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REVISTA INGENIO

Demographic Trends: Forecast of the Child Population From 0 to 3 years Old for the Year 2030

Tendencias Demográficas: Pronóstico de la Población Infantil de 0 a 3 años para el Año 2030

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Child poverty, child welfare, multiple regression, Fay-Herriot model, demographic projections

ABSTRACT
This paper estimates the number of children aged 0-3 living in poverty in Ecuador, using combined data from the 2014 Living Conditions Survey (LCS) and the 2010 Population and Housing Census (CPV), as the current data do not provide sufficient detail by region. To do so, we employ the Small Area Estimation (SAE) method, based on the Fay-Herriot model, which uses multiple linear regression to integrate survey and census data. This approach allows the analysis of specific sub-populations, such as cantons or districts, where surveys alone do not provide reliable results due to small samples. In addition, consumption-based poverty is simulated and the child population is projected up to 2030, comparing these projections with estimates from the Economic Commission for Latin America and the Caribbean (ECLAC) to verify their accuracy. The main purpose of this research is to provide accurate and detailed information on children in poverty, thus supporting the creation of effective public policies in Ecuador [1].

PALABRAS CLAVE
Pobreza infantil, bienestar infantil, regresión múltiple, modelo Fay-Herriot, proyecciones demográficas.

RESUMEN
Este trabajo calcula la cantidad de niños y niñas de 0 a 3 años en Ecuador que viven en condiciones de pobreza, utilizando información combinada de la Encuesta de Condiciones de Vida (ECV) 2014 y el Censo de Población y Vivienda (CPV) 2010, ya que los datos actuales no ofrecen suficiente detalle por regiones. Para ello, se emplea el método de Estimación para Áreas Pequeñas (SAE), basado en el modelo Fay-Herriot, que utiliza regresión lineal múltiple para integrar datos de encuestas y censos. Este enfoque permite analizar subpoblaciones específicas, como cantones o distritos, donde las encuestas por sí solas no brindan resultados confiables debido a muestras pequeñas. Además, se simula la pobreza basada en el consumo y se proyecta la población infantil hasta el año 2030, comparando estas proyecciones con estimaciones de la Comisión Económica para América Latina y el Caribe (CEPAL) para verificar su exactitud. El propósito principal de esta investigación es ofrecer información precisa y detallada sobre la infancia en pobreza, apoyando así la creación de políticas públicas efectivas en Ecuador.

1. Introduction

The absence of specific data on child poverty at the local level in Ecuador is a critical barrier to designing and implementing social policies that actually work. Without knowing how many children aged 0-3 face poverty in each canton or district, decision-makers are unable to distribute resources effectively or create programs that respond to the realities of the most neglected communities [1], [2]. This lack of detailed information not only hinders the fight against child poverty, but could also aggravate existing social and economic gaps in the country.

The lack of geographically disaggregated information for certain population groups, such as the child population, is a critical problem that directly affects decision-making in economic and social policies. In Ecuador, this limitation prevents the effective targeting of resources to areas of greatest need, which can exacerbate regional inequalities [2]. At the international level, similar

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countries such as Perú and Colombia face similar challenges, where the lack of disaggregated data has hindered the implementation of child poverty reduction programs [3]. This study is relevant because it offers an innovative methodological solution to overcome these limitations, allowing for better planning and resource allocation. The central research question is: How can the child population in Ecuador be estimated according to poverty levels using the Small Area Estimation methodology? This research is novel in combining survey and census data to generate accurate district-level estimates, which is crucial for the design of effective public policies in similar contexts [4].

The problem of the scarcity of disaggregated data is not unique to Ecuador. In several Latin American countries, this limitation has slowed progress in reducing poverty and inequality. For example, in Colombia, the lack of accurate information on rural areas has caused rural support programs to lose impact [5]. In México, the lack of detailed statistics at the municipal level has made it difficult for health policies to effectively reach indigenous communities [6]. These cases show how the absence of reliable data can hinder policy decisions in diverse contexts, highlighting the need for solutions such as the one this study proposes.

What makes this study special is its innovative approach in employing the Small Subpopulation Estimation (SAE) methodology, based on the Fay-Herriot model and multiple regression, to accurately estimate child poverty in specific regions of Ecuador. Unlike conventional methods, which typically rely on small sample surveys, this technique combines information from sources such as the 2014 Living Conditions Survey (LCS) and the 2010 Population and Housing Census (CPV), achieving robust results even in places where direct data are scarce [1]. This advance not only raises the quality of estimates, but also provides a practical tool for policy to reach where it is most needed.

The main objective of this work is to determine how many children aged 0-3 will be living in poverty in Ecuador by 2030, with a detailed breakdown by canton and district. The question guiding this research is: How many children aged 0-3 will be living in consumption poverty in 2030 in Ecuador, and how will this reality be distributed among the different regions of the country? Answering this question is key to guiding child development policies and ensuring that efforts are concentrated in the most critical areas.

The study of poverty and social injustice represents a complex challenge due to the interaction of multiple factors, elements and intrinsic variables that converge in the same objective. This problem has been the subject of much research and debate, which has proposed various concepts and realities that demonstrate that an individual cannot disassociate himself from a just environment that will keep him out of poverty and allow him to overcome the inequalities of his environment. The analysis of poverty encompasses various aspects. Some of these aspects are under the control of the individual, but most are influenced by social forces and economic and political power. The differences between theories and conceptualizations are based on how the problem of poverty and vulnerability is addressed. However, they all share the common goal of achieving a more equitable and just society to combat social inequality [7]. Approximately 700 million people live on less than $2.15 a day, which is considered the extreme poverty line. This situation remains prevalent in parts of sub-Saharan Africa, fragile and conflict-affected regions, and rural areas. After decades of progress, the rate of global poverty reduction began to slow in 2015, coinciding with moderate economic growth. The Sustainable Development Goal of eradicating extreme poverty by 2030 still seems unattainable.

The COVID-19 pandemic and a series of major shocks between 2020 and 2022 dealt a severe blow to efforts to reduce global poverty, setting back three years of progress. Low-income countries were hardest hit and have yet to recover. In 2022, a total of 712 million people were living in extreme poverty worldwide, an increase of 23 million compared to 2019. Poverty and inequality cannot be reduced without also addressing interrelated global challenges, such as slow economic growth, fragility and conflict, and climate change.

Climate change is hampering poverty reduction and poses a major threat to the future. The lives and livelihoods of the poor are most exposed to climate-related risks. Every year, millions of households fall into poverty or become trapped in poverty due to natural disasters. Higher temperatures are already causing declining productivity in Africa and Latin America, and will further reduce economic growth, especially in the poorest regions of the world. Eradicating poverty requires addressing its multiple dimensions. Countries cannot adequately address this problem without also improving people's well-being in a comprehensive manner, including more equitable access to health, education, and basic infrastructure and services, including digital services. Policymakers must intensify their efforts to grow their countries economies in ways that create high-quality jobs and employment and protect the most vulnerable. Employment is the surest way to reduce poverty and inequality. Its impact is further multiplied in communities and across generations by empowering women, girls and youth [8].

To further contextualize the relevance of our study, it is important to recognize that the small area estimation (SAE) methodology has been successfully applied in a variety of geographical and socio-economic contexts to address similar challenges related to measuring poverty and inequality at the local level [4]. For example, research in Latin American countries has used SAE to generate accurate poverty estimates in rural and marginalized areas where census data are limited or outdated [9]. These studies have shown that the SAE can be a valuable tool for evidence-based decision-making and targeting of public policies aimed at the most vulnerable population. By delving deeper into this previous research, we can better understand the strengths and limitations of the SAE and adapt its application to the specific case of Ecuador, in order to obtain more accurate and relevant results.

The Small Area Estimation (SAE) method is a powerful tool that has been successfully used in different countries to measure poverty and inequality at the local level. For example, in Latin America, recent studies have applied this approach to obtain accurate poverty data in rural and marginalized areas where census information is scarce or old [10]. Similarly, in the European Union, SAE is used to produce detailed regional statistics on income and living conditions, helping governments to target their policies more effectively [11]. In Canada, this method has been used to estimate the incidence of chronic diseases in indigenous communities, improving the allocation of resources for health programs [12]. These cases demonstrate how SAE can be adapted to different contexts, providing a solid basis for our analysis in Ecuador [1].

The identification of individuals in situations of vulnerability and poverty is the first essential step for the implementation, execution and monitoring of inclusion programs. This is fundamental to advance in the creation of opportunities that facilitate equality and social cohesion, also considering the gender approach as a cross-cutting element in any social policy [13]. Data from the VII population and VI housing census, conducted in 2010, are a key source for obtaining population information down to the lowest level of territorial disaggregation, i.e. at the district level. The variables that measure poverty through Unsatisfied Basic Needs (UBN) and consumption allow us to get closer to the social reality of individuals. However, the use of the UBN poverty indicator has certain limitations. Firstly, this type of poverty is based on a multidimensional logic that emphasizes services such as drinking water and sanitation, as well as housing conditions. Given the current national coverage of these services, which is low by international standards, lack of access may affect households that are not necessarily in vulnerable conditions. This can lead to an overestimation of the population in need of care [14].

According to the 2010 Population and Housing Census, the incidence of poverty measured by UBN was 60.1%, which represents the percentage of people in households that do not satisfy one or more basic needs. In contrast, poverty measured by consumption was 25.8% in 2014, indicating a percentage of people whose per capita consumption is below the poverty line. This suggests that regardless of the method used to estimate poverty, the Living Conditions Survey provides a more accurate estimate. According to [15], poverty measured through consumption is more aligned with the notion of vulnerability, as it depends mainly on the labor market and available resources [13]. The dependence of consumption poverty on factors such as labor demand and available resources implies that any macroeconomic shock can affect overall consumption levels among inhabitants, which has a significant impact on those in extreme poverty. Unlike poverty measured by UBN, the latter is more related to structural issues linked to the country's infrastructure and basic services. In the specific case of Ecuador, the components related to sanitation and overcrowding have the greatest influence on the indicator [14].

The current government is implementing a programmed to improve access to drinking water and sanitation, complementing housing initiatives. When a household has these basic services, it is automatically no longer considered poor; furthermore, the chances of falling back into this condition are minimal because UBN poverty is closely related to structural aspects [13]. This situation limits the design of projects aimed at creating conditions that foster both economic and social inclusion, which is crucial for achieving greater equity among members of society. Therefore, it is necessary to measure poverty from a perspective more focused on socio-economic components such as consumption poverty [14].

However, the initial sources to obtain these indicators present a maximum territorial disaggregation at the provincial and regional levels, which hinders effective planning at the cantonal and district levels. In this context, it is proposed to implement methodologies such as Small Area Estimation (SAE), which allows estimating population parameters based on census data applied to population subsets obtained through surveys [13]. SAE facilitates obtaining parameters measured in surveys and translating them to census data with high population disaggregation. This makes it possible to identify populations in small areas using variables not available in the 2010 Census but present in surveys such as the 2014 Living Conditions Survey [14].

This methodological proposal makes it possible to put into practice the fundamental concepts of the estimation of small areas, which responds to an estimation of population parameters. Consequently, we know that at present our country in particular, does not have geographically disaggregated information of the entire population in general, and specifically of a certain population group, which is used for planning and decision making for economic and social policy, as indicated by [4]. The identification of people in vulnerability and poverty is the first step for the implementation, execution and monitoring of inclusion programs, with the aim of making progress in the generation of opportunities that allow equality and social cohesion to be achieved, in addition to the intrinsic consideration of gender and ethnicity as a cross-cutting core of any social policy, as mentioned by [16].

The data from the VII population census and VI housing census of 2010, as a source from which population data is obtained up to the lowest territorial disaggregation level, i.e. district. According to [17], the variables poverty by Unsatisfied Basic Needs and poverty by consumption allow an approximation to be made of the social reality of individuals. The Small Area Estimation (SAE) methodology is a mathematical and statistical method that models information from one or more data sources to produce estimates of a variable of interest, for example poverty at the local level, as indicated by [18]. SAE is most useful when domain (sub-population) sample sizes are too small to provide adequate precision for estimators. Consequently, the methodology (SAE) will allow estimating at a disaggregated level the population of children aged 0-3 years from 2014 to 2030, based on the Living Conditions Survey of 2014 and the VII Population Census and VI Housing Census of 2010.

To fully understand the applicability and relevance of Small Area Estimation (SAE) in our context, it is essential to recognize its use and evolution in other countries and regions. Globally, SAE has been successfully implemented in a number of nations to address similar challenges related to measuring poverty and inequality at the local level. For example, in the European Union, the EAS is used to generate detailed regional statistics on income and living conditions, enabling member states to design more effective and targeted policies [19]. In Latin America, countries such as Brazil and México have used SAE to improve the accuracy of poverty estimates in rural and marginalized areas, where census data are limited or outdated [20].

The adoption of SAE is not only limited to poverty measurement, but also extends to other areas such as public health, education and agricultural development. In Canadá, for example, SAE is used to estimate the prevalence of chronic diseases in indigenous communities, facilitating the allocation of resources and the implementation of prevention programs [12]. In the African context, SAE has proven valuable for monitoring sustainable development indicators at the local level, allowing governments and non-governmental organizations to assess the impact of their interventions and adjust their strategies accordingly [21].

These examples illustrate the versatility and potential of SAE as a tool for evidence-based decision-making at the local level. By adapting and applying SAE in our specific context, we can benefit from lessons learned and best practices identified in other countries and regions, while addressing our own unique needs and challenges. The originality of our research lies in the combination of census data and household surveys to estimate child poverty at the small area level, which will allow us to generate valuable information for planning and policy design for the most vulnerable population.

Poverty and social inequality are complex issues that involve a variety of factors and require comprehensive approaches to their analysis. This study seeks to estimate how many children aged 0-3 live in poverty in Ecuador, using the Small Area Estimation (SAE) method to integrate data from the 2014 Living Conditions Survey (LCS) and the 2010 Population and Housing Census (CPV). This is intended to generate detailed estimates at the canton and district levels, providing valuable information for designing public policies that address the country's most vulnerable groups [8].

In order to enrich the theoretical and methodological framework of this study, a comprehensive review of recent scientific literature on the application of Small Area Estimation (SAE) in similar contexts has been conducted. This review has identified relevant studies that address specific methodological challenges, such as the selection of appropriate regression models, the validation of assumptions and the assessment of the sensitivity of estimates to different scenarios [22]. Research exploring the use of machine learning and big data techniques to improve the precision of small area estimates and overcome the limitations of traditional methods has also been included [23]. The incorporation of these recent studies helps to strengthen the evidence base of our research and place it in the context of more current debates on the measurement and analysis of child poverty.

Recent studies support the value of the SAE methodology in similar situations. For example, an analysis by [8], applied this technique to measure poverty in rural areas of Latin America, confirming its accuracy when compared to census data. At the national level, the National Institute of Statistics and Census of Ecuador [23] has started to use SAE to refine its official statistics, showing promising results. These experiences, both local and global, reinforce the strength and importance of the approach this study adopts.

This research has been based on an extensive review of the scientific literature, both in the field of Small Area Estimation (SAE) methodology and in the analysis of child poverty and demographic projections. Throughout the study, references are presented to support both the methodology and the data used in this study.

For studies that have used SAE in other geographical contexts, we recommend consulting the work of [24] in the field of public health, as well as the studies of [25] in the context of agriculture. These works provide concrete examples of how SEM can be applied in different areas and with different data sources.

In terms of updated data sources, the most recent World Bank and ECLAC reports on poverty and inequality in Latin America have been reviewed, as well as the most recent population and housing censuses of the countries in the region. These reports provide updated data on the socio-economic situation of the population and can be used to validate and complement the results of this study.

Finally, for recent studies on population projections and poverty, we have consulted the work of [26] on demographic trends at the global level, as well as the studies of [27] on poverty and inequality in the world. These works provide a global perspective on demographic trends and poverty, which can help contextualize the results of this study.

2. Methodology

2.1 SMALL AREA ESTIMATION

Small Area Estimation (SAE) techniques are a set of statistical methods for estimating parameters for small subpopulations. These techniques are especially useful when the subpopulation of interest is contained within a larger study. In this context, the term "small area" generally refers to a small geographical boundary, such as a province, canton, parish or district. It may also encompass a "small domain", which refers to a specific demographic group within a larger region [28].

When a survey is conducted at the national or state level, the sample size in small areas may be insufficient to generate accurate estimates. To address this challenge, additional data, such as census records, can be used, which are available for these small areas and help to obtain more reliable estimates [29]. The SAE methodology allows information to be obtained at levels of territorial disaggregation that cannot be achieved by standard methods. This is valuable as it provides reliable estimates on one or several relevant variables in areas where existing information is insufficient to provide valid estimates [30]. All SAE methods rely on auxiliary data available for sub-populations. However, in many cases, the information may be limited and only allow estimates to be made for larger geographic areas or certain population subgroups [31].

Since not all poverty-related variables are collected in a census that covers the entire population, it is essential to resort to tools that provide more detailed information on specific localities, such as surveys or administrative records [32]. The availability of accurate data on living conditions is essential for targeting policies and programs to reduce poverty. Having adequate poverty estimates is crucial for managing programs and allocating resources to local jurisdictions [28]. Identifying vulnerable and poor populations is essential for the design and implementation of programs that promote economic and social inclusion. This aims to generate opportunities that facilitate equality and social cohesion [30]. The SAE methodology is based on modelling information from various sources to produce estimates on variables of interest at the local level. It is particularly useful when sample sizes in the domains are too small to provide acceptable precision in the estimators [29].

According to [4], the Small Area Estimation (SAE) methodology is a valuable technique for obtaining reliable estimates for small areas, which are subpopulations with little or no sample information. This methodology uses mixed models, which combine information from the sample and from auxiliary sources, such as censuses or administrative records. This makes it possible to obtain more accurate and efficient estimators than direct estimators. In addition, the SAE methodology offers several methods to calculate the mean square error and confidence intervals, which are fundamental to measure the uncertainty of small area estimators. In recent years, the SAE methodology has incorporated advanced techniques, such as machine learning, to improve the performance and flexibility of small area estimators. These techniques allow adapting to changing conditions, and provide more accurate estimates for small areas. However, it is important to remember that these are only estimates and may be subject to errors and variations due to the uncertainty inherent in any estimation process.

The SAE methodology has a number of advantages over traditional estimation methods. Firstly, SAE allows more precise estimates to be obtained in small areas. Secondly, SAE allows information from different sources to be incorporated, which can improve the precision of the estimates. Third, SAE is a flexible technique that can be adapted to different types of data. All small area estimation (SAE) methods rely on auxiliary data available at the sub-population level, such as administrative records, specific surveys or data from the latest census. This information is essential to construct predictor variables that are integrated into a statistical model, which is then used to predict the values of the variable of interest in various small areas [29].

In order to generate estimates using SAE, it is essential to take into account several factors. It is necessary to assess whether there is a demand for such statistics, whether there is the commitment and willingness of an entity to provide methodological support and expert staff, whether the available information is sufficient, and whether the auxiliary data and variables of interest are correlated [32].

The relevance of these aspects lies in the fact that, over time, policy makers have increasingly started to use quantitative and qualitative information to design, implement and monitor projects and programs of public interest. National or regional information is no longer sufficient, especially in a context where decentralized public management is sought. There is a growing demand for data that provide more detailed and specific territorial disaggregation; for example, it is not uncommon to request information on specific population groups within certain parishes or districts [33]. Currently, various sources of information are used to adequately define target populations in order to direct concrete actions for the benefit of these communities. More detailed data therefore facilitates decision-making and is essential for the design of targeted public policies and realistic financial planning [34].

The main source of information used remains the census, as it provides a wide range of household data and covers the entire population, allowing for well-disaggregated information. However, since the census is conducted every ten years, many variables may lose relevance over time [31]. On the other hand, there are surveys that collect specific information more frequently; however, these only allow estimates to be made for large geographic areas or larger population groups.

Mechanisms need to be sought to generate more specific and disaggregated statistics. One option would be to modify the design of surveys to meet information needs or to increase the sample size of existing surveys, although this may involve high costs. Another alternative would be to collect information in smaller localities; however, this would require each local government to finance the process, which is not always feasible [10]. In this context, estimation techniques such as SAE are gaining popularity by providing statistical information at smaller territorial levels. SAE produces estimates on variables of interest using census data and other sources that provide more detailed information on specific localities [29].

The effectiveness of SAE methods depends to a large extent on the availability of suitable predictor variables that are measured uniformly across the population. It is crucial to analyses each variable used in the estimation and select the most appropriate predictive model. In addition, the effective use of SAE methods requires a thorough assessment of model quality. Finally, when estimating in smaller domains, it is important to validate their accuracy. Fortunately, there have been significant advances in the development of SAE models that minimize the mean square error and provide more accurate estimates [29].

To ensure the transparency and reproducibility of our study, it is important to provide additional details on the statistical models used and the data sources selected. In particular, the model for estimating consumption poverty is based on multiple linear regression [35]. The selection of the independent variables was made based on previous scientific literature and the availability of data in the selected sources, such as the 2010 Population and Housing Census and the 2014 Living Conditions Survey [14]. These data were carefully processed and validated to ensure their quality and reliability.

The Small Area Estimation (SAE) methodology was chosen because of its ability to overcome the limitations of traditional estimation methods, which often require large samples to generate accurate estimates [4]. In contrast, SAE allows combining survey data with census information to obtain reliable estimates at the local level, even in areas with small samples [35]. This methodology is particularly useful when seeking to analyze variables such as consumption poverty, which are not available in censuses but are available in surveys such as the Living Conditions Survey (LCS 2014) [14].

Econometric models, specifically multiple linear regression and generalized linear regression (GLS), were selected to integrate data from the 2014 LCS and the 2010 Census of Population and Housing (CPV). These models allow for predicting variables such as per capita consumption in small areas by relating them to demographic and socioeconomic factors [9]. The choice of these techniques is justified by their ability to handle multiple variables and correct for possible correlations between them, which is essential for obtaining accurate estimates of child poverty [36].

