascertain the total count of Indigenous populations and their constituents. To facilitate comprehensive analysis, we established 12 distinct groups, each representing a unique tribe, forming the basis for our multi-tribal examination. The researchers functioned as data analysts and statisticians, extracting critical insights, generating predictive summaries, conducting advanced econometric analyses, and formulating strategies for economic advancement. This pioneering initiative marks the first comprehensive effort of its kind in the Philippines and within academia, championing the welfare of Indigenous communities through quantitative and empirical means. This groundbreaking work represents a significant advancement in the academic sector's commitment to supporting the welfare of Indigenous populations. Table 1, sourced from the dataset, illustrates the 12 tribes of the Agta Tabangnon, providing an in-depth breakdown of the population dynamics within these indigenous communities.

The datasets are valuable for conducting poverty analytics and can serve as a replicable model for researchers studying Indigenous communities in different regions globally. Through the utilization of these datasets, one can extract key metrics including the watt index, gap index, severity statistics, and poverty incidence. Table 2 illustrates the poverty analytics centered on Indigenous populations in Southern Luzon, Philippines.

Table 3 presents a summary of the multidimensional poverty deprivation profiles of 12 indigenous tribes. The metrics outlined above serve as tools to

TABLE 1 Population dynamics of Indigenous people tribes in Southern Luzon, Philippines (2018–2020)

12 Tribes	Household			Population		
	N Indigenous	N Total	% Indigenous	N Indigenous	N Total	% Indigenous
Abucayan	102	515	19.8	426	2,041	20.9
Balaynan	130	307	42.3	656	1,417	46.3
Cagaycay	16	510	3.1	67	2,324	2.9
Catagbacan	123	842	14.6	603	3,833	15.7
Digdigon	115	639	18.0	557	2,980	18.7
Hiwacloy	101	453	22.3	451	2,037	22.1
Payatan	295	436	67.7	1,503	2,189	68.7
Pinaglabanan	153	468	32.7	741	2,290	32.4
Salog	106	441	24.0	478	1,859	25.7
San Isidro West	114	581	19.6	564	2,405	23.5
San Pedro Aroro	287	320	89.7	1,308	1,414	92.5
Tabgon	118	429	27.5	668	2,252	29.7
TOTAL	1,660	5,941	27.9	8,022	27,041	29.7

SOURCE: CBMS 2018–2020; PROCESSED BY RESEARCHERS THROUGH PYTHON, JUPYTER NOTEBOOK, EXCEL, R, & STATA

TABLE 2 Poverty analytics focusing on Indigenous populations in Southern Luzon, Philippines, 2018–2020

Tribes	Watts index	Poverty severity index	Poverty gap index	Headcount ratio
Abucayan	0.27	0.07	0.22	99.02
Balaynan	0.27	0.07	0.22	83.55
Cagaycay	0.21	0.05	0.17	81.25
Catagbacan	0.23	0.06	0.19	78.05
Digdigon	0.25	0.06	0.21	86.09
Hiwacloy	0.19	0.06	0.18	81.19
Payatan	0.26	0.07	0.21	96.61
Pinaglabanan	0.22	0.07	0.21	96.73
Salog	0.18	0.05	0.15	67.89
San Isidro West	0.23	0.06	0.19	85.96
San Pedro Aroro	0.20	0.05	0.17	74.22
Tabgon	0.25	0.07	0.20	78.81
12 Tribes (Average)	0.23	0.08	0.19	86.02

gauge poverty across various dimensions. Given the multifaceted nature of poverty, it is imperative to employ multidimensional variables for its assessment (Onsay, 2022, Onsay & Rabajante, 2024b; Reyes et al., 2011; Sobreviñas, 2020). With access to this dataset, the ability to measure and forecast poverty for the advancement of economic development within Indigenous communities becomes both plausible and practical. These variables encompass livelihood and income, employment, housing and settlement, water and sanitation, basic education, health and nutrition, as well as peace and order.