The sample used was based on a probability sampling design, ensuring representativeness of the population studied. Small areas were selected based on geographic relevance and data availability, allowing for adequate coverage of the most vulnerable regions [84]. For data analysis, Stata software was used, which offers advanced tools for implementing complex statistical models [37].

Independent variables were selected based on their relevance in explaining consumption poverty. Demographic variables such as age and gender were included, as well as socio-economic variables such as household income and parental education level [38]. Dummy variables, such as membership in a specific ethnic group, were included to capture significant differences in poverty among different population groups [39].

2.2 METHODOLOGICAL ASPECTS OF SAE

Domains can be defined on the basis of characteristics that segment the population into a set of sub-populations that are mutually exclusive. Generally, these domains are established according to geographical areas, such as states, provinces, municipalities, regions, districts or metropolitan areas, as well as by socio-demographic groups, which may include categories such as age, gender or ethnicity within a broader region [40]. Small area estimation (SAE) is classified into two types of estimators: direct and indirect. A direct estimator is based exclusively on sample information from a specific domain. This type of estimator can incorporate known auxiliary information, such as the values of an auxiliary variable X, X that is related to the variable of interest Y, Y. However, a disadvantage of direct estimators is that they can have large standard errors, especially if the sample size in the domain is small or non-existent [19], [41].

On the other hand, an indirect estimator uses values of the variable of interest Y, Y from a related domain or from a specific time period. This approach increases the "effective" sample size and reduces the standard error. The information used for these estimators is obtained from recent censuses or current administrative records. There are three main types of indirect estimators: the indirect domain estimator, which uses values from another domain; the indirect time estimator, which uses values from another period; and the estimator that combines both aspects, using values from another domain and another period simultaneously [28].

2.3 GENERAL MATHEMATICAL MODEL FOR INDIRECT ESTIMATION AT THE AREA LEVEL

In Small Area Estimation (SAE) [42], an area-level model is used when the data from a survey, such as the Living Conditions Survey (LCS 2014), is available for specific areas but lacks sufficient sample size to make reliable estimates at a smaller geographic level (e.g., cantons, districts). The area-level model combines these direct survey estimates with auxiliary information available for the entire population from sources like the Census of Population and Housing (CPV 2010).

In [42], indicates the general mathematical model for area-level SAE is based on the Fay-Herriot model, which assumes the following structure:

$$\widehat{Y_i} = X_i^T\beta + u_i + e_i \qquad i=1,\dots,m \qquad (1)$$

Where:

$\widehat{Y_i}$ is the direct estimate of the parameter of interest (e.g., poverty rate or consumption poverty) for area obtained from the survey (LCS 2014).

X_i^T is a vector of auxiliary variables for area (e.g., socio-economic variables from CPV 2010).

β is a vector of unknown regression coefficients that relate the auxiliary variables to the area-level estimates.

u_i is the random area effect, capturing the variation specific to area that is not explained by the auxiliary variables. It follows a normal distribution $u_i \sim N(0,\sigma_u^2)$.

e_i is the sampling error associated with the direct estimate $\widehat{Y_i}$, assumed to follow a normal distribution $e_i \sim N(0,\sigma_{e_i}^2)$.

2.3.1 Steps in the Model

1. Model specification: The Fay-Herriot model combines direct estimates from a survey with auxiliary data, assuming a linear relationship between the two.
2. Error structure:

e_i: The survey sampling error, which depends on the sample size in each area.

u_i: The area-level random effect, which accounts for unexplained variability between areas.

The goal is to estimate the population parameter for each area using both the survey data and the auxiliary data. The empirical best linear unbiased predictor (EBLUP) is often used for this purpose.

2.4. ESTIMATION PROCESS FOR THE FAY-HERRIOT MODEL

Step 1: Linear model setup

The model assumes that for each area i, the estimate $\widehat{Y_i}$ from the survey can be modeled as (1). The vector X_i contains the auxiliary variables (e.g., census data from CPV 2010), and the regression coefficients β describe the relationship between these variables and the survey estimate $\widehat{Y_i}$.

Step 2: Estimation of β using Generalized Least Squares (GLS)

The regression coefficients β are estimated using Generalized Least Squares (GLS), accounting for the heteroscedastic errors e_i across areas:

$$\widehat{\beta} = \left(\sum_{i=1}^{m} X_i^T V_i^{-1} X_i\right)^{-1}\left(\sum_{i=1}^{m} X_i^T V_i^{-1}\widehat{Y_i}\right) \qquad (2)$$

Where is the variance-covariance matrix for area , defined as:

$$V_i = \sigma_u^2 + \sigma_{e_i}^2 \qquad (3)$$

The term σ_u^2 is the variance of the area-specific effect u_i, and $\sigma_{e_i}^2$ is the sampling error variance of the direct survey estimate $\widehat{Y_i}$.

Step 3: Empirical Best Linear Unbiased Prediction (EBLUP)

Once the regression coefficients are estimated, the EBLUP for the parameter of interest (e.g., poverty rate) in area is given by:

$$Y_i^{\widehat{EBLUP}} = X_i^T\widehat{\beta} + \widehat{u}_i \qquad (4)$$

Where:

$$u_i = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_{e_i}^2}\left(\widehat{Y}_i - X_i^T\widehat{\beta}\right) \qquad (5)$$

This formula adjusts the direct estimate by incorporating the auxiliary data from , effectively combining the direct survey data with census information to produce a more reliable estimate at the area level.

2.4.1 Particular Model for LCS 2014 and CPV 2010

In your case, you have two data sources: Living Conditions Survey (LCS 2014): This provides direct estimates of consumption poverty but lacks sufficient sample size to give reliable estimates for smaller geographic areas (e.g., cantons or districts).

Census of Population and Housing (CPV 2010): This provides detailed auxiliary information at a highly disaggregated geographic level but does not contain direct measures of consumption poverty.

Given this, the indirect method should be applied at the area level because: LCS 2014 provides area-level estimates of poverty for larger areas (e.g., provinces), but these estimates are subject to high variability due to small sample sizes in some areas. CPV 2010 provides auxiliary data at smaller geographic levels (e.g., cantons or districts), which can be used to improve the estimates from LCS 2014. The particular model for your case would look like this (1). Where:

$\widehat{Y}_i$ is the direct estimate of consumption poverty for area from LCS 2014.

X_i^T is the vector of auxiliary variables (e.g., income levels, housing characteristics) from CPV 2010.

β is the vector of regression coefficients to be estimated.

u_i is the random area effect specific to area .

e_i is the sampling error from the LCS 2014 estimate.

2.4.2 Model interpretation: Auxiliary data from CPV 2010 helps predict the consumption poverty rate for smaller areas. Random effects () account for area-specific deviations not explained by the census data. The EBLUP estimator combines direct survey estimates from LCS 2014 with predictions based on census data from CPV 2010 to produce more accurate small-area estimates.

Decision: For your case, you should work at the area level because the data from LCS 2014 provides estimates for areas, while CPV 2010 provides auxiliary variables at a more detailed geographic level. By applying the Fay-Herriot model, you can improve the reliability of the consumption poverty estimates for small areas by combining the survey and census data.

2.5 LOGARITHMIC FAY-HERRIOT MODEL FOR INDIRECT ESTIMATION

In [42], it is indicated that, in order to include the logarithmic consumption poverty model in the indirect small area estimation (SAE) model, the formulation is slightly changed. The (ln) transformation helps deal with skewed distributions of the dependent variable (poverty by consumption), making the model more robust and suitable for handling extreme values. In this case, we model the logarithm of the poverty by consumption variable from the Living Conditions Survey (LCS 2014). The indirect model at the area level is now written as follows:

$$ln(\widehat{Y}_i) = X_i^T\beta + u_i + e_i \qquad i=1,\ldots,m \qquad (6)$$

$ln(\widehat{Y}_i)$ is the log-transformed direct estimate of consumption poverty for area from LCS 2014.

X_i^T is the vector of auxiliary variables (e.g., socio-economic indicators, housing conditions) from the Census of Population and Housing (CPV 2010).

β is the vector of regression coefficients to be estimated.

u_i is the random area effect, which accounts for unexplained variation specific to area . It follows a normal distribution $u_i \sim N(0,\sigma_u^2)$.

e_i is the sampling error associated with the direct estimate , assumed to follow a normal distribution $e_i \sim N(0,\sigma_{e_i}^2)$.

2.5.1 Estimation Steps with Logarithmic Model

Step 1: Linear Model in Log Space

The direct estimates from LCS 2014 are transformed by taking the logarithm of the poverty by consumption estimates (6). This model allows the log-transformed direct estimate to depend linearly on the auxiliary data from CPV 2010, with adjustments for random effects and sampling error.

Step 2: Estimation of using GLS (Generalized Least Squares)

As in the standard Fay-Herriot model, the regression coefficients are estimated using Generalized Least Squares (GLS). However, now we are working with the log-transformed estimates:

$$\widehat{\beta} = \left(\sum_{i=1}^{m} X_i^T V_i^{-1} X_i\right)^{-1} \left(\sum_{i=1}^{m} X_i^T V_i^{-1} ln(\widehat{Y}_i)\right) \qquad (7)$$

Where V_i is the variance-covariance matrix for area *i*, defined as:

$$V_i = \sigma_u^2 + \sigma_{e_i}^2 \qquad (8)$$

This accounts for both the variability between areas (through u_i) and the sampling error (through e_i).

Step 3: Empirical Best Linear Unbiased Prediction (EBLUP) in Log Space

The EBLUP for the log-transformed poverty by consumption in area is given by:

$$ln\left(\widehat{Y_i^{EBLUP}} = X_i^T\widehat{\beta} + \widehat{u}_i\right) \qquad (9)$$

Where:

$$\hat{u}_i = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_{e_i}^2}\left(ln\ (\hat{Y}_i) - X_i^T\hat{\beta}\right) \qquad (10)$$

This predictor combines the direct estimate of log-transformed poverty by consumption $ln\ (\hat{Y}_i)$ with predictions based on auxiliary data from CPV 2010, adjusted for area-specific random effects.

Step 4: Back-Transformation to Original Scale

To obtain the estimate of poverty by consumption on the original scale (non-logarithmic), the EBLUP estimates are back-transformed:

$$Y_i^{\widehat{EBLUP}} = exp\ \left(X_i^T\hat{\beta} + \hat{u}_i\right) \qquad (11)$$

This back-transformation gives the final estimate of poverty by consumption for area .

Particular Model for Log-transformed Consumption Poverty in Ecuador

For your case with LCS 2014 and CPV 2010, the logarithmic Fay-Herriot model applied to poverty by consumption would look like this:

$$ln\ (\hat{Y}_i) = X_i^T\beta + u_i + e_i \qquad i=1,\dots,m$$

$ln\ (\hat{Y}_i)$ is the log-transformed estimate of consumption poverty for area from LCS 2014.

X_i^T represents a set of auxiliary variables from CPV 2010, such as income, education, employment, housing conditions, and other socio-economic factors.

β is the vector of coefficients to be estimated.

u_i captures random area effects for area i, reflecting variations not explained by the auxiliary data.

e_i is the sampling error of the direct estimate from LCS 2014.

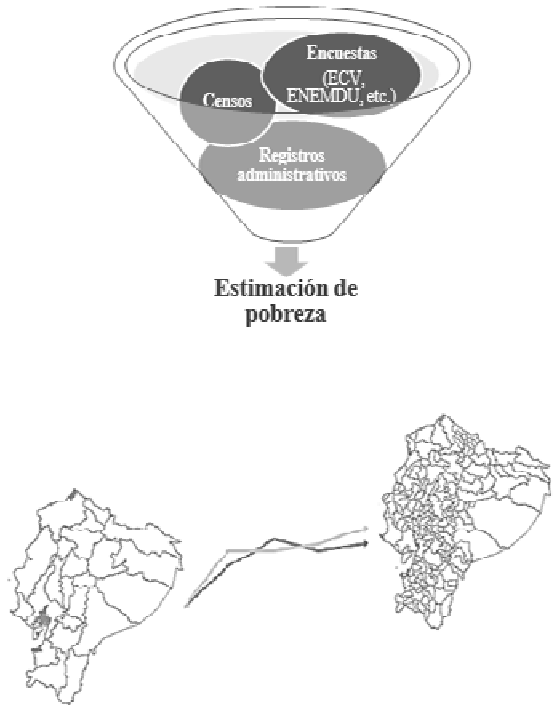
By taking the logarithm of the poverty by consumption variable, you ensure the model handles skewness and extreme values more effectively. The auxiliary data from CPV 2010 allows the model to make reliable predictions at smaller geographic levels (cantons, districts) where LCS 2014 alone would be unreliable due to small sample sizes. The back-transformation ensures that the final estimate is returned to the original scale of poverty by consumption after fitting the model.

This model improves the estimates of consumption poverty at smaller geographic areas by leveraging the detailed auxiliary information available from the census (CPV 2010), while correcting for small sample sizes in the survey (LCS 2014) through the log transformation and random effects adjustments.

2.6 APPLYING THE SAE METHODOLOGY IN ECUADOR

In the study by [43], he used the advanced statistical technique known as Small Area Estimation (SAE), summarized in Figure 1, to analyze consumption and poverty in specific areas of Ecuador. This technique is especially useful when trying to make precise estimates in small geographic areas where sample sizes are too small to provide reliable estimates.

Figure 1.
SAE scheme



For the application of the SAE in [43], we used the Indirect method called Multiple Regression Estimator at the geographic area level of the natural logarithm of poverty by consumption, whose mathematical formulation is described in the previous section. In this initial process we used the Guide for the use of databases of the National Institute of Statistics and Census [44], this involved several important steps to analyses and effectively use data from two main sources: the Living Conditions Survey (LCS) 2013 - 2014, and the VII Population Census and VI Housing Census (CPV) 2010.

Step 1: Data collection was conducted using the Living Conditions Survey (LCS) for the years 2013-2014. This survey provided a wide range of information on the living conditions of the inhabitants of Ecuador, covering aspects such as income, expenditure, education and health, among others. In parallel, data from the VII

Population Census and VI Housing Census (CPV) conducted in 2010 were used. In addition, dummy variables were generated for each category. Dummy variables are binary variables that represent categories or groups in a statistical analysis. For example, a dummy variable could be used to code gender, assigning a value of 1 for "male" and 0 for "female". These variables allow categorical information to be included in the analysis, which generally only accepts numerical data [45].

Dummy variables are fundamental in statistical analysis, as they allow the inclusion of qualitative variables in models that require numerical data. These variables take binary values (0 or 1) and are used to represent specific attributes or categories within the data set. For example, when analyzing the impact of gender in a regression model, a dummy variable can be created to indicate whether an individual is female (1) or not (0), in [22]. This makes it easier to interpret how categorical differences affect the dependent variable in the model [46]. In summary, the creation of dummy variables is a crucial step in statistical analysis that allows for the integration of qualitative information into quantitative models. This approach not only improves the analytical power of the model, but also allows for more precise conclusions about how different categories influence the variables of interest [47].

Step 2: The homogenization of the databases was carried out in this process. In [24], he explains that reconciliation involves aligning or correlating data from different sources so that they are comparable with each other. In this case, the aim was to identify common variables between the Living Conditions Survey (LCS) and the Population and Housing Census (CPV). This means that variables that were present in both databases were selected for further analysis.

Standardization is an essential step in data analysis, as it ensures that information extracted from different sources is consistent and comparable. By identifying common variables between the LCS and the LCP, joint analysis of the data is facilitated, leading to more robust and informed conclusions about living conditions in Ecuador. Once homogenization is complete, aggregation at the household level follows, followed by a critique of the data. This step is crucial in any analysis, as it involves checking the data for errors, inconsistencies or outliers that may distort the results. In this case, outliers were removed and the database was cleaned, preparing it for the next phase of the process [48]. Table 1 presents the homologous variables obtained. In addition, in [43], the code necessary to carry out the homologation and aggregation of variables at the household level can be found.

Step 3: After standardizing and cleaning the two databases at the household level, the dependent and independent variables were identified. Dependent variables are those variables that we seek to predict or explain, while independent variables are used to make that prediction or explanation. In this analysis, the dependent variable was consumption poverty, while the independent variables were demographic and socio-economic in nature. It should be noted that only variables included in both databases were considered, as presented in Table 1 [24]. Simultaneously, econometric models were developed with data from both sources to predict per capita consumption. Econometric models are fundamental statistical tools in economics that allow for the examination of relationships between different variables. In this case, the variables selected for the models were similar to those used in the VII Population and VI Housing Census (2010), which ensured consistency in the analysis across data sources [49].

Once the models were developed, they were applied to census data, allowing for predictions of per capita consumption in specific geographic areas. These predictions were then used to calculate the consumption poverty rate in the districts of interest. In this case, poverty was determined by considering as poor those individuals whose per capita consumption was below a pre-established threshold [43] study provided a clear picture of consumption poverty in specific areas of Ecuador. By employing the Small Area Estimation (SAE) technique, accurate estimates were achieved even in areas with small sample sizes, highlighting the importance of advanced statistical techniques in economic and social studies [48].

In summary, the process allowed us to extract valuable information from the Living Conditions Survey (LCS) and the Population and Housing Census (CPV), facilitating a better understanding of consumption poverty at the household level in Ecuador. Subsequently, econometric models were estimated using Ordinary Least Squares (OLS) and Generalized Least Squares (GLS), following the SAE methodology. In addition, heteroskedasticity issues were analyzed using non-constant variance models, as recommended in the literature [40]. Finally, these parameters were applied to the census data, allowing us to predict consumption and construct the consumption poverty rate in small areas, robust to the level of the 365 Ecuadorian districts [49].

Step 4: Coding and application of the SAE methodology was carried out. This process began with the use of the Living Conditions Survey (LCS) standardized at household level. From this database, an explanatory model was created for each province, modelling the natural logarithm of per capita consumption. This approach is common in econometric analysis, as it allows transforming the data to make it more manageable and reduce the influence of extreme values on the results [49]. Subsequently, we integrated the analysis of heteroskedasticity, a common feature in economic data, which refers to the non-constant variation of errors in a regression model. This step was essential to fit the models appropriately, as heteroscedastic errors can influence the precision of

Table 1.

Indicators and/or standardized variables included in the methodology

Nº	Variable Name	Description	Azuay	Bolívar	Cañar	Carchi	Cotopaxi	Chimborazo	El Oro	Esmeraldas	Guayas	Imbabura	Loja	Los Ríos	Manabí	Morona Santiago	Napo	Pastaza	Pichincha	Tungurahua	Zamora Chinchipe	Galápagos	Sucumbíos	Orellana	Santo Domingo de los Tsáchilas	Santa Elena
1	C	Constant -	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	Analfabeto	Head of household is illiterate	1	1	0	1	1	1	0	1	1	1	1	0	0	0	1	1	0	1	1	0	1	0	0	0
3	analfabeto_cl	Percentage of heads of household who cannot read and write at cluster level	1	0	1	1	1	0	1	1	1	0	0	1	0	1	1	0	0	1	1	0	1	1	0	0
4	cocina_ex	The household has a kitchen exclusively for the use of the household.	1	0	0	0	0	0	1	1	1	0	0	1	0	0	0	0	1	0	0	0	0	0	1	0
5	cocina_ex_cl	Percentage of households that have a kitchen exclusively for household use at cluster level	0	0	1	1	0	1	1	0	0	0	0	0	1	1	1	0	1	0	1	0	1	1	0	1
6	edad_p	Average household age	1	1	1	0	0	1	1	0	1	1	0	0	1	0	1	0	1	1	1	0	1	0	0	0
7	edad_p_cl	Average household age at cluster level	1	1	1	0	1	1	0	1	1	0	0	1	1	0	1	1	0	1	0	0	1	1	1	1
8	edad2	Age squared of the household	0	1	0	0	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0
9	edad2 cl	Age squared average household age at cluster level	1	0	1	0	0	1	1	0	0	0	1	1	1	1	1	0	0	1	1	1	0	1	0	0
10	edad2_p	Average age of the household squared	1	0	1	1	1	1	1	1	1	1	0	0	1	0	1	0	1	1	1	0	1	1	1	1
11	edad2_p_cl	Mean squared household age at cluster level	1	1	1	0	1	1	0	0	1	0	1	1	0	1	1	0	1	1	1	1	1	1	1	0
12	h01	Number of bedrooms in the dwelling	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	0	1	0	1	1	1
13	h01_cl	Average number of bedrooms in the dwelling at the cluster level	1	1	1	1	0	1	1	0	1	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1
14	h04_2	The shower is shared with other households	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	1	0	0	0	0	0	0
15	h04_3	No shower	1	1	1	1	1	0	1	1	1	0	1	0	1	0	0	1	1	1	1	0	0	0	1	0
16	h15_3	You own the house and you are paying for it	0	0	0	0	1	0	1	1	1	0	0	0	1	0	1	0	1	1	0	0	0	0	1	0
17	h15_4	Housing is owned and fully paid for	1	0	1	1	0	0	1	0	0	0	0	1	0	0	0	0	1	1	0	1	0	0	1	0
18	h15_5	The house is ceded	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0
19	h15_6	Housing is received by services	0	0	0	1	0	1	1	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	1	0
20	internet	The household has internet service	1	1	1	1	1	1	1	0	1	1	1	1	1	0	0	1	1	1	1	1	0	1	1	1
21	internet_cl	Percentage of households having internet service at cluster level	1	1	1	1	0	1	0	0	1	0	1	0	1	1	0	0	1	0	0	0	1	0	0	0
22	migra_d	Household received money from friends or relatives abroad in the last 12 months	0	1	0	0	0	0	1	0	1	0	1	1	0	0	0	0	0	0	0	0	1	1	0	1
23	migra_d_cl	Percentage of households that in the last 12 months received money from friends or relatives abroad at cluster level	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0
24	mujer	If the head of household is female	0	0	1	0	0	1	0	0	0	0	0	1	0	0	1	0	0	1	0	0	0	1	1	0
25	mujer_cl	Percentage of female heads of household by cluster	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1	1	0	1	0	1	0
26	nivel_2	Level of education of the head of household: GBS	0	0	1	0	0	1	1	0	0	0	0	1	0	0	0	1	1	0	0	1	0	0	1	1
27	nivel_3	Level of education of the head of household: incomplete secondary education	0	0	1	0	0	1	1	0	1	0	1	1	1	0	0	1	1	1	0	1	0	0	1	1
28	nivel_4	Level of education of the head of household: medium	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1
29	nivel_5	Level of education of head of household: non-university tertiary education	1	0	1	0	0	1	1	0	1	1	0	1	0	1	1	0	1	1	1	1	1	0	1	0
30	nivel_6	Level of education of the head of household: university education	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	1
31	no_empleo	Head of household is unemployed	0	0	0	1	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	1	1	0
32	no_empleo_cl	Percentage of unemployed household heads	1	1	1	0	0	1	1	0	0	1	1	0	0	0	0	1	0	1	1	0	1	0	0	0
33	p03	Age of head of household	0	1	0	1	0	0	1	0	1	0	1	0	0	0	1	0	0	0	0	0	1	0	1	0
34	p03_cl	Average age of heads of households at cluster level	1	0	1	0	1	1	1	0	0	1	1	1	1	1	1	1	0	1	1	0	0	1	0	1
35	p16_2	Ethnicity of head of household: Afro-descendant	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	p16_3	Ethnicity of head of household: Montubio	1	0	1	1	0	0	1	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0	0
37	p16_4	Ethnicity of the head of household: mixed race	0	0	1	0	1	0	0	1	0	1	0	0	0	1	1	0	0	1	1	0	0	0	0	0
38	p16_5	Ethnicity of head of household: white or other	1	0	0	0	0	1	0	1	0	1	1	0	0	1	1	1	0	1	0	0	1	1	0	0
39	p34_2	Marital or conjugal status of the head of household: common-law union	0	0	1	0	0	1	1	0	0	0	1	1	0	0	0	1	1	0	0	0	1	1	0	0
40	p34_3	Marital or conjugal status of the head of household: separated	0	0	0	0	0	1	0	0	0	1	0	0	1	0	1	0	0	0	0	0	0	0	0	1
41	p34_4	Marital or conjugal status of the head of household: divorced	0	0	0	0	0	0	0	0	1	1	0	1	1	0	0	0	0	1	0	0	0	0	0	0
42	p34_5	Marital or conjugal status of the head of household: widowed	0	1	0	0	0	1	0	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
43	p34_6	Marital or conjugal status of the head of household: single	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0	0	0	1	1	1
44	pa_ad	Suitable housing wall materials	1	0	1	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	1	0	0	0	1	1
45	pa_ad_cl	Percentage of dwellings with adequate wall materials at cluster level	1	0	1	1	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
46	pi_ad	Suitable flooring materials	1	0	0	1	1	1	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0
47	pi_ad_cl	Percentage of dwellings with adequate flooring materials at cluster level	0	0	1	1	0	1	0	1	1	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0
48	rat_dp	Male/Female Ratio at household level	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1
49	rat_dp_cl	Average Male/Female Ratio at cluster level	1	0	0	0	0	1	0	0	1	0	1	0	1	1	0	0	0	1	0	0	0	0	0	0
50	rural	Rural areas	0	0	0	1	0	0	1	0	1	0	1	1	1	0	0	0	1	0	1	0	1	0	0	1
51	T_am	Number of persons over 65 per household	0	0	1	1	0	1	1	0	1	0	0	1	1	1	1	1	0	0	1	1	1	0	0	0
52	T_am_cl	Percentage of people aged 65+ at cluster level	1	0	1	1	0	1	1	0	1	1	0	0	1	1	0	0	0	1	0	0	1	0	0	0
53	T_me	Number of persons aged 5-17 per household	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1
54	T_me_cl	Percentage of households with 5–17-year-olds at cluster level	1	0	1	1	1	0	1	1	1	0	1	0	1	1	1	0	1	0	1	0	1	1	0	0
55	T_nn	Number of persons under 5 per household	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1
56	T_nn_cl	Percentage of households with persons older than 5 years old at cluster level	0	1	1	1	1	0	0	0	1	0	0	0	0	0	1	1	0	1	0	0	1	1	0	0
57	T_ped	Number of persons with disabilities per household	1	1	1	0	1	0	1	0	1	1	1	0	1	0	0	0	1	1	0	0	1	1	1	0
58	T_ped_cl	Percentage of households with persons with disabilities at cluster level	0	0	1	0	0	1	0	0	1	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0
59	T_per	Number of persons per household	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
60	T_per_cl	Average number of people at cluster level	1	0	0	1	0	1	1	0	1	0	0	0	0	0	1	1	1	0	1	0	1	1	0	1
61	te_ad	Adequate roofing materials	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	1	0	1
62	te_ad_cl	Percentage of dwellings with adequate roofing materials at cluster level	0	1	0	0	1	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0
63	telef_f	Household has conventional telephone service	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1
64	telef_f_cl	Percentage of households with conventional telephone service at cluster level	0	0	0	0	0	1	1	1	0	0	0	1	1	0	0	0	1	1	1	0	0	1	0	0
65	tvcable	The household has cable television service	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
66	tvcable_cl	Percentage of households with cable TV service at cluster level	0	0	0	1	0	0	1	1	0	0	0	0	1	1	0	0	0	0	1	0	0	0	0	0
67	v08_2	The water supply is piped outside the house but on the lot.	0	1	1	1	1	1	1	0	0	1	0	0	1	0	1	1	1	1	0	0	1	1	1	1
68	v08_3	Water supply is piped outside the dwelling, lot or land	0	0	0	0	1	0	0	0	0	0	0	0	1	0	1	0	1	1	0	0	1	0	0	0
69	v08_4	Water supply is not piped but received by other means.	1	0	1	0	1	1	0	0	0	0	0	1	1	1	1	1	1	1	0	1	1	1	1	1
70	v09_2	Type of toilet facilities: toilet and septic tank	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	1	1	0	1	0	0	0	0	0
71	v09_3	Type of toilet facilities: toilet and cesspool	0	0	0	1	1	0	0	1	0	0	0	0	0	1	0	0	1	1	1	0	0	1	0	0
72	v09_4	Type of toilet: latrine	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0
73	v09_5	Type of toilet: none	0	0	0	1	0	1	0	0	0	1	0	1	0	1	0	0	0	0	1	0	1	1	0	1
74	v12a	Number of energy-saving light bulbs used by the household	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
75	v12a_cl	Average number of saved light bulbs used by households at the cluster level	1	0	1	1	0	1	1	1	0	1	0	1	0	1	1	0	1	0	1	0	1	0	1	1
76	vap_2	Main access to the house: cobblestones	0	0	0	0	0	0	0	1	0	1	1	1	1	1	0	0	1	1	1	0	1	1	1	0
77	vap_3	Main access to the dwelling: ballasted/dirt road	1	1	1	0	0	0	1	0	1	1	1	0	0	0	1	0	1	0	0	0	0	1	1	0
78	vap_4	Main access to the dwelling: pathway/walkway/other	1	1	1	0	0	0	0	0	1	1	1	0	0	0	0	0	1	0	0	1	0	1	0	0
79	vap_5	Main access to the dwelling: river/sea/lake	1	0	0	0	0	0	0	0	1	0	0	1	1	0	1	0	0	0	0	0	1	1	0	0
80	vtv_2	Type of housing: flat in house or building	0	0	0	0	1	0	1	1	1	0	1	1	0	0	0	1	1	0	0	0	1	0	1	1
81	vtv_3	Type of housing: room in a tenement house	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
82	vtv_4	Type of dwelling: half-hut, hut or hut	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0
83	vtv_5	Type of dwelling: ranch	0	0	0	1	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1	1

Source: [15]

the estimated coefficients and thus the reliability of per capita consumption predictions [48].

The output of these routines was a matrix of estimated coefficients, which was subsequently used to estimate consumption poverty in Ecuador's Census of Population and Housing CPV database. This step allowed us to apply the models fitted in the LCS to the CPV, thus generating more accurate predictions about the distribution of consumption poverty at the provincial level, which is key for planning effective public policies in the country. The coding used in [43] is shown below:

```
* ------------------------------------------------------------- *
* Small Sample Estimation (SAE)
                         *
* Consumption Poverty Estimation from LCS 2014 in CPV 2010 * *
* General Estimation Syntax *
* *------------------------------------------------------------- *

clear all
set more off
set matsize 11000
set maxvar 30000
set seed 1234

/* ------------------------------------------------------------- *
Declare Programme in Mata for GLS estimation
* ------------------------------------------------------------- */

mata
void sigma(real scalar N, real scalar Ncl){

//*** 1. Construct the Omega matrix for GLS with clustered errors.
Si=J(N, N, 0)
M=st_matrix("max")
m=st_matrix("min")

sigma2_h=st_matrix("sigma2_h")
sigma2_cl=st_matrix("sigma2_cl")

for (cl=1; cl<=Ncl; cl++)  {
m_=m[cl,1]
M_=M[cl,1]
for (i=m_; i<=M_; i++) {
for (j=m_; j<=M_; j++) {
        if (j==i){
                Si[j,i]=sigma2_h[i,1];
        }
        if (j!=i){
                Si[j,i]=sigma2_cl[i,1];
        }
    }
  }
}

//*** 2. Estimation v'a GLS

y=st_matrix("y")
X=st_matrix("X")

// Estimation of coefficients
inv_Si=invsym(Si)
b_gls=invsym(X'*inv_Si*X)*X'*inv_Si*y

// Variance-Covariance Coefficient Variance Matrix Estimation
V_gls=invsym(X'*inv_Si*X)

// Adjustment Estimation (R^2)
e=y-X*b_gls
sse=e'e
iota=J(N,1,1)
y_=y-iota*mean(y)
sst=y_'y_
R2=1-sse/sst

// Matrix of Coefficients and Standard Errors
se = sqrt(diagonal(V_gls))
report=(b_gls, se, b_gls:/se)

// Extract matrices back to Stata
st_matrix("report", report)
st_matrix("R2", R2)
st_matrix("b_gls", b_gls)
st_matrix("V_gls", V_gls)
}
end

/* -------------------------------------------------------------*
        Call database
* -------------------------------------------------------------*/
```

```
use "C:/SAE_2/1. Databases /base_hogares.dta", clear
forv d=1/24{  /* Start of loop for provinces */
preserve
*local d=1
keep if dominio==`d'

/* -------------------------------------------------------------*
	Definitions
* -------------------------------------------------------------*/
*gen ln_con=ln(cpcf)
* Declare dependent variable (dep) and independent variable (ind)
global dep ln_con
global ind	T_per T_nn T_me T_am T_pcd rat_dp p03 edad2_ ///
			edad_p edad2_p rural p16_2-p16_5 mujer nivel_2-nivel_6 p34_2-p34_6 analfabeto no_empleo ///
			migra_d vap_2-vap_5 v09_2-v09_5 h01 v08_2-v08_4 h04_2-h04_3 telef_f internet tvcable h15_3-h15_6 v12a ///
			te_ad pa_ad pi_ad vtv_2-vtv_5 cocina_ex T_per_cl-cocina_ex_cl

* Declare cluster level
gen cluster=ciudad

/* -------------------------------------------------------------*
Estimation of the Consumption Model for each domain
* ------------------------------------------------------------ */

***	1. Initial adjustment by OLS
reg $dep $ind, vce(r)

* Eliminate omitted variables in OLS (Must run more than once for some provinces)
global ind: colnames(e(b))
global ind= subinstr("$ind", "_cons", "", .)

forv r=1/100 {
foreach x of global ind {
local a = substr("`x'",1,2)
	if "`a'" == "o." {
	global ind = regexr("$ind", "`x'", "")
	}
}
}

* Selecting independent variables with 10% significance or less using a backward stepwise
sw, pr(.10): reg $dep $ind, vce(r)
keep if e(sample)

* Extract variables used effectively
global ind: colnames(e(b))
global ind= subinstr("$ind", "_cons", "", .)

* Create matrix X with actually used variables including a column of 1's
gen c=1
global ind2 "${ind} c"

*** 2. Decompose errors between parts of each household and cluster.
scalar K=colsof(r(table))
predict res, residual
egen res_cl=mean(res), by(cluster)
gen  sigma2_cl=res_cl^2
gen  res_h=res-res_cl
gen  e2=res_h^2

mkmat $dep, mat(y)
mkmat $ind2, mat(X)

/* -------------------------------------------------------------*
Estimation of the Heterocedasticity Model for each domain
* -------------------------------------------------------------*/

qui sum e2
scalar A=1.05*r(max)
gen het=ln(e2/(A-e2))
reg het $ind, vce(r)
scalar K_a=colsof(r(table))
scalar sigma_r=e(rss)/(e(N)-K_a)
predict xb if e(sample), xb
gen B=exp(xb)
gen    sigma2_ch=(A*B/(1+B))+0.5*sigma_r*(A*B*(1-B)/((1+B)^3))
gen sigma2_h=sigma2_ch+sigma2_cl

* Output matrices
mat a_het`d'=e(b)
mat a_V`d'=e(V)
```

```
/* ---------------------------------------------------------------*
        Estimation of the Model v'a GLS
* ----------------------------------------------------------------*/

*** 1. Construction of estimated sigma matrix of variance covariance of errors **Diagonal elements equal to variance of each household + variance of the cluster component **Off-diagonal elements equal to variance of the cluster component within the cluster

** 1.1 Initial definitions *Order the clusters
egen ncl=group(cluster)
sort ncl
*Identify the number of clusters
qui sum ncl
local Ncl=r(max)
*Identify the size of each cluster
bysort cluster: gen s_cl=_N
*Identify the starting position of each cluster
gen m_cl = 1 if ncl == 1
forval po = 2 / `Ncl' {
        local i = `po' - 1
        qui sum s_cl if ncl == `i'
        local max1 = r(max)
        qui sum m_cl if ncl == `i'
        local max = `max1'+r(max)
        replace m_cl = `max' if ncl == `po'
}
*Set upper limit for each cluster
gen M_cl=m_cl+s_cl-1

*Minimum and Maximum Matrices to fill clusters in the variance-covariance matrix
qui mean m_cl, over(ncl)
mat min=e(b)'

qui mean M_cl, over(ncl)
mat max=e(b)'

** 1.2 Filling in the estimated sigma matrix
mkmat sigma2_cl, mat(sigma2_cl)
mkmat sigma2_h, mat(sigma2_h)
local N=_N

** 1.3 Estimation of the declared function in Mata
mata sigma(`N', `Ncl')

** 1.4 Output matrices
mat b`d'=b_gls'
mat V`d'=V_gls'

mat dom=J(K,1,`d')
mat mod`d'=(dom, report)
mat rownames mod`d'=$ind2
mat R2_=(nullmat(R2_)\(`d',R2))
mat N=(nullmat(N)\(`d',_N))
mat msigma_r=(nullmat(msigma_r)\(`d',sigma_r))
mat mA=(nullmat(mA)\(`d',A))

**1.5 Extract cluster variance matrices
collapse (mean)sigma2_cl, by(cluster)
cd "C:/SAE_2/3. Estimacion/Resultados"
save "eta_`d'.dta", replace

/* ---------------------------------------------------------------*
        Simulations of coefficients
* ----------------------------------------------------------------*/

/* Create 100 random vectors of coefficients for each province averaging the vector estimated by GLS (or OLS in case of the alpha model) and their respective variance-covariance matrices. */

** Alpha Model (Heteroscedasticity Model)
local d1= colsof(a_het`d')
drawnorm a_het1-a_het`d1', n(100) mean(a_het`d') cov(a_V`d') clear
local i=0
macro drop inda
        foreach x of global ind2 {
        local i = `i'+1
        rename a_het`i' a_`x'
        global inda "$inda a_`x'"
        }
gen dominio = `d'
gen sim = _n
reshape wide $inda, i(dominio) j(sim)
tempfile alpha_`d'
save `alpha_`d''

**Beta Model (Model of the mean)
drawnorm b1-b`d1', n(100) mean(b`d') cov(V`d') clear
local i=0
macro drop indb
```

```
		foreach x of global ind2 {
		local i = `i'+1
		rename b`i' b_`x'
		global indb "$indb b_`x'"
		}
gen dominio = `d'
gen sim = _n
reshape wide $indb, i(dominio) j(sim)
tempfile beta_`d'
save `beta_`d''
restore
} /* Loop closure for provinces */

* Create a single coefficient file for all 24 provinces after running the loop.
global var "alpha beta"
foreach x of global var {
use ``x'_1', clear
		forval p = 2 / 24 {
		append using ``x'_`p''
		}

cd "C:/SAE_2/3. Estimation/Results "
save `x', replace
}

cd "C:/SAE_2/3. Estimation/Results "

use beta, clear
merge 1:1 dominio using alpha
drop _m
order dominio, first

cd "C:/SAE_2/3. Estimation/Results "
save "sim_b.dta", replace

*Crear matriz de etas por cluster
use eta_1, clear
		forval p = 2 / 24 {
		append using eta_`p'
		}

cd "C:/SAE_2/3. Estimation/Results "
save "eta_T.dta", replace

* Create matrix of variance parameters per household
clear
svmat msigma_r
svmat mA
drop mA1
rename msigma_r1 dominio
rename msigma_r2 sigma_r
rename mA2 A
save "A_sigma.dta", replace

**Extract model matrices, fit levels and sample sizes
mat2txt2 R2_ N using Ajuste.txt, replace
mat2txt2 R2_ N using Ajuste.txt, replace

mat2txt2 mod1 ///
mod2 ///
mod3 ///
mod4 ///
mod5 ///
mod6 ///
mod7 ///
mod8 ///
mod9 ///
mod10 ///
mod11 ///
mod12 ///
mod13 ///
mod14 ///
mod15 ///
mod16 ///
mod17 ///
mod18 ///
mod19 ///
mod20 ///
mod21 ///
mod22 ///
mod23 ///
mod24 using modelos.txt, replace
```

Step 5: Corresponding simulations were carried out using the standardized Census of Population and Housing (CPV) base together with the matrices and coefficients obtained in Step 4. These simulations allow for the inherent variability in the models, and are a common approach in econometrics to assess the robustness of estimates. In this case, 100 simulations were run to estimate per capita consumption poverty at the household level, which is essential to obtain a more accurate and detailed picture of the distribution of poverty [50].