4. Research Potential and Conclusion

Through utilizing comprehensive datasets encompassing all Indigenous households and populations in this work, we circumvent known limitations like sampling errors, thereby reinforcing both internal and external validity

TABLE 3 Multidimensional poverty profile of 12 Indigenous people (2018–2020)

Multidimensional poverty indicators		Totals	Affected households		Affected population	
			N	%	N	%
Health and Nutrition	Children under 5 years old who died	Total HH with children under 5 years old = 757, total population of children under 5 years old = 1,066	11	1.5	11	1.0
	Women who died due to pregnancy related causes		0	0.0	0	0.0
	Malnourished children 0–5 years old	Total HH with children aged 0–5 years old = 843, total population of children aged 0–5 years old = 1,297	104	12.3	109	8.4
Housing	Household living in makeshift housing		80	4.8	381	4.8
	Household that are informal settlers		183	11.0	904	11.3
Water and Sanitation	Household without access to safe water		374	22.5	1,863	23.2
	Household without access to sanitary toilet facility		448	27.0	2,068	25.8

TABLE 3 Multidimensional poverty profile of 12 Indigenous people (2018–2020) (*cont.*)

Multidimensional poverty indicators		Totals	Affected households		Affected population	
			N	%	N	%
Basic Education	Children aged 6–11 years old who are not attending elementary	Total HH with children aged 6–11 = 831, total population of children aged 6–11 years old = 1,430	278	33.5	562	39.3
	Children aged 12–15 years old who are not attending Junior High School	Total HH with children aged 12–15 years old = 606, total population of children aged 12–15 years old = 854	342	56.4	529	61.9
	Children aged 16–17 years old not attending Senior High School	Total HH with children aged 16–17 = 331, total population of children aged 16–17 = 352	271	81.9	288	81.8
Income and Livelihood	Household with income below poverty threshold		1,428	86.0	7,223	90.0
	Household with income below food threshold		1,230	74.1	6,301	78.6

TABLE 3 Multidimensional poverty profile of 12 Indigenous people (2018–2020) (*cont.*)

Multidimensional poverty indicators		**Totals**	**Affected households**		**Affected population**	
			N	**%**	**N**	**%**
	Household who experienced food shortage		17	1.0	102	1.3
	Unemployed members of the labor force	Total HH with members of the labor force = 1,423, total population of members of the labor force = 1,979	44	3.1	46	2.3
Peace and Order	Victims of crime		14	0.8	14	0.2

Note: The consolidated multidimensional poverty deprivation profile encompasses 12 Indigenous tribes, comprising a total of 1,660 households and a population of 8,022 individuals.

assumptions. The high-quality dataset, free of biases, provides a foundation for economic development strategies in developing nations and impoverished regions inhabited by Indigenous communities. Researchers can leverage this dataset to access raw baseline data and indicators of multidimensional poverty, enabling the calculation and simulation of various poverty metrics specific to Indigenous tribes. Utilizing advanced data analytics techniques, subsequent investigators can extract valuable insights into population dynamics, health, education, livelihood, and other critical aspects affecting Indigenous communities. Predictive and prescriptive analytics, along with econometric models, offer empirical evidence to support poverty theories and inform policy decisions. These datasets not only facilitate research endeavors but also enable policy mapping and targeting efforts aimed at addressing vulnerabilities and promoting economic advancement among Indigenous populations globally. The outcomes of policy targeting can guide resource allocation and the formulation of tailored strategies to combat poverty effectively. By adapting to local conditions and utilizing rigorous methodologies, policymakers can develop flexible plans that align with the evolving needs of Indigenous communities. Collaborations between government authorities, academic institutions, and commercial organizations can further enhance poverty reduction initiatives and economic development efforts. This integrated approach as hereby recommended by researchers, supported by comprehensive datasets and advanced analytics, serves as a catalyst for interdisciplinary research, policy development, and community engagement to uplift Indigenous populations and foster sustainable economic growth.

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Author Contributions

Emmanuel Onsay: conceptualization, data curation, methodology, investigation, software, visualization, validity tests, writing—original draft preparation; Jomar Rabajante: conceptualization, methodology, supervision, writing—reviewing and editing, project administration, funding acquisition.

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