Each of these 100 simulations generated a different estimate of consumption poverty, capturing possible fluctuations in the data and ensuring that the predictions are more representative of reality. These multiple simulations approach is useful when working with estimates in econometrics, as it allows for more reliable results to be obtained by averaging the different simulations, thus reducing uncertainty in the models [51]. From these estimates, the population of children aged 0-3 living in consumption poverty at the household level was selected. This step was key to identifying the most vulnerable groups and targeting more effective public policies. The precise estimates obtained through this process allow the design of targeted interventions that have a direct impact on improving the living conditions of the child population [43]. The coding is presented below:

```
* ---------------------------------------------------------- *
* Small Sample Estimation (SAE)                          *
*Estimation of Consumption Poverty from LCS 2014 in CPV 2010 *
*Simulations in the CPV
* ------------------------------------------------------------*

clear all
macro drop _all
set more off
set matsize 11000
set maxvar 30000
set seed 1234

/* ---------------------------------------------------------- *
        Create simulation bases
* ------------------------------------------------------------*/

* For speed of calculation, each simulation of coefficients needs to be separated (100 bases are created - 1 for each simulation).
cd "C:/SAE_2/3. Estimation/Results "
use sim_b, clear
forval y = 1 / 100 {
        foreach x of varlist b_T_per1 - a_te_ad100 {
        local v : var label `x'
        tokenize "`v'"
                        if `y' == `1' {
                        global var "$var `2'`1'"
                        }
        }
        preserve
        keep dominio $var
        cd "C:/SAE_2/3. Estimacion/Temp"
        recode b_* a_* (.=0)
        save sim_`y'.dta, replace
        restore
        macro drop var
}
/* ------------------------------------------------------------*
        Call CPV database
* ------------------------------------------------------------*/
use "C:\SAE_2\1. Databases \base_trabajo_cpv.dta", clear
*sample 10

gen cluster=ciudad

*Demographic composition of the household
egen T_per=sum(numpers), by(id_hogar)
gen menor=(p03>=5 & p03<=17)
egen T_nn=sum(p_5), by(id_hogar)
egen T_am=sum(p_65), by(id_hogar)
egen T_me=sum(menor), by(id_hogar)
egen T_h=sum(num_hom), by(id_hogar)
egen T_m=sum(num_muj), by(id_hogar)
gen rat_hm=T_h/T_m
gen rat_dp=(T_nn+T_me+T_nn)/T_per
egen edad_p=mean(p03), by(id_hogar)
gen edad2_p=edad_p^2
gen edad2_=p03^2
gen pcd=(p08==1)
egen T_pcd=sum(pcd), by(id_hogar)

* Ethnic recoding
recode p16 (2/4=2)

* Recoding level of education
gen     nivel=0 if p23==1
replace nivel=1 if p23>=2 & p23<=4
replace nivel=1 if p23==5 & p24<=3
replace nivel=1 if p23==6
replace nivel=2 if p23==5 & p24>3 & p24<6
replace nivel=2 if p23==7 & p24<3
replace nivel=3 if p23==5 & p24==6
replace nivel=3 if p23==7 & p24==3
replace nivel=4 if p23==8
replace nivel=5 if p23==9 | p23==10
```

```
label define nivel 0"Ninguna" 1"EGB" 2"Media Incompleta" 3"Media" 4"Superior no Universitaria" 5"Universitaria"
label val nivel nivel

* Identification of suitable housing materials
gen te_ad=(v01>=1 & v01<=4)
gen pa_ad=(v03>=1 & v03<=4)
gen pi_ad=(v05>=1 & v05<=5)

* Keeping only the head of household and household information
keep if p02==1

*** Create dummies for each variable to create the X matrix of the GLS model.
foreach v in p16 nivel p34 vap v09 v08 h04 h15 vtv {
qui tab `v', gen(`v'_)
}

* Correct ethnicity others for few remarks. Joins whites
replace p16_5=1 if p16_6==1

* Correct housing access others for few remarks. Joins *a sendero
replace vap_4=1 if vap_6==1

* Correct antichresis housing tenure for few observations. Joins *a  arriendo
replace h15_1=1 if h15_2==1

* Correct dwelling type shack and hut for few observations. Joins *a mediagua
replace vtv_4=1 if vtv_6==1 | vtv_7==1
gen rural=(urp==2)
gen mujer=(p01==2)
gen analfabeto=(p19==2)
gen no_empleo=(p27==2)
gen migra_d=(m1==2)
gen telef_f=(h07==1)
gen internet=(h09==1)
gen tvcable=(h11==1)
gen cocina_ex=(h02==1)

* Cluster level average variables
foreach v in T_per T_nn T_me T_am T_pcd rat_dp edad_p edad2_p p03 edad2_ mujer ///
        analfabeto no_empleo migra_d h01 telef_f internet tvcable v12a ///
        te_ad pa_ad pi_ad cocina_ex {
        egen `v'_cl=mean(`v'), by(ciudad)
        }

clonevar dominio=provincia

*Keep only variables to be used
keep cluster id_hogar dominio T_per T_nn T_me T_am T_pcd rat_dp p03 edad2_ ///
        edad_p edad2_p rural p16_2-p16_5 mujer nivel_2-nivel_6 p34_2-p34_6 analfabeto no_empleo ///
        migra_d vap_2-vap_5 v09_2-v09_5 h01 v08_2-v08_4 h04_2-h04_3 telef_f internet tvcable h15_3-h15_6 v12a ///
        te_ad pa_ad pi_ad vtv_2-vtv_5 cocina_ex T_per_cl-cocina_ex_cl

*Identifying the independent (explanatory) variables
global  ind T_per T_nn T_me T_am T_pcd rat_dp p03 edad2_ ///
        edad_p edad2_p rural p16_2-p16_5 mujer nivel_2-nivel_6 p34_2-p34_6 analfabeto no_empleo ///
        migra_d vap_2-vap_5 v09_2-v09_5 h01 v08_2-v08_4 h04_2-h04_3 telef_f internet tvcable h15_3-h15_6 v12a ///
        te_ad pa_ad pi_ad vtv_2-vtv_5 cocina_ex T_per_cl-cocina_ex_cl

*Keep only remarks with complete information.
foreach v in $ind{
drop if `v'==.
}

order dominio cluster id_hogar, first

/* -------------------------------------------------------------*
        Simulations
* -------------------------------------------------------------*/

* Run each of the 100 simulations
forv s=1/100{
disp `s'
preserve

cd "C:/SAE_2/3. Estimacion/Temp"
destring dominio, replace
```

```
* Call the normalisation parameters of heteroscedasticity per domain
merge m:1 dominio using "C:/SAE_2/3. Estimacion/Resultados/A_sigma.dta"
drop _m

* Call eta estimates (cluster-level heteroscedasticity)
merge m:1 cluster using "C:/SAE_2/3. Estimacion/Resultados/eta_T.dta"
drop if _m==2
drop _m
egen sigma2_cl_=mean(sigma2_cl), by(dominio)
replace sigma2_cl=sigma2_cl_ if sigma2_cl==.

* Call the model coefficients Alpha and Beta for each simulation.
merge m:1 dominio using sim_`s'
keep if _m==3
drop _m

* Estimate the logarithm of per capita consumption according to the beta model (ln_con_d)
*Estimate the heteroscedasticity according to the alpha model (B_)
gen ln_con_d=b_c`s'
gen B_=a_c`s'
foreach v of varlist $ind {
di "`v'"
replace ln_con_d=ln_con_d + `v'*b_`v'`s'
replace B_=B_ + `v'*a_`v'`s'
}

gen B=exp(B_)

gen  sigma2_ch=(A*B/(1+B))+(0.5*sigma_r*(A*B*(1-B)/((1+B)^3)))

* Randomly estimate assuming normality the error components (at household level u_h and cluster level u_c).
gen u_h=rnormal(0, sqrt(sigma2_ch))
gen u_c=rnormal(0, sqrt(sigma2_cl))

* Bringing together the three components of estimated per capita consumption
egen ln_con=rsum(ln_con_d u_h u_c)
gen con_pc`s'=exp(ln_con)
keep id_hogar con_pc`s'

* Store a baseline of the results for each household of the 100 simulations of the estimated per capita consumption.
cd "C:/SAE_2/3. Estimation/Results "
if `s'==1{
        save cpv_con_.dta, replace
        }
else{
        merge 1:1 id_hogar using cpv_con_.dta, nogen
        save cpv_con_.dta, replace
        }

restore
}

/* -------------------------------------------------------------*
        Poverty Estimation
* -------------------------------------------------------------*/
cd "C:\SAE_2\1. Databases "
use "base_trabajo_cpv.dta", clear
gen id_sector=substr(id_hogar,1,12)

merge m:1 id_sector using "id_hogar-circuitos.dta"
drop if _m==2
drop _m

keep id_hogar izodec idist ciudad urp p01 p03 p08

cd "C:/SAE_2/3. Estimacion/Resultados"
merge m:1 id_hogar using "cpv_con_.dta"

keep if _m==3
drop _m

gen canton=substr(ciudad, 1, 4)
gen prov_=substr(ciudad, 1, 2)

*sample 2

*Define the poverty line of the LCS 2014
scalar lp=83.22367

* Estimate for each household 100 poverties according to its estimated per capita income in each of the 100 simulations.
forv s=1/100{
```

```
        gen pobre`s'=(con_pc`s'<lp)
}

* Creating care populations
gen cnh=(p03>=0 & p03<=3)
gen cibv=(p03>=1 & p03<=3)
gen joven=(p03>=15 & p03<=29)
gen ad_m=(p03>=65 & p03!=.)
gen pcd=(p08==1)
gen nac=1

*Create planning area with prefix Z
tostring izodec, replace
gen z="Z"
egen zonap=concat(z izodec)

* Create province with prefix P
cap tostring prov_, replace
gen p="P"
egen prov=concat(p prov_)

keep pobre* cnh cibv joven ad_m pcd nac zonap idist can-
ton prov

* Create poverty for each population for each simulation
foreach p in cnh cibv joven ad_m pcd nac {
        foreach d in nac zonap idist canton prov {
                foreach stat in mean sum {
                        preserve
                        collapse (`stat') pobre* if `p'==1,
by(`d')
                        cd "C:/SAE_2/3. Estimation/Re-
sults "
                        tempfile `p'_`d'_`stat'
                        rename `d' id
                        capture tostring id, replace
                        forv i=1/100{
                                rename pobre`i' po-
bre_`p'_`i'
                        }
                        save "``p'_`d'_`stat''", replace
                        restore
                }
        }
}

foreach stat in mean sum {
        foreach p in cnh cibv joven ad_m pcd nac {
                use "``p'_nac_`stat''", clear
                foreach d in zonap idist canton prov {
                        append using "``p'_`d'_`stat''"
                        }
                cd "C:/SAE_2/3. Estimacion/Temp"
                save `p'_`stat'.dta, replace
        }
}

foreach stat in mean sum {
        cd "C:/SAE_2/3. Estimacion/Temp"
        use cnh_`stat', clear
        foreach p in cibv joven ad_m pcd nac {
                append using `p'_`stat'
        }
        cd "C:/SAE_2/3. Estimation/Results "
        collapse (sum) pobre*, by(id)
        save "pobreza_res_`stat'.dta", replace
}
/* --------------------------------------------------------------*
Output files
* --------------------------------------------------------------*/
foreach stat in mean sum {
        cd "C:/SAE_2/3. Estimation/Results "
        use "pobreza_res_`stat'.dta", clear
        reshape long pobre_cnh_ pobre_cibv_ pobre_jo-
ven_ pobre_ad_m_ pobre_pcd_ pobre_nac_, i(id) j(s)

collapse (mean) cnh=pobre_cnh_ cibv=pobre_cibv_ jo-
ven=pobre_joven_ ad_m=pobre_ad_m_ pcd=pobre_pcd_
nac=pobre_nac_ ///
  (sd) cnh_sd=pobre_cnh_ cibv_sd=pobre_cibv_ joven_
sd=pobre_joven_ ad_m_sd=pobre_ad_m_ pcd_sd=po-
bre_pcd_ nac_sd=pobre_nac_, by(id)

        gen l=length(id)
        sort l id
        drop l

        foreach u in cnh cibv joven ad_m pcd nac{
                gen `u'_cv=`u'_sd/`u'*100
        }
        export excel using "C:/SAE_2/3. Estimation/Re-
sults/Base_final_`stat'.xls", firstrow(variables) replace
}
```

2.7 LOGARITHMIC FAY-HERRIOT MODEL FOR INDIRECT ESTIMATION AND ITS RELATION TO THE MULTIPLE LINEAR REGRESSION MODEL FOR THE LOGARITHM OF CONSUMPTION POVERTY

The Fay-Herriot model [42], is a methodology used for indirect estimation in small areas, where sample size is limited. It is generally applied in situations such as censuses or national surveys, where data are scarce in certain geographic areas or sub-populations. The model assumes that direct estimates of a target variable for a small area can be improved by using auxiliary variable information and empirical models. From the above syntax, the Fay-Herriot model is identified mainly in the estimation structure using the generalized least squares (GLS) method and in the way variance components are handled. The model is presented in the following form:

2.7.1 Fay-Herriot mathematical model (logarithmic).

In [31], the Fay-Herriot model for small area estimation is given in (6).

2.7.2 Parameter estimation

In the syntax provided, generalized least squares (GLS) methods are used to estimate the coefficients and the variances of the model components (heteroscedasticity and cluster variance). This is observed in the following code fragment the application of the formula for the estimated coefficients by GLS is: , donde is the variance-covariance matrix of the errors, which in this case has been estimated by separating the variance of each household and the errors at the cluster level.

// Coefficient estimation using GLS
inv_Si = invsym(Si)
b_gls = invsym(X'*inv_Si*X)*X'*inv_Si*y

Here, the inversion of the variance-covariance matrix is performed that this represented as ( ) and it is estimated , the fitted coefficients of the model.

2.7.3. Decomposition of errors

The Fay-Herriot model takes into account the decomposition of errors into two components:

- Within-household variance : individual variance for each unit within an area or cluster.
- Inter-cluster variance : variance between the different areas or clusters. This treatment is evident in the syntax with the creation of the variance matrices:

gen sigma2_cl = res_cl^2
gen res_h = res - res_cl
gen e2 = res_h^2

2.7.4 Logarithmic model

The dependent variable modelled is the natural logarithm of per capita consumption. This is stated with:

gen ln_con = ln(cpcf)

This suggests that the Fay-Herriot model is being fitted to a log-transformed dependent variable. Model summary, the model implemented is a GLS-adjusted Fay-Herriot model, considering heteroskedasticity and variance effects at the cluster level, and applying a log transformation to the dependent variable to model per capita consumption in small areas. In mathematical terms, the model can be expressed as:

$$ln\left(Consumo_i\right)=X_i'\beta+u_i+e_i \qquad i=1,\ldots,m \tag{12}$$

Where the coefficients are estimated and variances (cluster) and (household) using generalized least squares, and an adjustment for heteroskedasticity is included using , the diagonal variance-covariance matrix.

2.8 RESULTS OBTAINED FROM THE APPLICATION OF THE FAY-HERRIET MODEL IN THE PARAMETER ESTIMATION AND THE ADJUSTED MODEL

When applying the Fay-Herriot model in parameter estimation, it is essential to verify that the assumptions of the model are met to ensure the validity and reliability of the results. The Analysis of Variance - ANOVA, indicates that the Fay-Herriot model has proven to be a valuable tool in the analysis of complex data, particularly in contexts where estimation for small areas is crucial. As shown in table 2, the variability decomposition shows that the sum of squares of the regression reaches a value of 9,634.1391, reflecting the portion of variability explained by the model. With 82 degrees of freedom, the mean square of the regression stands at 117.490, indicating a considerable explanation of the variability in the data [42]. On the other hand, the residuals present a sum of squares of 4,698.2966, with 27.696 degrees of freedom, suggesting a considerable sample size and a mean square of residuals of 0.16963809, a value that evidences the accuracy of the model in minimizing estimation errors [24]. The R^2 of approximately 0.67 (67.2%) underlines the relevance of the included auxiliary variables, as they explain more than two-thirds of the variability in the data, which is remarkable in small-area estimation contexts where data are often sparse and of higher variability [27]. This model not only provides reliable estimates, but also offers a solid basis for evidence-based decision-making, especially in situations where precision in geographically defined areas is essential for social and economic interventions [52]. Table 3 (annexes) presents the estimation of the consumption poverty parameters obtained by the Fay-Herriot model.

Table 2.
ANOVA - Analysis of Variance

Source of variation	SS	Df.	MS
Regression	9,634.1391	82	117,490
Residues	4,698.2966	27696	0.16963809
Total	14,332.4357	27778	0.51596356

Number of obs.	=	27.779
F(82, 27696)	=	692.59
Prob > F	=	0,0000
R^2	=	0.6722
R^2 – Adjusted	=	0.6712
Root MSE	=	0.41187

Source: [15]

The following graph presents the kernel density estimate of the model residuals together with a theoretical normal distribution for comparison. The solid curve represents the estimated distribution of the observed residuals, while the dotted line shows a normal distribution with the same mean and standard deviation.

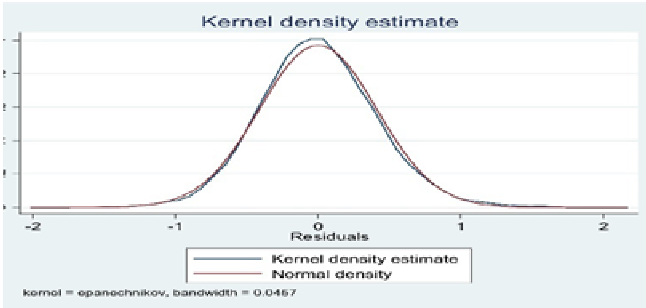
Regarding the shape of the curve, it is observed that the kernel estimate closely resembles a normal distribution, which is a good sign for the Fay-Herriot model. However, there are some interesting details:

- The higher part of the kernel curve looks a bit flatter compared to the theoretical normal distribution.
- The tails of the kernel curve seem to spread out a bit more, suggesting that there might be more extreme values than we would expect in a standard normal distribution.

The bandwidth used in the kernel estimation is 0.0457, which determines how much the data is smoothed. A smaller bandwidth would make the curve follow the raw data more closely, while a larger one would produce a smoother curve.

In summary, the residuals of the Fay-Herriot model are approximately normally distributed, which is essential for the model to be valid. The similarity between the kernel curve and the theoretical normal distribution indicates that the residuals comply quite well with the assumption of normality. However, the small differences in the shape of the curve suggest that the residuals might have a slightly leptokurtic distribution, i.e. with heavier tails than those of a standard normal distribution. Although this slight deviation from normality is noticeable, it does not invalidate the model completely [40], [53].

Figure 2.
Kernel density estimation



Source: [15]

Figure 3 presents a visual comparison between the quantiles of the residuals of the Fay-Herriot model and the corresponding quantiles of a theoretical normal distribution. In this graph, each point represents an observed residual, while the straight line shows the normal distribution expected under the assumption of normality.

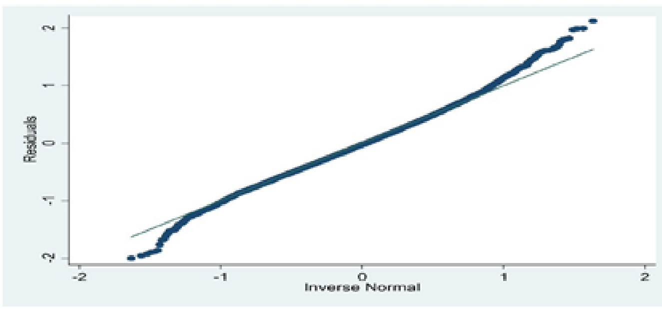
In general, most of the points align quite well with the reference line, suggesting that the residuals follow an approximately normal distribution. This alignment is especially noticeable in the central range of the data, where the residuals fit well to the expected theoretical distribution.

However, at the extremes of the distribution, particularly at the bottom left of the graph, a slight deviation of the points from the straight line is observed. This deviation can be interpreted as an indication that the residuals have slightly heavier tails than those of a standard normal distribution, which is consistent with the previous observation of a leptokurtic distribution in the kernel density curve analysis.

In conclusion, the residuals of the Fay-Herriot model reasonably comply with the assumption of normality, which is fundamental for the validity of the statistical inferences of the model. Although there is a slight trend towards heavier tails, this deviation is not sufficient to invalidate the model. However, it may be beneficial to perform a more detailed analysis of the residuals to identify possible outliers or patterns not captured by the current model. Overall, the model proves adequate for the data analyzed, providing a solid basis for estimates and predictions in small area contexts [40], [54].

Figure 3.

Distribution of Residuals for the Fay-Herriot Model



Source: [15]

Figure 4, which presents the residuals versus fitted values, provides a detailed insight into the behavior of the Fay-Herriot model. The residuals, which represent the differences between the observed values and those predicted by the model, are randomly distributed around the reference line (zero), which is a positive sign. This dispersion around zero suggests that the model is not systematically biased, i.e. it does not tend to consistently underestimate or overestimate the true values.

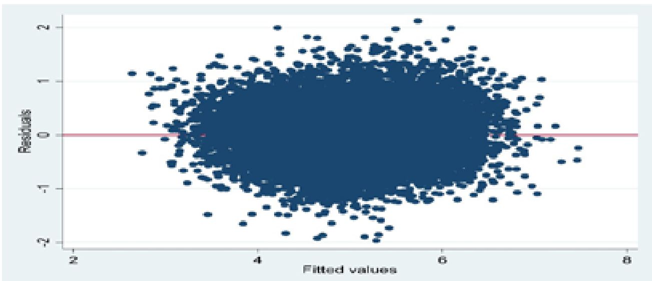
Homoscedasticity, i.e. the constancy of the variance of the residuals over the fitted values, is clearly seen in the graph. This feature is fundamental in regression models, as violations of this assumption could indicate problems in the specification of the model or the need for transformations in the variables.

Furthermore, the absence of discernible patterns in the distribution of residuals (such as systematic curves or trends) indicates that the model has adequately captured the relationship between the explanatory variables and the dependent variable. This suggests that the auxiliary variables included in the model are relevant and that the functional form of the model is appropriate.

Finally, no extreme residuals are identified that could distort the results, which is important for the robustness of the estimates. Taken together, these features of the residual plot versus fitted values support the validity of the Fay-Herriot model for these data, fulfilling the assumptions necessary for statistical inference to be reliable in small-area estimation contexts [40], [54].

Figure 4.

Residuals versus Fitted Values in the Fay-Herriot Model



Source: [15]

Table 3 (Annexes) presents a GLS-adjusted Fay-Herriot model obtained in [43], with the logarithm of consumption as the dependent variable. Household characteristics and their impact on consumption are analyzed, showing estimated coefficients, standard errors, t-values, and confidence intervals for each independent variable and the intercept. The table shows that consumption is influenced by various socio-demographic and economic characteristics, providing a broad picture of the determinants of welfare in terms of household consumption.

From the results obtained, a thorough and detailed analysis was carried out which considers the following:

- **Household size and composition:** Household size and composition, in particular the number of children aged 0-3 years, have significant effects on consumption poverty. As the number of dependents increases, be they children or older adults, per capita consumption tends to decrease, suggesting greater economic pressure on larger households or households with more dependents.
- **Education:** Education emerges as a key driver of consumption, with higher levels of education associated with higher levels of consumption, highlighting the importance of education in the fight against poverty.
- **Technological and housing conditions:** Ownership of technological goods such as fixed telephone, internet, and cable TV is positively related to consumption, reflecting a higher standard of living in households with access to these technologies.
- **Gender:** Households where the reference person is female tend to have slightly lower consumption, which could point to differences in economic opportunities between men and women.
- **Regional differences:** Households in rural areas have slightly higher consumption compared to urban areas, although this effect is small, suggesting that geographical differences are not as pronounced in this sample.

Additionally, Table 4 and Map 1, presents the goodness of fit R^2 of the econometric models used through the SAE methodology for each of the domains analyzed. The R^2 of the models, as a whole, are above the 50% recommended in the literature [42], [55]. Next, we include the values corresponding to the coefficient of determination - goodness of fit, which is obtained in the estimation of small areas at the National level where we observe that: The R^2 measures what percentage of the variability in the dependent variable (e.g. consumption) is explained by the independent variables included in the Fay-Herriet Model. This is in the multiple regression model [42]. An R^2 value close to 1 indicates that the model explains the variability of the data well. A value close to 0 indicates that the model does not explain the variability well. In the table, the R^2 values vary from 0.60 (Carchi) to 0.82 (Napo), indicating that the model has different levels of explanatory power depending on the region. A higher R^2 suggests that the model is more appropriate for that region.

In addition to this the number of observations (n) refers to how many data were used to estimate the model in each domain. Regions with more observations, such as Guayas (2973) and Pichincha (2880), tend to have more robust models because the sample is larger. Regions with fewer observations, such as Morona Santiago (611) or Galápagos (556), might have less precise estimates due to the smaller sample size. Consequently, we look at the quality of the model by region: Where Regions with good fit: Napo (R^2 = 0.82), Morona Santiago (R^2 = 0.79), Pastaza (R^2 = 0.75), Orellana (R^2 = 0.76). The model explains more than 75% of the variability in these regions, indicating that the model is highly predictive. Regions with moderate fit: Azuay (R^2 = 0.70), Chimborazo (R^2 = 0.69), Loja (R^2 = 0.67), among others. The model performs well in these regions, but there could still be factors not captured by the model. Regions with the lowest fit: Carchi (R^2 = 0.60), El Oro (R^2 = 0.62), Guayas (R^2 = 0.61), Galápagos (R^2 = 0.62). Although the model still explains a significant proportion of the variability, there is room for improvement in these regions, perhaps by considering additional variables or adjusting the model.

Adicionalmente, en el anexo se incluyen resultados obtenidos

Table 4.

Goodness-of-fit R_2 of econometric models

Dominio	R^2	Number of observations
AZUAY	0.70	1929
BOLÍVAR	0.63	855
CAÑAR	0.66	923
CARCHI	0.60	858
COTOPAXI	0.63	1089
CHIMBORAZO	0.69	1117
EL ORO	0.62	1950
ESMERALDAS	0.66	1037
GUAYAS	0.61	2973
IMBABURA	0.72	1051
LOJA	0.67	1139
LOS RÍOS	0.62	1219
MANABÍ	0.67	1231
MORONA SANTIAGO	0.79	611
NAPO	0.82	681
PASTAZA	0.75	570
PICHINCHA	0.68	2880
TUNGURAHUA	0.67	1151
ZAMORA CHINCHIPE	0.67	682
GALÁPAGOS	0.62	556
SUCUMBÍOS	0.67	735
ORELLANA	0.76	652
SANTO DOMINGO DE LOS TSÁCHILAS	0.65	976
SANTA ELENA	0.66	914

Source: [15]

It is crucial to recognize that child poverty is not a one-dimensional phenomenon, but is influenced by a complex interaction of socio-economic and demographic factors. While our analysis has focused on variables such as consumption and unmet basic needs, it is important to consider the possible influence of other factors not considered that could affect children's vulnerability. For example, parental education, especially that of the mother, has been shown to be a key factor in reducing child poverty, as it influences employment opportunities and household income [21].

In addition, access to basic services such as quality health, nutrition and education plays a critical role in child development and long-term poverty prevention [56]. The availability and quality of these services can vary significantly across regions and communities, which may explain some of the observed differences in child poverty levels. In addition, factors such as domestic violence, child abuse and lack of access to a safe and stimulating environment can have a negative impact on children's well-being and increase their risk of falling into poverty [57].

For future research, it would be advisable to explore the inclusion of these additional variables in the small area estimation model in order to gain a more complete and accurate understanding of the factors contributing to child poverty. This may require additional data collection through targeted surveys or the use of administrative data sources such as health and education records. By broadening the scope of our analysis, we will be able to identify more effective and targeted interventions to break the cycle of poverty and ensure a better future for all children.

3. Results and discussion

As mentioned in the methodological section, once the multiple linear regression models were estimated for each of the domains, simulations were carried out for each domain. It should be noted that methodologically, the estimation of consumption poverty using the SAE Small Area Estimation, particularly in the Fay-Herriet model involved most of the time and work. Finally, once the consumption poverty levels were calculated down to the smallest geographical disaggregation, i.e. the districts, we proceeded to make projections for the population of children aged 0-3 years, up to the year 2030 [43].

3.1 ANALYSIS OF THE INCIDENCE OF CONSUMPTION POVERTY

Consumption poverty is analyzed at different geographical levels, showing significant variations between provinces, cantons and districts. At the national level, the consumption poverty rate is 25.8%, but varies considerably in regions such as the highlands and the coast, where rates can be up to 30% higher in rural areas [14]. This geographical heterogeneity is crucial for the implementation of public policies, as it allows targeting resources to areas of greatest need and designing interventions adapted to local conditions. For example, conditional cash transfer programs that have proven effective in reducing child poverty can be applied in areas with high poverty rates [3]. Heterogeneity of poverty helps in policy implementation by allowing better allocation of resources to the most vulnerable populations, which can improve the effectiveness of social interventions [2].

Table 5.

Consumption poverty for children aged 0-3 years, by Province

Province	Incidence	Children from 0 to 3 years old	Standard deviation	Coefficient of variation
Napo	81,3%	7.121	2,0%	2,5%
Chimborazo	79,1%	24.929	3,1%	3,9%
Santa Elena	67,4%	17.726	6,4%	9,5%
Bolívar	66,1%	8.078	4,4%	6,7%
Zamora Chinchipe	60,9%	4.532	6,6%	10,9%
Esmeraldas	59,8%	25.358	2,3%	3,9%
Imbabura	55,4%	16.440	2,0%	3,6%
Morona Santiago	54,4%	6.142	2,5%	4,6%
Manabí	53,1%	51.156	3,5%	6,5%
Los Ríos	48,2%	28.339	2,0%	4,1%
Sucumbíos	45,6%	6.081	6,2%	13,5%
Cotopaxi	45,4%	13.494	2,9%	6,3%
Loja	42,4%	13.794	3,7%	8,6%
Tungurahua	40,6%	13.843	2,3%	5,8%
Azuay	39,4%	20.734	3,3%	8,4%
Guayas	37,6%	99.474	3,0%	8,0%
Carchi	37,4%	4.301	2,4%	6,4%
Pastaza	36,9%	2.124	4,0%	10,9%
Orellana	36,3%	4.035	2,7%	7,5%
Santo Domingo de los Tsáchilas	34,1%	10.371	2,8%	8,2%
Pichincha	25,1%	46.329	1,9%	7,5%
El Oro	18,5%	7.867	2,5%	13,4%
Cañar	15,2%	2.635	3,1%	20,2%
Galápagos	1,2%	20	0,7%	61,0%
National total	**41,1%**	**434.926**	**0,9%**	**2,3%**

Source: [15]

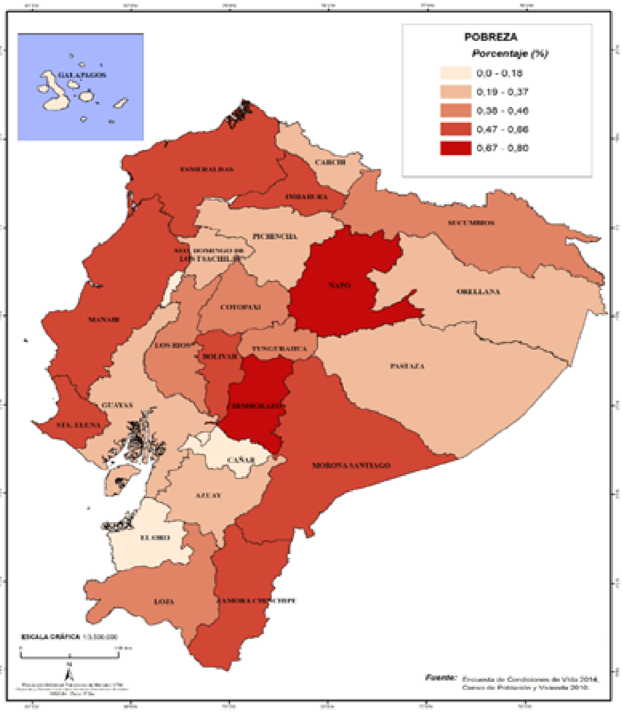
It is important to mention that the incidence of consumption poverty shows significant variations across age groups. In this case, consumption poverty in children aged 0-3 years was 41.1% respectively at the national level. The provincial disaggregation is shown in Table 5 on the incidence of poverty in children aged 0-3 years in different provinces of Ecuador, together with the standard deviation and the coefficient of variation (CV), which indicate the precision and variability of the estimates.

- Poverty incidence: Represents the percentage of children aged 0-3 living in poverty in each province. The provinces with the highest incidence of child poverty are Napo (81.3%), Chimborazo (79.1%) and Santa Elena (67.4%), while Galápagos (1.2%) has the lowest incidence.
- Number of children: Shows the total number of children aged 0-3 affected by poverty in each province. The provinces with the highest number of children in poverty are Guayas (99,474), Manabí (51,156) and Pichincha (46,329), due to their larger child population. On the other hand, Galapagos has the lowest number of children aged 0 to 3 (20), which coincides with its low incidence of poverty.
- Standard deviation: A measure of dispersion that indicates how much estimates of poverty incidence vary. Provinces with a higher standard deviation, such as Santa Elena (6.4%) and Zamora Chinchipe (6.6%), have greater uncertainty in their estimates, while provinces such as Pichincha (1.9%) and Esmeraldas (2.3%) show less variability in estimates.
- Coefficient of variation (CV): The CV is a measure that reflects the ratio of the standard deviation to the mean, indicating the relative precision of the estimates. A lower CV suggests greater precision. The table shows that Gálapagos (61%), Cañar (20.2%) and El Oro (13.4%) have high coefficients of variation, suggesting that poverty estimates in these provinces have greater uncertainty. In contrast, Napo (2.5%) and Esmeraldas (3.9%) have lower Coefficients of Variation, indicating greater reliability in their estimates.

Below, in Map 2, the distribution of consumption poverty for children aged 0-3 years is presented at the disaggregation level as Planning Zones [43], Planning Zone 1 (53.9%) and Planning Zone 3 (53.1%) show the highest consumption poverty scores for children aged 0-3 years. On the other hand, planning zone 9 (22.3%) reflects the best situation at the level of this entire population and for the country as a whole. Planning zones 2, 4 and 8 show rates below the national average (see Annex Table 6).

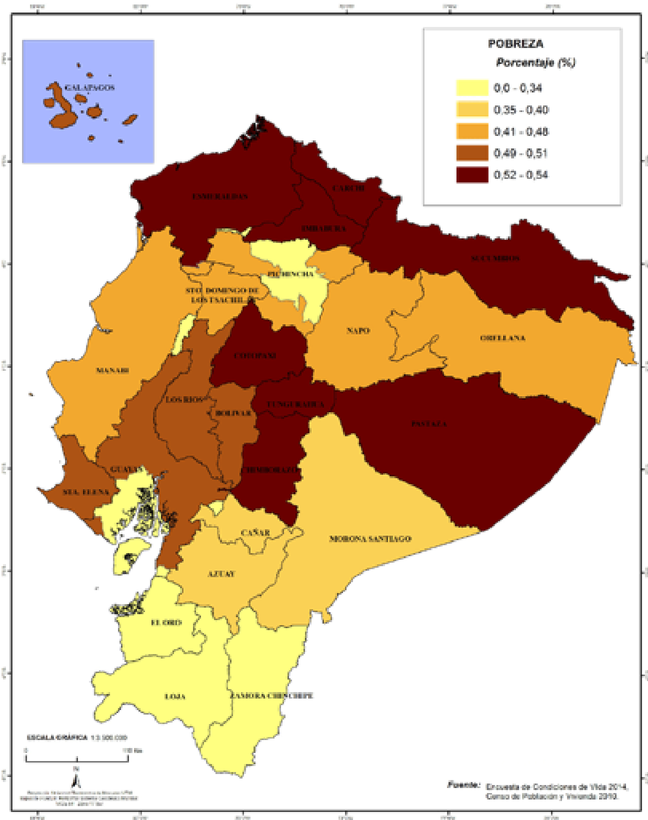
Map 1.

Consumption poverty for children aged 0-3 years, by Province



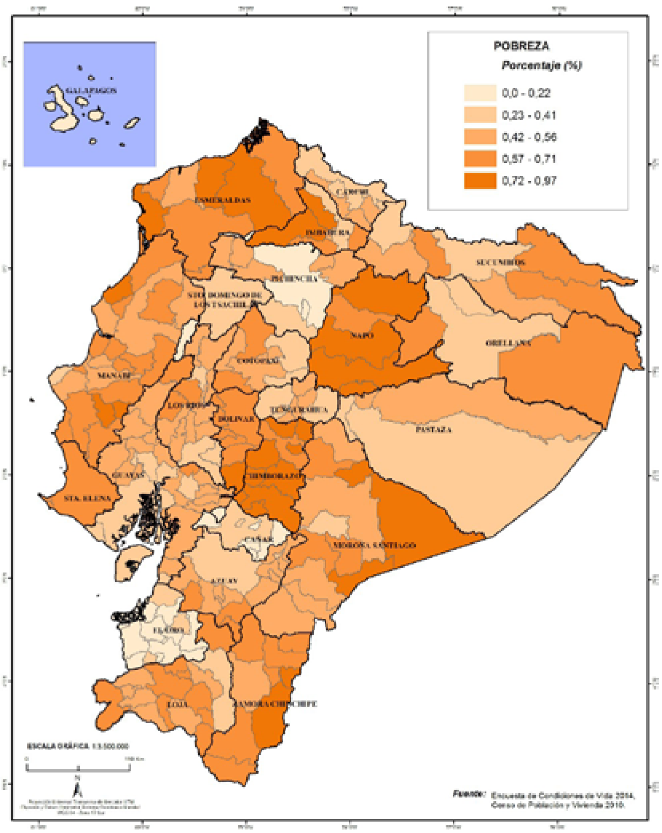
Map 2.

Consumption poverty for children aged 0-3 years, by Planning Area



Map 3.

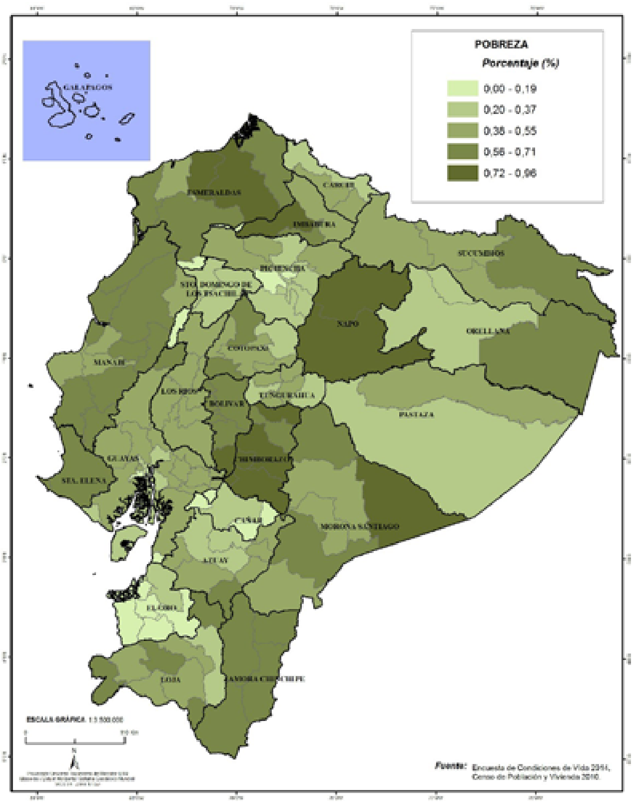
Consumption poverty for children aged 0-3 years, by Canton



Source: [15]

Map 4.

Consumption poverty for children aged 0-3 years, by Distrito



Source: [15]

In addition, Map 3 shows the distribution of poverty by consumption for children aged 0 to 3 years, at the cantonal level, where it was observed that the cantons with the highest incidence of consumption poverty are: Guamote (97.8%), Colta (95.5%), Carlos Julio Arosemena Tola (92.7%). Meanwhile, the cantons with the lowest incidence of consumption poverty are: Santa Cruz (1.4%), Isabela (0.6%), San Cristóbal (0.3%).

Finally, Map 4 shows the distribution of consumption poverty for children aged 0 to 3 years old at the district level, where the districts with the highest consumption poverty rates are: 06D04 (96.9%), 14D05 (87.5%), 06D05 (83.8%) and the districts with the lowest rates are: 03D03 (10.2%), 03D01 (6.2%), 20D01 (1%). In summary, the results show that there is significant heterogeneity in consumption poverty within territorial units in Ecuador. This allows for better targeting of public policies at the disaggregated level [43], (see Annex Estimation of consumption poverty for children 0-3 years old, according to the SAE methodology).

3.2 ESTIMATED POPULATION OF CHILDREN AGED 0 TO 3 YEARS OLD UP TO 2030, BY CONSUMPTION POVERTY.

The projection of the child population up to 2030 was made using the SAE methodology, which allows estimating consumption poverty in small areas. However, the lack of updated Living Conditions Survey (LCS) data introduces uncertainty into the projections, as recent economic changes can significantly affect consumption levels [2]. To mitigate this problem, econometric models were used that adjust the projections according to current economic trends. In addition, a homogeneous distribution of poverty in the areas studied was assumed, which could affect accuracy if not met. It is important to consider methodological adjustments to reflect possible variations in the distribution of poverty and improve the accuracy of the projections [58].

The methodology used to project the population of children aged 0-3 until 2030 is based on the use of advanced statistical techniques. These techniques allow for more precise estimates in small geographic areas where sample sizes are insufficient to provide reliable data. This methodological approach is particularly relevant in contexts where traditional data sources cannot accurately capture child population dynamics at the local level [59].

It is important to note that there is no update of the Living Conditions Survey (LCS), only the one conducted in the years 2013-2014. This survey is crucial as it provides detailed information on the living conditions and demographic structure of the Ecuadorian population. The lack of updating of this data source limits the ability to make more accurate projections on the child population. Population estimates depend on current data, and the absence of such data can compromise the accuracy of the results [60].

In addition, the demographic projections are based on the latest available information, including socio-economic and demographic data. If these sources are not up to date, projections may not adequately reflect recent changes in population structure, which could lead to less effective or inefficient public policy decisions [61].

A relevant aspect to highlight is that, despite the update of the VII Population and VI Housing Census of 2010 to the VIII Population, VII Housing and I Communities Census of 2022, the use of the latter census is not recommended for the application of the Small Area Estimation (SAE). This is because differences in the methodologies used in the 2010 and 2022 censuses may significantly affect the accuracy and validity of the SAE. The SAE relies on consistent and representative data to generate reliable estimates at the local level [4]. One of the main considerations is the change in data collection methodology. While the 2010 Census was conducted on a single day with student participation, the 2022 Census adopted a mixed approach, including both virtual and face-to-face collection. This change may have an impact on the coverage and representativeness of the data at the local level, which is critical for the proper functioning of SAE models, which require homogeneous and reliable data [62].

In addition, the 2022 Census incorporated new variables in its questionnaire, such as questions on sexual identity, pet ownership and female fertility. These variables open up new possibilities for analysis and estimation at the small area level. However, they also imply the need for adjustments to previously employed SAE models, as these must be adapted to the new types of data collected [63]. Finally, comparability of data between the 2010 and 2022 censuses will be a significant challenge. Differences in methodologies and variables collected could hinder longitudinal analyses and, consequently, the efficient application of the SAE. This challenge requires detailed evaluation to ensure that estimates remain valid and accurate [64]. Methodological changes, especially in the questionnaire for the 2010 and 2022 Censuses in Ecuador, could have important implications for the implementation of the Small Area Estimation (SAE). These modifications affect both the coverage and representativeness of the data, as well as the variables available for analysis at the local level. As a result, the accuracy of population projections may be limited. In particular, when working with models that rely on consistent data, any variation in data sources can compromise the reliability of estimates [40].

Going forward, it will be essential to closely monitor the quality and comparability of census data to ensure accurate application of the SAE. Methodological changes must be carefully managed to avoid distortions in the results obtained from the new data. Consistency in data collection and comparability with previous censuses are critical to ensure that estimates remain reliable and useful for decision-making [63]. Despite these limitations, the present study successfully used the methodology of [43] to make annual projections of the population of children aged 0-3 years until 2030. These projections provide a valuable tool for planning in key sectors such as education, health and social services. In these areas, accurate population estimates are crucial for allocating resources and designing services efficiently.

From a methodological perspective, the projection of the population of children aged 0-3 towards 2030 required the use of alternative data sources and was developed in two different scenarios. In both cases, data derived from income poverty were used as the fundamental basis. Income poverty is an economic indicator that measures the ability of an individual or household to meet their basic needs from their income. This measure is crucial because it provides an accurate picture of the economic constraints faced by families, which is critical for accurate demographic projections [65]. The information on income poverty used for these projections comes from the National Survey of Employment, Unemployment and Underemployment (National Survey on Employment, Unemployment and Underemployment, ENEMDU). This survey, which is administered periodically by the National Institute of Statistics and Census (INEC) of Ecuador, collects data on the employment situation of the population, including employment, unemployment and underemployment. Given that the economic situation of households significantly influences demographic dynamics, the ENEMDU becomes a key source for the analysis and construction of long-term population estimation models [66].

We decided to use the income poverty measure instead of consumption poverty because of limitations in the data available to calculate the latter. Consumption poverty is calculated from the Living Conditions Survey (LCS), which is conducted on a non-periodic basis. There was an 8-year gap between the last LCS rounds, which implies that the data may be outdated and not adequate for reliable annual forecasting. This represents a significant challenge for long-term projections [67]. In contrast, the National Survey of Employment, Unemployment and Underemployment (ENEMDU) is conducted periodically, which provides more recent and relevant information for annual population projections. This is crucial when considering the evolution of income poverty, which can directly influence population dynamics. Therefore, we have chosen to use ENEMDU data to obtain more accurate estimates of the population of children aged 0-3 years around 2030 [66].

The use of income poverty as an indicator of the economic situation of an individual or household is a common practice in population projection studies. This measure allows for a more accurate capture of the economic fluctuations that directly affect households, which in turn impacts on demographic trends. In this sense, income poverty becomes a suitable proxy for assessing the current socio-economic situation and projecting future scenarios [65].

In economic terms, an individual income can be broken down into two main components: consumption and savings. This can be expressed by the equation Y=C+A, where Y represents total income, C consumption and A savings. A person's consumption is strongly influenced by his or her level of income, which can be modelled by the equation C=kY, where k is the marginal propensity to consume. This propensity indicates the fraction of an increase in income that is spent on consumption rather than saving. There is a direct and positive relationship between income and consumption: as income increases, so does consumption. Generally, changes in income lead to changes in consumption in similar proportions. However, in some contexts, such as in Ecuador, savings can be very limited. In such cases, income becomes a good proxy for consumption, which means that it can be used to represent the level of economic well-being of an individual or household [68].

The relationship between income, savings and consumption is fundamental to understanding the economic situation of a household. Income poverty is a measure based on this relationship and is used to make accurate poverty estimates for small geographic areas and specific population groups. By considering how income affects both consumption and savings, it is possible to obtain a clearer picture of the economic well-being of different segments of the population [69]. This methodology is particularly relevant for designing public policies to address the economic needs of the most vulnerable communities. Therefore, by analyzing consumption behavior and its relationship to income, it is possible to deduce how variations in income impact people standard of living. Accurate estimates of poverty and well-being are crucial for implementing effective strategies to promote social and economic development [70].

3.2.1.First scenario

The first scenario (see Annex Table 4), which is based on the following assumptions to estimate the population of children aged 0-3 years according to consumption poverty:

1. The variation in the growth rate of income poverty is constant at -8.87%, according to the latest data from the National Survey of Employment, Unemployment and Underemployment [71].
2. Poverty is evenly distributed across the country. - The incidence of poverty in the five self-reported cities does not show statistically significant variations.

3. This scenario uses the ENEMDU data, and the SAE methodology to predict consumption and construct the consumption poverty rate for the different population subgroups defined in the districts.

3.2.2.Second scenario

An approach based on growth rates derived from Ecuador Gross Domestic Product (GDP) is used to estimate the population of children aged 0-3 until 2030. This analysis assumes that variations in the level of production, and hence economic income, influence poverty levels in different regions of the country. This is considered to be a conservative scenario (see Annex Table 5), given that the country has relatively low annual growth rates. The methodology is based on several assumptions:

- **Income elasticity of poverty reduction:** Defined as the percentage change in poverty resulting from a 1% increase in per capita income. This elasticity is held constant and is calculated using the most recent data on income poverty variation provided by the National Survey of Employment, Unemployment and Underemployment (ENEMDU), as well as ECLAC growth projections for the same year.
- **Homogeneous distribution of poverty:** Poverty is assumed to be evenly distributed across the territory.
- **Minimum thresholds in the projections:** No projection is lower than an established minimum threshold. In this context, rates of change of GDP per capita are calculated using growth estimates provided by ECLAC and population projections published by INEC. The paper includes poverty elasticity calculations and projections for the child population aged 0-3 years, considering consumption poverty at the district level [72].

This approach allows for a deeper understanding of how economic changes affect vulnerable populations. Income elasticity is crucial for assessing the impact of economic policies on poverty, as a higher elasticity indicates that an increase in income has a significant effect on poverty reduction. Moreover, by considering a homogeneous distribution, it aims to simplify the analysis, although in practice there may be significant variations between different regions [73]. Finally, by setting lower limits on the projections, it ensures that the estimates do not underestimate the real needs of the child population. This is essential for designing effective policies to address deprivation and promote social well-being. The resulting projections provide valuable information for planning resources and services for this critical age group [74].

3.2.3.Additional clarifications:

- Adjustments to the SAE methodology: To improve accuracy, additional variables reflecting recent economic changes could be incorporated or the model could be adjusted to account for possible biases in the distribution of poverty [4].
- Homogeneous distribution of poverty: A homogeneous distribution was assumed to simplify the model, but if poverty is not evenly distributed, this could affect the precision of the estimates. It would be useful to explore models that incorporate geographical variations in the distribution of poverty [75].
- Projection scenarios: In the first scenario, historical data were used without significant adjustment to reflect current trends. In the second scenario, adjustments were included to reflect recent economic changes, allowing for a more realistic projection of the child population [9].

3.3 ANALYSIS OF THE RESULTS OBTAINED IN THE SCENARIOS.

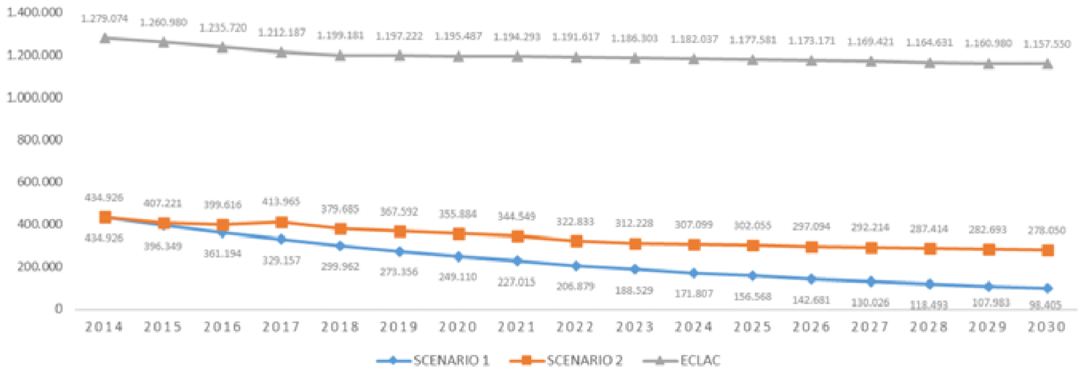
CELADE estimates of the child population in Latin America are relevant to this analysis, as they provide a comparative framework for assessing regional demographic trends [76]. Figure 5 compares Ecuador child population projection scenarios with CELADE estimates, showing significant differences in the population growth rate. Factors such as education and birth control are crucial to explain these differences, as they directly influence population dynamics and poverty reduction [77]. The two projections differ in their approach: the first is based on historical trends, while the second incorporates adjustments to reflect recent economic changes, resulting in a more conservative projection of the child population in high-poverty areas.

In Figure 5 illustrates that a decline in the population of children aged 0-4 years is anticipated in all projected scenarios between 2022 and 2030. This trend can be attributed to a number of factors, such as declining birth rates, changes in population policies, as well as improvements in education and increased knowledge about birth control. CELADE estimates, which cover children up to the age of 4, show a more gradual decline. This might suggest that ECLAC foresees a slow change in the current conditions affecting the child population. In contrast, estimates from other scenarios, obtained using the SAE methodology, show more rapid reductions for children aged 0-3 in consumption poverty. This suggests that these scenarios anticipate more significant or rapid changes in the conditions impacting this age group [78].

It is crucial to note that these projections are merely hypothetical scenarios and that future reality may be subject to multiple unforeseen factors. While downward trends may cause concern, they may also reflect positive outcomes, such as increased access to education and birth control. Therefore, while the graph provides valuable insight into child population projections, it is critical to

Figure 5.

Estimation of girls and boys from 0 to 3 years old according to the SAE methodology, vs. Estimation of the population of girls and boys from 0 to 4 years old according to ECLAC until 2030.



Source: [15]

contextualize these data with other metrics and socio-economic factors to gain a full understanding of the situation [79]. Finally, in assessing these projections, it is essential to consider how they relate to public policies and social programs aimed at supporting families and fostering a favorable environment for child growth. The interaction between demographic changes and the policies implemented will be critical in addressing future challenges related to population and social well-being [80].

To facilitate understanding of the results obtained, it is useful to make clearer comparisons between the different scenarios considered in the study. In particular, the simulation to estimate consumption poverty and project the child population up to 2030 (see Annex Table 6) reveals significant differences between the baseline, pessimistic and optimistic scenarios [35]. In the baseline scenario, child poverty is projected to increase moderately compared to current levels, while the pessimistic scenario shows a considerable increase due to factors such as the economic slowdown and rising unemployment. In contrast, in the optimistic scenario, child poverty is projected to decline due to the implementation of effective public policies and inclusive economic growth. These comparisons provide a better understanding of the potential impact of different factors and policies on the evolution of child poverty in Ecuador.

3.4 DISCUSSION

The application of the Small Area Estimation (SAE) methodology in this study has overcome the limitations of traditional estimation methods, providing accurate results at the local level. However, it is important to recognize that the utility of SAE is not without its challenges. One of the main advantages of SAE is its ability to integrate survey and census data, which facilitates obtaining reliable estimates in small areas [13]. However, the transition between positive results and limitations needs to be smoothed to maintain a clear thread.

Variations in census questions and collection methodology can introduce biases or errors in the data used for EDC, affecting the precision of estimates [58]. To mitigate these problems, strategies such as cross-validation of data and adjustment of models to reflect changes in local conditions can be implemented [75]. In addition, the lack of updating of the Living Conditions Survey (LCS) hinders the application of the methodology, as recent economic changes may not be reflected in the data, affecting the accuracy of the projections [2].

Undetected variations at the community level or within ethnic groups can have significant implications for the accuracy of estimates. For example, if community-specific cultural or socio-economic differences are not considered, models may not adequately capture local needs [39]. In terms of model performance, a good fit was observed in urban areas, but limitations affected rural areas more, where the lack of updated data was more pronounced [23].

A fundamental aspect to consider in the interpretation of the results obtained through SAE lies in the inherent limitations of this methodology. While SAE offers a valuable tool for generating estimates at the disaggregated level, it is crucial to recognize that its accuracy and validity depend to a large extent on the selection of auxiliary variables and their representativeness in the different geographical contexts analyzed [4]. The choice of variables that are not strongly correlated with the variable of interest, or that have measurement biases, can compromise the reliability of the estimates and lead to erroneous conclusions about the distribution of child poverty. It is also important to bear in mind that the SAE is based on statistical models that simplify the complexity of social reality, which can lead to the omission of relevant factors that influence children's vulnerability [75].

The discussion of the results of this study is enriched by linking them closely to their practical and theoretical implications, as well as by contrasting them with findings from another relevant research in the field [9]. For example, our results on the impact of maternal education on child poverty are consistent with previous studies that have shown a strong correlation between these two factors [81]. However, we also found some significant differences compared to research conducted in other geographical contexts, suggesting the importance of considering the specific characteristics of the Ecuadorian population when designing public policies aimed at reducing child poverty [82]. By analyzing these similarities and differences, we can gain a deeper understanding of the factors that influence child poverty and design more effective interventions tailored to local needs.

The results obtained by applying the SAE methodology make it possible to generate precise estimates of the incidence of consumption poverty for different age groups, especially for children aged 0-3 years, at provincial, cantonal, parish and district levels (see Annex Table 6). This level of disaggregation is not possible with traditional statistical methods, which makes the SAE methodology a crucial tool for planning and decision-making in public policy. The ability to estimate poverty rates more accurately at the district level provides government institutions with a solid basis for designing more effective and targeted strategies [4].

The usefulness of the SAE methodology is particularly evident when considering the limitations of current data sources, which do not allow reliable statistical inferences to be generated in small areas using conventional methods. SAE overcomes these limitations by exploiting both census and survey data and allows for the creation of tight and robust predictions in small population domains. The results of this approach show significant variations in consumption poverty levels between different planning areas, provinces, cantons and districts, highlighting the geographical heterogeneity of the poverty phenomenon. This underlines the need for specific and targeted policies to address these regional disparities [80].

At the district level, the results obtained through SAE are a valuable tool to visualize and understand consumption poverty gaps in the country. However, the unavailability of certain household-level socio-economic variables in the Census restricts the use of some predictors, which may limit the precision of the estimates. Moreover, methodological differences between the 2010 and 2022 censuses present additional challenges in the implementation of the SAE. These changes may affect the consistency and comparability of the data, underscoring the importance of adjusting methodologies to maintain the reliability of the analyses [83].

Comparison of the 2010 and 2022 Ecuadorian censuses reveals important methodological discrepancies that compromise the accuracy of small area estimates (SAE). Changes in questionnaire design, data collection techniques, population size and composition, and the amount of information collected affect the comparability of data and the accuracy of SAE estimates. Alterations in the questionnaires make direct comparison with the 2022 census difficult, introducing potential biases. Demographic changes also influence the accuracy of estimates if they are not adequately considered. To ensure the validity and reliability of the SAE estimates, it is essential to take these differences into account and adjust the methodology [84].

The lack of an update of the National Living Conditions Survey (LCS) hinders the application of the SAE methodology, limiting the possibility of integrating auxiliary information to improve the precision of the estimates. While acknowledging the limitations of the data sources used in this study, the models employed showed a good fit to the available data [40]. Finally, the limited spatial resolution of the data sources may prevent the detection of minor variations at the community or ethnic group level. Despite this limitation, the methodological approach used is useful for small area-level analysis [52].

While our study has revealed significant variations in consumption poverty levels between different regions, it is crucial to delve deeper into the underlying reasons for these disparities. Factors such as the economic structure of each region, the availability of employment, levels of education and the public policies implemented can influence the distribution of wealth and the vulnerability of households. For example, regions with a higher concentration of informal agricultural activities may be more susceptible to poverty due to commodity price volatility and lack of access to financial services and training [84].

Likewise, regions with a higher proportion of indigenous or Afro-descendant populations may face additional barriers to accessing employment and education opportunities due to discrimination and social exclusion [85]. Lack of investment in infrastructure and basic services in rural and marginalized areas can also contribute to perpetuating poverty and limiting economic development. To better understand these dynamics, it would be advisable to conduct detailed case studies in some of the regions with the highest levels of poverty, in order to identify the specific factors that are contributing to the situation and design more effective interventions tailored to local needs.

It is important to recognize the inherent limitations of any study based on statistical data, especially in areas where the available information presents a higher level of uncertainty. In our case, the representativeness of the LCS data may be limited in some regions, which could affect the validity of our projections. In addition, there may be measurement errors or biases in the data, which could influence the results. It is therefore essential to interpret our findings with caution and to recognize that there are margins of error associated with our estimates.

To improve the accuracy and reliability of future research, it would be advisable to explore the possibility of combining different data sources, such as administrative records, household surveys and satellite data, in order to obtain a completer and more accurate picture of the child poverty situation. It is also important to invest in training local staff in data collection and analysis to ensure the quality and relevance of the information. By addressing these limitations, we will be able to generate more solid and useful evidence for decision-making and the implementation of public policies aimed at the most vulnerable population.

It is essential to recognize that the SAE methodology has certain limitations that must be considered when interpreting the results and designing public policies based on them. One of the main challenges of SAE lies in the potential bias introduced by the selection of auxiliary variables, which may not be representative of the socio-economic reality of all the geographical areas analyzed [25]. To mitigate this risk, it is crucial to conduct a thorough analysis of the quality and relevance of the variables used, as well as to assess their ability to capture the specific dynamics of each local context.

It is also important to bear in mind that the SAE relies on survey data that may not be updated frequently enough to reflect the socio-economic changes occurring in society [86]. In this sense, it is advisable to complement survey data with information from other sources, such as administrative records and geographic information systems, in order to obtain a completer and more accurate picture of the child poverty situation [86].

Furthermore, it is crucial to recognize that poverty dynamics can vary significantly over time and in different geographical contexts, which can influence the effectiveness of policy programs designed on the basis of these data [87]. Therefore, it is necessary to conduct regular evaluations of implemented programs and adjust strategies based on the results obtained, in order to ensure that interventions are relevant and effective in reducing child poverty.

Living Conditions Surveys (LCS) play a crucial role in policy formulation by providing detailed information on the socio-economic characteristics of households and their access to basic services [88]. LCS data can influence the design of policy interventions for social inclusion and poverty reduction by identifying the most vulnerable groups and targeting resources where they are most needed. However, it is important to bear in mind that LCA are only one tool among many, and that their effectiveness depends on the quality of the data collected, the thoroughness of the analysis carried out and the political will to implement the recommendations derived from the results.

The findings of this study, which estimate the population of children in poverty in Ecuador using SAE, provide a notable advance in knowledge about this problem at the local level. Compared to previous research in Latin America, such as that of [10], which used SAE to measure rural poverty, our work stands out for focusing specifically on children aged 0-3 years in Ecuador, a group little studied at this scale. The results show great diversity in poverty levels across regions, provinces, cantons and districts, highlighting the need for detailed data to target resources efficiently. Furthermore, when comparing our projections with those of ECLAC, we find a reasonable alignment, which reinforces the reliability of our estimates in the face of the scarcity of updated territorial data in the country [2]. This innovative approach not only improves the precision of estimates in small areas, but also establishes a starting point for future studies on child poverty and vulnerability, providing policy makers with a key tool to prioritize interventions where they are most needed [10].

4. Conclusions

This study has demonstrated the usefulness of the SAE methodology for estimating consumption poverty in small areas, specifically contributing to this end by providing accurate estimates at the district level. The results obtained allow for a more specific identification of the target population required for decision-making regarding the implementation of specific public policies. By using recent data from 2014 to 2025 and projections up to 2030, a clear picture of demographic trends and child poverty in Ecuador is provided. This approach is particularly useful for the country economic and social planning, as it allows targeting resources in areas of greatest need and designing interventions tailored to local conditions.

One of the main contributions of this study is the ability to optimize the use of available information, combining survey and census data to generate accurate estimates. The numerical values of the estimates and indicators provide evidence of the credibility and precision of the SAE methodology, which allows for better public policy decision-making [53]. Furthermore, this study sets an important precedent for future research by demonstrating the feasibility of the SAE in the Ecuadorian context.

Limitations of the study, such as the lack of updated Living Conditions Survey (LCS) data, suggest the need for additional research to validate the results and explore new methodologies. It is recommended that future studies consider incorporating updated administrative data and conducting sensitivity analyses to assess the impact of the assumptions used in the projections [2]. The identification of vulnerable groups has been consolidated in this study, allowing for a better understanding of social and economic inequalities in Ecuador.

Emphasize the importance of replication of the method and its relevance in the field of social change. In a context of constant social and economic change, the SAE methodology offers a valuable tool for monitoring and evaluating the impact of public policies on child poverty reduction. Its replication in different geographical and social contexts can contribute to a better understanding of the dynamics of poverty and the identification of effective strategies to overcome it [8].

The SAE methodology provides accurate and reliable estimates of population variables at detailed geographical levels, which is essential for national socio-economic planning [89]. In the Ecuadorian context, the application of the SAE has made it possible to estimate consumption poverty at the district level between 2014 and 2030, facilitating the precise identification of populations requiring priority attention for the design of targeted public policies [86]. This analysis reveals considerable variability in consumption poverty levels between different regions, provinces, cantons and districts, highlighting the need for disaggregated data for efficient resource allocation [90]. Heterogeneity at the district level is particularly significant, and the availability of reliable data at this scale allows for better management of social inclusion programs [91]. In summary, the SAE methodology proves to be an effective tool for generating reliable estimates, even for small geographical areas, thus fulfilling a crucial need in public planning and management.

This study identifies, with great geographical precision, the most vulnerable population groups, which facilitates the efficient allocation of public resources for social assistance programs [92]. The integration of gender and ethnic perspectives is crucial for designing interventions that promote equity and social inclusion [93]. By applying econometric models to data from the 2014 Living Conditions Survey (LCS) and the 2010 Population Census, vulnerability estimates have been obtained at the district level, maximizing the use of available information [94]. The SAE methodology has proven to be a valuable **tool** for identifying unmet needs at the local level, enabling more informed and effective public decision-making [89]. The possibility of replicating this study periodically would allow for monitoring socio-economic evolution and adapting strategies to changing social realities [95].

The regression model employed shows a good fit in most geographical regions, with R^2 values generally above 0.60, indicating that the model explains more than 60% of the variability in consumption [96]. However, a less satisfactory fit is observed in some specific regions, such as Carchi and Guayas, suggesting the need for improvements or the incorporation of additional variables to optimize the model in these areas [97]. To improve the fit of the model in regions with R^2 values close to 0.60, it is recommended to explore the inclusion of additional explanatory variables or to re-evaluate the model specification. This could involve the consideration of region-specific socio-economic or geographical factors [98].

In regions with a limited number of observations, even if the R^2 is high, the uncertainty in the results can be considerable. In these cases, further data collection or the application of additional statistical techniques is recommended to strengthen the conclusions [99]. The model performs better in regions with higher R^2 values and a larger number of observations, such as Napo and Orellana, which increases the reliability of the results obtained in these areas. This contrast highlights the importance of data quality and quantity for the accuracy of econometric models [100]. The provinces of Napo and Chimborazo have a high prevalence of child poverty, which justifies the prioritization of resources and public policies in these regions. Targeted intervention is required to improve socio-economic and infrastructure conditions, with the aim of significantly reducing child poverty levels in these areas [101].

The high variability in poverty estimates in provinces such as Galápagos, Cañar and Zamora Chinchipe demands special attention. The lower precision of estimates in these areas suggests the need to improve the quality of data collection and the design of more targeted interventions to ensure a more reliable assessment of the situation and the effectiveness of implemented policies [102]. Despite having relatively moderate poverty rates (Guayas: 37.6%, Manabí: 53.1%, Pichincha: 25.1%), the provinces of Guayas, Manabí and Pichincha are home to a high number of children in poverty. This indicates that the implementation of programs aimed at this vulnerable population would have a significant impact on poverty reduction at the national level. It is crucial to develop and implement specific programs that address the particular needs of this population [103].

Provinces such as El Oro and Cañar, despite exhibiting low child poverty rates (18.5% and 15.2%, respectively), show high variability in their estimates, indicating considerable uncertainty in the data. It is essential to continue monitoring these provinces to confirm whether the low incidence of poverty is a real trend or an artefact of measurement imprecision. Rigorous monitoring will help determine the need for targeted interventions [58]. The formu10lation of effective child poverty reduction policies must consider not only the magnitude of the problem in each province, but also the quality and reliability of the available data. Prioritizing interventions based on accurate and reliable data is crucial to ensure that resources are allocated efficiently and that the strategies implemented are truly effective [104].

In order to enrich the comparative analysis and contextualize our findings, we have expanded the references section to include relevant international studies that have applied the SAE methodology in other contexts [105]. These studies address a variety of issues related to child poverty, such as the measurement of food insecurity, access to health and education services, and the impact of public policies on poverty reduction [106]. By examining this research, we can gain a broader perspective on the challenges and opportunities associated with implementing SAE in different geographical and socio-economic contexts, and adapt best practices to the Ecuadorian reality [107].

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Annexes

Table 3.

Estimation of consumption poverty parameters

ln_con	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
_cons	5,054579	0,1943018	26,01	0,0000	4,673738	5,435420
T_per	-0,1849809	0,004099	-45,13	0,0000	-0,1930151	-0,1769466
T_nn	0,1968746	0,0107344	18,34	0,0000	0,1758347	0,2179145
T_me	0,1011308	0,0057637	17,55	0,0000	0,0898337	0,1124279
T_am	-0,0602178	0,0076539	-7,87	0,0000	-0,0752198	-0,0452159
T_pcd	-0,064163	0,0067434	-9,51	0,0000	-0,0773804	-0,0509455
rat_dp	-0,5575776	0,0270586	-20,61	0,0000	-0,6106139	-0,5045413
p03	-0,0042259	0,0015088	-2,8	0,0050	-0,0071832	-0,0012685
edad2_	0,0000331	0,0000139	2,39	0,0170	5,94E-06	0,0000603
edad_p	0,0125164	0,0015418	8,12	0,0000	0,0094944	0,0155383
edad2_p	-0,0001247	0,0000134	-9,32	0,0000	-0,0001509	-0,0000985
rural	0,0212506	0,0074766	2,84	0,0040	0,0065961	0,0359052
p16_2	0,0929644	0,0144991	6,41	0,0000	0,0645455	0,1213832
p16_3	0,1053171	0,0151142	6,97	0,0000	0,0756924	0,1349418
p16_4	0,0987475	0,0092817	10,64	0,0000	0,0805549	0,11694
p16_5	0,1496131	0,0168492	8,88	0,0000	0,116588	0,1826383
mujer	-0,0398968	0,0086264	-4,62	0,0000	-0,056805	-0,0229886
nivel_2	0,0463438	0,0150709	3,08	0,0020	0,016804	0,0758836
nivel_3	0,1248864	0,0194194	6,43	0,0000	0,0868235	0,1629493
nivel_4	0,1692531	0,0170471	9,93	0,0000	0,1358399	0,2026662
nivel_5	0,2381168	0,0273787	8,7	0,0000	0,1844531	0,2917805
nivel_6	0,3887886	0,0177058	21,96	0,0000	0,3540843	0,423493
p34_2	-0,031441	0,0070084	-4,49	0,0000	-0,0451778	-0,0177042
p34_3	0,0290773	0,0112747	2,58	0,0100	0,0069783	0,0511762
p34_4	0,0906552	0,0154005	5,89	0,0000	0,0604695	0,1208409
p34_5	0,0514007	0,0122753	4,19	0,0000	0,0273404	0,075461
p34_6	-0,0121323	0,0115162	-1,05	0,2920	-0,0347047	0,01044
analfabeto	-0,063958	0,0126419	-5,06	0,0000	-0,0887368	-0,0391793
no_empleo	-0,0158142	0,008339	-1,9	0,0580	-0,0321591	0,0005306
migra_d	0,0422481	0,0081524	5,18	0,0000	0,0262689	0,0582272
vap_2	-0,0722079	0,0111353	-6,48	0,0000	-0,0940337	-0,050382
vap_3	-0,0586908	0,0064927	-9,04	0,0000	-0,0714168	-0,0459648
vap_4	-0,0938256	0,0105939	-8,86	0,0000	-0,1145902	-0,073061
vap_5	-0,0520068	0,0411179	-1,26	0,2060	-0,1325999	0,0285863
v09_2	0,0242875	0,0074351	3,27	0,0010	0,0097144	0,0388606
v09_3	-0,0393046	0,011603	-3,39	0,0010	-0,0620472	-0,0165621
v09_4	-0,0308275	0,0185361	-1,66	0,0960	-0,0671593	0,0055042
v09_5	-0,0369643	0,0129003	-2,87	0,0040	-0,0622495	-0,0116791
h01	0,0552463	0,0032684	16,9	0,0000	0,0488401	0,0616525
v08_2	-0,0914424	0,0073258	-12,48	0,0000	-0,1058013	-0,0770835
v08_3	-0,0396555	0,0264744	-1,5	0,1340	-0,0915467	0,0122356
v08_4	-0,1080225	0,0104776	-10,31	0,0000	-0,128559	-0,0874859
h04_2	-0,0503693	0,0129574	-3,89	0,0000	-0,0757663	-0,0249722
h04_3	-0,0933007	0,0085004	-10,98	0,0000	-0,1099619	-0,0766394
telef_f	0,125342	0,007444	16,84	0,0000	0,1107514	0,1399326
internet	0,1345116	0,0081625	16,48	0,0000	0,1185126	0,1505105
tvcable	0,177595	0,00684	25,96	0,0000	0,1641884	0,1910017
h15_3	0,0781627	0,0166848	4,68	0,0000	0,0454597	0,1108656
h15_4	0,0516225	0,0087074	5,93	0,0000	0,0345555	0,0686895
h15_5	0,0231404	0,0096073	2,41	0,0160	0,0043095	0,0419712
h15_6	0,0555352	0,0195722	2,84	0,0050	0,0171727	0,0938978
v12a	0,0252396	0,0008545	29,54	0,0000	0,0235647	0,0269146
te_ad	0,0254308	0,0211323	1,2	0,2290	-0,0159896	0,0668512
pa_ad	-0,0574557	0,0254689	-2,26	0,0240	-0,107376	-0,0075354
pi_ad	0,0507765	0,0120756	4,2	0,0000	0,0271077	0,0744453

vtv_2	0,0669437	0,0085981	7,79	0,0000	0,0500909	0,0837965
vtv_3	-0,0113254	0,0155061	-0,73	0,4650	-0,0417182	0,0190673
vtv_4	-0,0328144	0,0115216	-2,85	0,0040	-0,0553972	-0,0102316
vtv_5	-0,0803702	0,0277981	-2,89	0,0040	-0,1348559	-0,0258845
cocina_ex	0,0300794	0,0059608	5,05	0,0000	0,0183959	0,0417629
T_per_cl	-0,0773363	0,0203935	-3,79	0,0000	-0,1173087	-0,037364
T_nn_cl	0,1625616	0,0536592	3,03	0,0020	0,0573869	0,2677364
T_me_cl	-0,0034573	0,0282182	-0,12	0,9020	-0,0587665	0,0518518
T_am_cl	0,0593213	0,0449806	1,32	0,1870	-0,0288428	0,1474854
T_pcd_cl	-0,1433981	0,0350462	-4,09	0,0000	-0,2120905	-0,0747058
rat_dp_cl	-0,5178252	0,1589009	-3,26	0,0010	-0,8292788	-0,2063715
edad_p_cl	0,0075774	0,0097266	0,78	0,4360	-0,0114873	0,0266421
edad2_p_cl	-0,0002427	0,0000813	-2,99	0,0030	-0,000402	-0,0000834
p03_cl	-0,00767	0,0095427	-0,8	0,4220	-0,0263743	0,0110342
edad2__cl	0,0000665	0,0000851	0,78	0,4340	-0,0001003	0,0002334
mujer_cl	-0,111091	0,0342351	-3,24	0,0010	-0,1781936	-0,0439884
analfabeto_cl	0,1662323	0,0369349	4,5	0,0000	0,093838	0,2386265
no_empleo_cl	-0,0140697	0,0450944	-0,31	0,7550	-0,1024571	0,0743176
migra_d_cl	0,1869325	0,041368	4,52	0,0000	0,1058491	0,268016
h01_cl	-0,1104284	0,01241	-8,9	0,0000	-0,1347527	-0,0861041
telef_f_cl	0,1285071	0,0255726	5,03	0,0000	0,0783834	0,1786307
internet_cl	0,1339712	0,0407815	3,29	0,0010	0,0540374	0,213905
tvcable_cl	-0,0778569	0,0216295	-3,6	0,0000	-0,1202519	-0,035462
v12a_cl	0,0341016	0,0034544	9,87	0,0000	0,0273309	0,0408724
te_ad_cl	0,7739045	0,058824	13,16	0,0000	0,6586066	0,8892025
pa_ad_cl	-0,1189062	0,0333034	-3,57	0,0000	-0,1841826	-0,0536298
pi_ad_cl	-0,0504654	0,0288163	-1,75	0,0800	-0,1069468	0,0060159
cocina_ex_cl	-0,019565	0,017731	-1,1	0,2700	-0,0543185	0,0151886

Source: [15]

Table 4.

SCENARIO 1: Estimated consumption poverty of children aged 0-3 years, according to the methodology (SAE) up to 2030

Income elasticity of poverty reduction			-0,0887	-0,0887	-0,0887	-0,0887	-0,0887	-0,0887	-0,0887	-0,0887	-0,0887	-0,0887	-0,0887	-0,0887	-0,0887	-0,0887	-0,0887	-0,0887
Geographical Identifier	id	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
National	1	434.926	396.349	361.194	329.157	299.962	273.356	249.110	227.015	206.879	188.529	171.807	156.568	142.681	130.026	118.493	107.983	98.405
Esmeraldas, Imbabura, Carchi, Sucumbíos.	Z1	52.180	47.551	43.333	39.489	35.986	32.794	29.885	27.234	24.818	22.617	20.611	18.783	17.117	15.599	14.215	12.954	11.805
Pichincha (excepto el cantón Quito), Napo, Orellana	Z2	22.378	20.393	18.584	16.936	15.434	14.065	12.817	11.680	10.644	9.700	8.840	8.056	7.341	6.690	6.097	5.556	5.063
Cotopaxi, Tungurahua, Chimborazo, Pastaza	Z3	54.391	49.566	45.170	41.164	37.513	34.186	31.154	28.391	25.873	23.578	21.487	19.581	17.844	16.261	14.819	13.505	12.307
Manabí, Santo Domingo de los Tsáchilas	Z4	61.528	56.070	51.097	46.565	42.435	38.671	35.241	32.115	29.266	26.670	24.304	22.148	20.184	18.394	16.762	15.275	13.920
Santa Elena, Guayas (excepto los cantones de Guayaquil, Samborondón y Durán), Bolívar, Los Ríos y Galápagos	Z5	89.586	81.639	74.398	67.799	61.785	56.305	51.311	46.760	42.612	38.832	35.388	32.249	29.389	26.782	24.406	22.241	20.268
Cañar, Azuay, Morona Santiago.	Z6	29.512	26.894	24.509	22.335	20.354	18.549	16.904	15.405	14.039	12.794	11.659	10.625	9.683	8.824	8.041	7.328	6.678
El Oro, Loja, Zamora Chinchipe	Z7	26.193	23.869	21.752	19.823	18.065	16.463	15.003	13.672	12.459	11.354	10.347	9.429	8.593	7.831	7.136	6.503	5.926
Guayaquil, Samborondón y Durán	Z8	64.053	58.372	53.195	48.477	44.177	40.259	36.688	33.434	30.468	27.766	25.303	23.059	21.014	19.150	17.451	15.903	14.492
Distrito Metropolitano de Quito.	Z9	35.107	31.993	29.155	26.569	24.212	22.064	20.107	18.324	16.699	15.218	13.868	12.638	11.517	10.495	9.564	8.716	7.943
AZUAY	P01	20.734	18.895	17.219	15.692	14.300	13.032	11.876	10.823	9.863	8.988	8.191	7.464	6.802	6.199	5.649	5.148	4.691
BOLÍVAR	P02	8.078	7.362	6.709	6.114	5.572	5.078	4.628	4.218	3.844	3.503	3.192	2.909	2.651	2.416	2.202	2.007	1.829
CAÑAR	P03	2.635	2.401	2.188	1.994	1.817	1.656	1.509	1.375	1.253	1.142	1.041	949	865	788	718	654	596
CARCHI	P04	4.301	3.919	3.571	3.254	2.965	2.702	2.462	2.244	2.045	1.864	1.699	1.548	1.411	1.286	1.172	1.068	973
COTOPAXI	P05	13.494	12.297	11.206	10.212	9.306	8.481	7.729	7.043	6.418	5.849	5.330	4.857	4.426	4.033	3.675	3.349	3.052
CHIMBORAZO	P06	24.929	22.718	20.703	18.867	17.194	15.669	14.279	13.012	11.858	10.806	9.848	8.975	8.179	7.454	6.793	6.190	5.641
EL ORO	P07	7.867	7.169	6.533	5.954	5.426	4.945	4.506	4.106	3.742	3.410	3.108	2.832	2.581	2.352	2.143	1.953	1.780
ESMERALDAS	P08	25.358	23.108	21.058	19.190	17.488	15.937	14.523	13.235	12.061	10.991	10.016	9.128	8.318	7.580	6.908	6.295	5.737
GUAYAS	P09	99.474	90.651	82.610	75.283	68.606	62.521	56.976	51.922	47.317	43.120	39.295	35.810	32.634	29.739	27.101	24.697	22.506
IMBABURA	P10	16.440	14.982	13.653	12.442	11.338	10.332	9.416	8.581	7.820	7.126	6.494	5.918	5.393	4.915	4.479	4.082	3.720
LOJA	P11	13.794	12.570	11.455	10.439	9.513	8.669	7.900	7.199	6.560	5.978	5.448	4.965	4.525	4.124	3.758	3.425	3.121
LOS RÍOS	P12	28.339	25.826	23.535	21.447	19.545	17.811	16.231	14.791	13.479	12.283	11.194	10.201	9.296	8.471	7.720	7.035	6.411
MANABÍ	P13	51.156	46.619	42.484	38.716	35.282	32.153	29.301	26.702	24.334	22.176	20.209	18.417	16.783	15.294	13.937	12.701	11.574
MORONA SANTIAGO	P14	6.142	5.598	5.101	4.649	4.237	3.861	3.519	3.207	2.923	2.664	2.428	2.213	2.017	1.838	1.675	1.526	1.391
NAPO	P15	7.121	6.490	5.914	5.389	4.911	4.475	4.078	3.716	3.386	3.086	2.812	2.563	2.336	2.129	1.940	1.768	1.611
PASTAZA	P16	2.124	1.936	1.764	1.608	1.465	1.335	1.217	1.109	1.011	921	839	765	697	635	579	528	481
PICHINCHA	P17	46.329	42.220	38.475	35.062	31.952	29.118	26.535	24.181	22.036	20.081	18.300	16.677	15.198	13.850	12.622	11.502	10.482
TUNGURAHUA	P18	13.843	12.615	11.496	10.476	9.547	8.700	7.928	7.225	6.584	6.000	5.468	4.983	4.541	4.138	3.771	3.437	3.132

ZAMORA CHINCHIPE	P19	4.532	4.130	3.764	3.430	3.126	2.849	2.596	2.366	2.156	1.965	1.791	1.632	1.487	1.355	1.235	1.125	1.025
GALÁPAGOS	P20	20	18	16	15	14	13	12	11	10	9	8	7	6	5	5	5	5
SUCUMBÍOS	P21	6.081	5.542	5.050	4.602	4.194	3.822	3.483	3.174	2.892	2.635	2.401	2.188	1.994	1.817	1.656	1.509	1.375
ORELLANA	P22	4.035	3.677	3.351	3.054	2.783	2.536	2.311	2.106	1.919	1.749	1.594	1.453	1.324	1.207	1.100	1.002	913
SANTO DOMINGO DE LOS TSÁCHILAS	P23	10.371	9.451	8.613	7.849	7.153	6.519	5.941	5.414	4.934	4.496	4.097	3.734	3.403	3.101	2.826	2.575	2.347
SANTA ELENA	P24	17.726	16.154	14.721	13.415	12.225	11.141	10.153	9.252	8.431	7.683	7.002	6.381	5.815	5.299	4.829	4.401	4.011

Table 5.

SCENARIO 2: Estimated consumption poverty of children aged 0-3 years, according to the methodology (SAE) up to 2030

Income elasticity of poverty reduction			-0,0637	-0,0187	0,0359	-0,0828	-0,0318	-0,0318	-0,0318	-0,0630	-0,0329	-0,0164	-0,0164	-0,0164	-0,0164	-0,0164	-0,0164	-0,0164
Geographical Identifier	id	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
National	1	434.926	407.221	399.616	413.965	379.685	367.592	355.884	344.549	322.833	312.228	307.099	302.055	297.094	292.214	287.414	282.693	278.050
Esmeraldas, Imbabura, Carchi, Sucumbíos.	Z1	52.180	48.856	47.944	49.666	45.553	44.102	42.697	41.337	38.732	37.460	36.845	36.240	35.645	35.060	34.484	33.918	33.361
Pichincha (excepto el cantón Quito), Napo, Orellana	Z2	22.378	20.953	20.562	21.300	19.536	18.914	18.312	17.729	16.612	16.066	15.802	15.542	15.287	15.036	14.789	14.546	14.307
Cotopaxi, Tungurahua, Chimborazo, Pastaza	Z3	54.391	50.926	49.975	51.769	47.482	45.970	44.506	43.088	40.372	39.046	38.405	37.774	37.154	36.544	35.944	35.354	34.773
Manabí, Santo Domingo de los Tsáchilas	Z4	61.528	57.608	56.532	58.562	53.712	52.001	50.345	48.742	45.670	44.170	43.444	42.730	42.028	41.338	40.659	39.991	39.334
Santa Elena, Guayas (excepto los cantones de Guayaquil, Samborondón y Durán), Bolívar, Los Ríos y Galápagos	Z5	89.586	83.879	82.313	85.269	78.208	75.717	73.305	70.970	66.497	64.313	63.257	62.218	61.196	60.191	59.202	58.230	57.274
Cañar, Azuay, Morona Santiago.	Z6	29.512	27.632	27.116	28.090	25.764	24.943	24.149	23.380	21.906	21.186	20.838	20.496	20.159	19.828	19.502	19.182	18.867
El Oro, Loja, Zamora Chinchipe	Z7	26.193	24.524	24.066	24.930	22.866	22.138	21.433	20.750	19.442	18.803	18.494	18.190	17.891	17.597	17.308	17.024	16.744
Guayaquil, Samborondón y Durán	Z8	64.053	59.973	58.853	60.966	55.917	54.136	52.412	50.743	47.545	45.983	45.228	44.485	43.754	43.035	42.328	41.633	40.949
Distrito Metropolitano de Quito.	Z9	35.107	32.871	32.257	33.415	30.648	29.672	28.727	27.812	26.059	25.203	24.789	24.382	23.982	23.588	23.201	22.820	22.445
AZUAY	P01	20.734	19.413	19.050	19.734	18.100	17.524	16.966	16.426	15.391	14.885	14.641	14.401	14.164	13.931	13.702	13.477	13.256
BOLÍVAR	P02	8.078	7.564	7.423	7.690	7.053	6.828	6.611	6.400	5.997	5.800	5.705	5.611	5.519	5.428	5.339	5.251	5.165
CAÑAR	P03	2.635	2.467	2.421	2.508	2.300	2.227	2.156	2.087	1.955	1.891	1.860	1.829	1.799	1.769	1.740	1.711	1.683
CARCHI	P04	4.301	4.027	3.952	4.094	3.755	3.635	3.519	3.407	3.192	3.087	3.036	2.986	2.937	2.889	2.842	2.795	2.749
COTOPAXI	P05	13.494	12.634	12.398	12.843	11.779	11.404	11.041	10.689	10.015	9.686	9.527	9.371	9.217	9.066	8.917	8.771	8.627
CHIMBORAZO	P06	24.929	23.341	22.905	23.727	21.762	21.069	20.398	19.748	18.503	17.895	17.601	17.312	17.028	16.748	16.473	16.202	15.936
EL ORO	P07	7.867	7.366	7.228	7.488	6.868	6.649	6.437	6.232	5.839	5.647	5.554	5.463	5.373	5.285	5.198	5.113	5.029
ESMERALDAS	P08	25.358	23.742	23.299	24.136	22.137	21.432	20.749	20.088	18.822	18.204	17.905	17.611	17.322	17.037	16.757	16.482	16.211
GUAYAS	P09	99.474	93.138	91.399	94.681	86.840	84.074	81.396	78.804	73.837	71.411	70.238	69.084	67.949	66.833	65.735	64.655	63.593
IMBABURA	P10	16.440	15.393	15.106	15.648	14.352	13.895	13.452	13.024	12.203	11.802	11.608	11.417	11.229	11.045	10.864	10.686	10.510
LOJA	P11	13.794	12.915	12.674	13.129	12.042	11.658	11.287	10.928	10.239	9.903	9.740	9.580	9.423	9.268	9.116	8.966	8.819
LOS RÍOS	P12	28.339	26.534	26.038	26.973	24.739	23.951	23.188	22.449	21.034	20.343	20.009	19.680	19.357	19.039	18.726	18.418	18.115
MANABÍ	P13	51.156	47.898	47.004	48.692	44.660	43.238	41.861	40.528	37.974	36.727	36.124	35.531	34.947	34.373	33.808	33.253	32.707
MORONA SANTIAGO	P14	6.142	5.751	5.644	5.847	5.363	5.192	5.027	4.867	4.560	4.410	4.338	4.267	4.197	4.128	4.060	3.993	3.927
NAPO	P15	7.121	6.668	6.543	6.778	6.217	6.019	5.827	5.641	5.285	5.111	5.027	4.944	4.863	4.783	4.704	4.627	4.551
PASTAZA	P16	2.124	1.989	1.952	2.022	1.855	1.796	1.739	1.684	1.578	1.526	1.501	1.476	1.452	1.428	1.405	1.382	1.359
PICHINCHA	P17	46.329	43.378	42.568	44.096	40.444	39.156	37.909	36.702	34.389	33.259	32.713	32.176	31.647	31.127	30.616	30.113	29.618
TUNGURAHUA	P18	13.843	12.961	12.719	13.176	12.085	11.700	11.327	10.966	10.275	9.937	9.774	9.613	9.455	9.300	9.147	8.997	8.849
ZAMORA CHINCHIPE	P19	4.532	4.243	4.164	4.314	3.957	3.831	3.709	3.591	3.365	3.254	3.201	3.148	3.096	3.045	2.995	2.946	2.898
GALÁPAGOS	P20	20	19	19	20	18	17	16	15	14	14	14	14	14	14	14	14	14
SUCUMBÍOS	P21	6.081	5.694	5.588	5.789	5.310	5.141	4.977	4.818	4.514	4.366	4.294	4.223	4.154	4.086	4.019	3.953	3.888
ORELLANA	P22	4.035	3.778	3.707	3.840	3.522	3.410	3.301	3.196	2.995	2.897	2.849	2.802	2.756	2.711	2.666	2.622	2.579
SANTO DOMINGO DE LOS TSÁCHILAS	P23	10.371	9.711	9.530	9.872	9.055	8.767	8.488	8.218	7.700	7.447	7.325	7.205	7.087	6.971	6.856	6.743	6.632
SANTA ELENA	P24	17.726	16.597	16.287	16.872	15.475	14.982	14.505	14.043	13.158	12.726	12.517	12.311	12.109	11.910	11.714	11.522	11.333

Source: [15]

Table 6.

Estimation of consumption poverty of children aged 0-3 years, according to the methodology (SAE).

Geographical Identifier		Incidence (%)	Standard deviation (%)	Coefficient of variation (%)
1	National	41,1	1,03	2,54
1	Planning zone 1	53,9	1,20	2,23
2	Planning zone 2	47,7	1,70	3,58
3	Planning zone 3	53,1	1,53	2,89
4	Planning zone 4	48,0	2,54	5,28
5	Planning zone 5	50,3	1,71	3,39
6	Planning zone 6	35,2	2,70	7,69
7	Planning zone 7	31,6	2,59	8,21
8	Planning zone 8	33,6	2,72	8,10
9	Planning zone 9	22,3	1,95	8,75
1	Napo	81,3	4,23	11,15
6	Chimborazo	79,1	4,98	7,47
24	Santa Elena	67,4	3,18	22,72
2	Bolívar	66,1	3,54	9,42
5	Zamora Chinchipe	60,9	3,07	6,93
8	Esmeraldas	59,8	3,62	4,61
10	Imbabura	55,4	3,67	20,34
8	Morona Santiago	54,4	1,89	3,18
9	Manabí	53,1	2,67	7,16
10	Los Ríos	48,2	1,96	3,52
11	Sucumbíos	45,6	4,05	9,57
5	Cotopaxi	45,4	2,26	4,87
11	Loja	42,4	3,21	6,10
18	Tungurahua	40,6	2,56	4,67
1	Azuay	39,4	2,31	2,86
9	Guayas	37,6	4,34	12,27
4	Carchi	37,4	1,98	7,86
16	Pastaza	36,9	2,79	6,98
19	Orellana	36,3	6,06	9,66
23	Santo Domingo de los Tsáchilas	34,1	0,46	47,73
17	Pichincha	25,1	4,37	9,63
7	El Oro	18,5	4,09	11,55
3	Cañar	15,2	2,71	8,02
20	Galápagos	1,2	6,57	9,98
0101	Cuenca	32,6	3,72	11,43
0102	Girón	50,7	6,93	13,67
0103	Gualaceo	46,5	6,01	12,92
0104	Nabón	63,8	6,31	9,89
0105	Paute	46,3	5,89	12,73
0106	Pucara	62,4	8,13	13,02
0107	San Fernando	44,5	6,91	15,52
0108	Santa Isabel	46,4	5,57	12,01
0109	Sigsig	53,6	6,14	11,45

0110	Oña	69,4	7,18	10,35
0111	Chordeleg	42,7	5,95	13,93
0112	El Pan	48,1	9,82	20,39
0113	Sevilla de Oro	49,5	7,29	14,72
0114	Guachapala	38,8	10,65	27,49
0115	Camilo Ponce Enríquez	52,5	5,32	10,14
0201	Guaranda	67,1	4,40	6,56
0202	Chillanes	77,5	5,80	7,48
0203	Chimbo	65,5	5,99	9,16
0204	Echeandía	63,7	6,16	9,68
0205	San Miguel	64,2	5,79	9,01
0206	Caluma	57,3	6,84	11,94
0207	Las Naves	70,5	6,75	9,58
0301	Azogues	6,7	2,79	41,73
0302	Biblián	4,8	2,93	60,87
0303	Cañar	28,7	3,77	13,14
0304	La Troncal	10,2	4,40	42,96
0305	El Tambo	21,1	4,46	21,12
0306	Deleg	6,0	3,23	53,37
0307	Suscal	26,7	7,18	26,91
0401	Tulcán	30,2	3,79	12,54
0402	Bolívar	52,6	4,99	9,50
0403	Espejo	40,9	4,98	12,16
0404	Mira	54,3	4,44	8,18
0405	Montufar	45,9	4,18	9,10
0406	San Pedro de Huaca	28,2	5,71	20,26
0501	Latacunga	37,3	2,66	7,13
0502	La Maná	45,4	3,51	7,73
0503	Pangua	57,1	4,23	7,41
0504	Pujilí	51,7	4,99	9,66
0505	Salcedo	40,8	3,11	7,63
0506	Saquisilí	49,9	3,92	7,86
0507	Sigchos	61,6	5,05	8,20
0601	Riobamba	68,3	5,03	7,37
0602	Alausí	86,5	2,66	3,07
0603	Colta	95,5	1,80	1,88
0604	Chambo	78,8	4,23	5,37
0605	Chunchi	75,1	6,34	8,44
0606	Guamote	97,8	1,41	1,44
0607	Guano	84,5	3,99	4,72
0608	Pallatanga	84,4	3,90	4,62
0609	Penipe	79,1	6,19	7,82
0610	Cumanda	76,9	6,32	8,22
0701	Machala	14,5	3,35	23,15
0702	Arenillas	22,6	4,23	18,74
0703	Atahualpa	14,5	5,07	35,07
0704	Balsas	20,1	4,99	24,78

0705	Chilla	31,4	8,78	27,94
0706	El Guabo	27,1	4,28	15,76
0707	Huaquillas	16,8	3,90	23,26
0708	Marcabelí	26,6	5,57	20,91
0709	Pasaje	21,7	3,91	18,05
0710	Piñas	12,0	4,32	36,00
0711	Portovelo	20,1	4,69	23,35
0712	Santa Rosa	18,1	4,01	22,16
0713	Zaruma	19,9	5,28	26,48
0714	Las Lajas	22,6	6,05	26,81
0801	Esmeraldas	47,9	2,15	4,48
0802	Eloy Alfaro	73,3	2,77	3,78
0803	Muisne	75,1	2,95	3,92
0804	Quinindé	65,6	2,17	3,31
0805	San Lorenzo	62,5	3,22	5,15
0806	Atacames	59,1	2,70	4,58
0807	Rioverde	78,5	2,60	3,31
2302	La Concordia (*)	57,5	2,96	5,15
0901	Guayaquil	33,6	2,80	8,32
0902	Alfredo Baquerizo Moreno	57,9	3,92	6,77
0903	Balao	47,5	4,63	9,74
0904	Balzar	50,4	3,50	6,94
0905	Colimes	55,5	4,10	7,39
0906	Daule	37,0	2,29	6,19
0907	Duran	35,1	2,69	7,67
0908	Empalme	56,8	3,41	6,00
0909	El Triunfo	48,2	3,11	6,47
0910	Milagro	41,7	2,98	7,14
0911	Naranjal	48,2	3,28	6,80
0912	Naranjito	47,7	3,35	7,02
0913	Palestina	48,7	3,48	7,15
0914	Pedro Carbo	42,4	4,00	9,44
0916	Samborondón	26,3	1,91	7,26
0918	Santa Lucía	47,6	4,24	8,92
0919	Salitre	55,4	3,96	7,15
0920	San Jacinto de Yaguachi	47,8	3,21	6,72
0921	Playas	37,1	4,68	12,62
0922	Simón Bolívar	52,2	3,82	7,32
0923	Coronel Marcelino Maridueña	42,9	3,17	7,38
0924	Lomas de Sargentillo	39,2	4,32	11,03
0925	Nobol	44,9	4,01	8,92
0927	General Antonio Elizalde	45,7	2,99	6,54
0928	Isidro Ayora	42,9	4,12	9,60
1001	Ibarra	39,3	1,89	4,80
1002	Antonio Ante	52,7	2,06	3,91
1003	Cotacachi	74,6	2,49	3,34
1004	Otavalo	69,6	2,51	3,60

1005	Pimampiro	70,3	2,66	3,78
1006	San Miguel de Urcuquí	79,0	3,09	3,91
1101	Loja	29,3	3,88	13,26
1102	Calvas	49,3	4,50	9,14
1103	Catamayo	43,3	5,45	12,58
1104	Celica	51,7	4,73	9,15
1105	Chaguarpamba	59,5	5,07	8,52
1106	Espíndola	68,7	4,51	6,56
1107	Gonzanama	62,1	4,99	8,04
1108	Macara	42,6	5,02	11,78
1109	Paltas	58,3	4,05	6,96
1110	Puyango	52,7	5,00	9,48
1111	Saraguro	61,9	4,83	7,79
1112	Sozoranga	67,0	5,53	8,26
1113	Zapotillo	61,6	5,44	8,83
1114	Pindal	56,0	4,83	8,62
1115	Quilanga	59,4	5,75	9,68
1116	Olmedo	67,6	5,77	8,54
1201	Babahoyo	40,5	2,52	6,21
1202	Baba	55,0	2,69	4,89
1203	Montalvo	40,0	2,77	6,92
1204	Puebloviejo	47,5	3,20	6,75
1205	Quevedo	40,4	2,64	6,53
1206	Urdaneta	45,7	2,76	6,03
1207	Ventanas	43,7	2,85	6,53
1208	Vinces	48,7	2,44	5,01
1209	Palenque	61,7	2,74	4,44
1210	Buena Fe	52,6	2,96	5,62
1211	Valencia	56,1	2,90	5,18
1212	Mocache	57,6	2,50	4,34
1213	Quinsaloma	53,6	2,53	4,71
1301	Portoviejo	43,3	3,65	8,43
1302	Bolívar	59,3	2,90	4,89
1303	Chone	55,7	2,82	5,06
1304	El Carmen	47,8	3,56	7,46
1305	Flavio Alfaro	58,8	3,85	6,54
1306	Jipijapa	65,7	4,86	7,41
1307	Junín	63,5	4,02	6,33
1308	Manta	38,8	3,30	8,50
1309	Montecristi	50,0	5,85	11,69
1310	Paján	71,4	3,56	4,99
1311	Pichincha	64,8	3,39	5,23
1312	Rocafuerte	48,9	4,43	9,07
1313	Santa Ana	68,0	3,01	4,42
1314	Sucre	57,2	4,10	7,16
1315	Tosagua	56,9	3,96	6,97
1316	24 de Mayo	75,6	2,98	3,94

1317	Pedernales	63,1	3,25	5,15
1318	Olmedo	73,8	3,00	4,06
1319	Puerto López	63,0	5,45	8,66
1320	Jama	75,9	4,12	5,42
1321	Jaramijó	57,3	6,86	11,97
1322	San Vicente	55,5	4,70	8,46
1401	Morona	47,1	3,38	7,17
1402	Gualaquiza	50,5	2,47	4,89
1403	Limón Indanza	53,3	2,87	5,39
1404	Palora	56,0	3,25	5,81
1405	Santiago	59,5	3,64	6,12
1406	Sucúa	34,9	3,94	11,29
1407	Huamboya	86,7	2,91	3,36
1408	San Juan Bosco	51,7	4,11	7,96
1409	Taisha	87,5	2,38	2,72
1410	Logroño	68,9	3,57	5,18
1411	Pablo Sexto	59,7	5,48	9,19
1412	Tiwintza	77,0	2,72	3,53
1501	Tena	77,8	2,18	2,80
1503	Archidona	89,7	2,10	2,34
1504	El Chaco	77,9	5,17	6,64
1507	Quijos	68,0	5,37	7,89
1509	Carlos Julio Arosemena Tola	92,7	3,43	3,70
1601	Pastaza	35,2	4,23	12,03
1602	Mera	30,4	4,34	14,29
1603	Santa Clara	44,1	6,41	14,55
1604	Arajuno	47,3	8,31	17,56
1701	Quito	22,3	1,95	8,75
1702	Cayambe	53,3	2,73	5,13
1703	Mejía	35,5	3,07	8,65
1704	Pedro Moncayo	51,1	3,35	6,56
1705	Rumiñahui	21,8	1,96	9,00
1707	San Miguel de los Bancos	53,0	4,41	8,31
1708	Pedro Vicente Maldonado	49,9	3,92	7,85
1709	Puerto Quito	55,0	3,74	6,81
1801	Ambato	38,2	2,56	6,70
1802	Baños de Agua Santa	26,7	2,98	11,16
1803	Cevallos	31,0	4,00	12,89
1804	Mocha	39,2	5,16	13,16
1805	Patate	48,1	3,65	7,58
1806	Quero	52,3	4,79	9,15
1807	San Pedro de Pelileo	45,1	3,86	8,55
1808	Santiago de Pillaro	45,4	3,81	8,40
1809	Tisaleo	44,5	4,25	9,56
1901	Zamora	53,4	6,62	12,39
1902	Chinchipe	61,2	9,14	14,92
1903	Nangaritza	81,2	5,83	7,18

1904	Yacuambi	71,8	6,39	8,90
1905	Yantzaza	65,1	5,91	9,08
1906	El Pangui	60,4	4,84	8,02
1907	Centinela del Cóndor	59,9	5,98	9,99
1908	Palanda	65,1	9,07	13,93
1909	Paquisha	74,4	9,19	12,35
2001	San Cristóbal	0,3	0,33	131,97
2002	Isabela	0,6	0,85	145,36
2003	Santa Cruz	1,4	0,68	48,17
2101	Lago Agrio	40,7	4,63	11,39
2102	Gonzalo Pizarro	43,1	5,03	11,66
2103	Putumayo	63,0	4,84	7,69
2104	Shushufindi	47,8	4,48	9,36
2105	Sucumbíos	35,7	5,97	16,72
2106	Cascales	56,5	5,30	9,37
2107	Cuyabeno	59,6	5,40	9,05
2201	Orellana	27,5	4,38	15,95
2202	Aguarico	69,2	4,59	6,64
2203	La Joya de los Sachas	32,6	4,81	14,74
2204	Loreto	63,3	3,66	5,78
2301	Santo Domingo	33,8	2,71	8,02
2401	Santa Elena	66,7	6,63	9,94
2402	La Libertad	64,2	7,55	11,76
2403	Salinas	66,6	6,05	9,08
9901	Las Golondrinas (**)	65,6	2,17	3,31
9903	Manga del Cura (**)	47,8	3,56	7,46
9904	El Piedrero (**)	48,2	3,11	6,47
01D01	01D01	31,5	3,86	12,25
01D02	01D02	33,5	3,63	10,83
01D03	01D03	51,1	6,28	12,30
01D04	01D04	45,7	5,91	12,94
01D05	01D05	64,9	6,30	9,71
01D06	01D06	46,3	6,47	13,97
01D07	01D07	52,5	5,32	10,14
01D08	01D08	53,6	6,14	11,45
02D01	02D01	67,1	4,40	6,56
02D02	02D02	77,5	5,80	7,48
02D03	02D03	64,7	5,79	8,94
02D04	02D04	62,1	6,32	10,19
03D01	03D01	6,2	2,72	43,68
03D02	03D02	27,6	3,85	13,95
03D03	03D03	10,2	4,40	42,96
04D01	04D01	30,1	3,86	12,84
04D02	04D02	48,0	3,93	8,19
04D03	04D03	46,9	4,45	9,49
05D01	05D01	37,3	2,66	7,13
05D02	05D02	45,4	3,51	7,73

05D03	05D03	57,1	4,23	7,41
05D04	05D04	51,2	4,61	9,01
05D05	05D05	61,6	5,05	8,20
05D06	05D06	40,8	3,11	7,63
06D01	06D01	68,8	4,95	7,19
06D02	06D02	83,9	3,45	4,11
06D03	06D03	80,3	5,08	6,32
06D04	06D04	96,9	1,44	1,49
06D05	06D05	83,8	4,11	4,91
07D01	07D01	24,3	4,00	16,49
07D02	07D02	14,5	3,35	23,15
07D03	07D03	19,3	4,74	24,58
07D04	07D04	15,9	4,26	26,87
07D05	07D05	19,0	3,87	20,37
07D06	07D06	18,1	4,01	22,16
08D01	08D01	47,9	2,15	4,48
08D02	08D02	73,3	2,77	3,78
08D03	08D03	65,0	2,46	3,79
08D04	08D04	65,6	2,17	3,31
08D05	08D05	62,5	3,22	5,15
08D06	08D06	78,5	2,60	3,31
08D07	08D07	57,5	2,96	5,15
09D01	09D01	32,9	2,70	8,20
09D02	09D02	35,2	2,87	8,15
09D03	09D03	24,6	2,54	10,31
09D04	09D04	32,7	2,87	8,79
09D05	09D05	11,6	1,47	12,65
09D06	09D06	27,4	2,68	9,77
09D07	09D07	32,8	2,84	8,65
09D08	09D08	51,4	3,80	7,39
09D09	09D09	18,3	1,64	8,99
09D10	09D10	47,3	4,53	9,56
09D11	09D11	55,0	3,64	6,62
09D12	09D12	48,0	3,54	7,37
09D13	09D13	51,3	3,39	6,61
09D14	09D14	41,7	3,91	9,37
09D15	09D15	56,8	3,41	6,00
09D16	09D16	47,7	2,98	6,26
09D17	09D17	41,7	2,98	7,14
09D18	09D18	46,6	3,14	6,73
09D19	09D19	40,1	2,76	6,89
09D20	09D20	55,4	3,96	7,15
09D21	09D21	47,8	3,21	6,72
09D22	09D22	37,1	4,68	12,62
09D23	09D23	26,3	1,91	7,26
09D24	09D24	35,1	2,69	7,67
10D01	10D01	44,4	1,85	4,17

10D02	10D02	64,8	2,27	3,51
10D03	10D03	74,6	2,49	3,34
11D01	11D01	29,3	3,88	13,26
11D02	11D02	48,2	5,15	10,69
11D03	11D03	58,3	4,05	6,96
11D04	11D04	53,0	4,59	8,65
11D05	11D05	68,7	4,51	6,56
11D06	11D06	53,3	4,51	8,46
11D07	11D07	50,0	4,92	9,84
11D08	11D08	61,9	4,83	7,79
11D09	11D09	61,6	5,44	8,83
12D01	12D01	43,2	2,37	5,48
12D02	12D02	46,8	2,81	6,02
12D03	12D03	43,5	2,41	5,55
12D04	12D04	45,7	2,64	5,78
12D05	12D05	51,8	2,36	4,55
12D06	12D06	54,0	2,83	5,24
13D01	13D01	43,4	3,66	8,43
13D02	13D02	42,7	3,95	9,25
13D03	13D03	64,9	4,90	7,55
13D04	13D04	71,1	2,80	3,94
13D05	13D05	47,8	3,56	7,46
13D06	13D06	60,7	3,09	5,10
13D07	13D07	56,2	2,88	5,13
13D08	13D08	64,8	3,39	5,23
13D09	13D09	71,4	3,56	4,99
13D10	13D10	66,9	3,27	4,88
13D11	13D11	56,8	4,18	7,36
13D12	13D12	52,9	4,03	7,61
14D01	14D01	47,1	3,38	7,17
14D02	14D02	71,7	2,59	3,61
14D03	14D03	41,7	3,57	8,56
14D04	14D04	50,7	2,57	5,07
14D05	14D05	87,5	2,38	2,72
14D06	14D06	60,0	2,65	4,41
15D01	15D01	81,8	2,05	2,51
15D02	15D02	73,8	5,03	6,81
16D01	16D01	34,7	4,19	12,08
16D02	16D02	47,3	8,31	17,56
17D01	17D01	47,0	3,73	7,95
17D02	17D02	22,2	2,75	12,37
17D03	17D03	23,1	1,92	8,32
17D04	17D04	24,2	2,09	8,65
17D05	17D05	16,4	1,51	9,24
17D06	17D06	18,6	1,88	10,13
17D07	17D07	26,2	2,27	8,67
17D08	17D08	24,1	2,15	8,91

17D09	17D09	26,8	2,40	8,98
17D10	17D10	52,6	2,83	5,38
17D11	17D11	29,0	2,44	8,40
17D12	17D12	52,9	3,65	6,89
18D01	18D01	40,9	2,42	5,92
18D02	18D02	36,2	2,72	7,52
18D03	18D03	26,7	2,98	11,16
18D04	18D04	45,7	3,72	8,14
18D05	18D05	45,4	3,81	8,40
18D06	18D06	44,6	4,15	9,30
19D01	19D01	57,0	6,11	10,71
19D02	19D02	70,6	6,26	8,87
19D03	19D03	63,3	8,86	14,01
19D04	19D04	63,7	5,44	8,54
20D01	20D01	1,0	0,46	47,73
21D01	21D01	48,0	4,58	9,53
21D02	21D02	40,7	4,63	11,39
21D03	21D03	61,5	4,86	7,91
21D04	21D04	47,8	4,48	9,36
22D01	22D01	32,6	4,81	14,74
22D02	22D02	35,2	4,02	11,43
22D03	22D03	69,2	4,59	6,64
23D01	23D01	31,9	2,70	8,46
23D02	23D02	35,9	2,78	7,76
23D03	23D03	57,5	2,96	5,15
24D01	24D01	66,7	6,63	9,94
24D02	24D02	65,2	6,67	10,23

(*) Updated code

(**) Aggregates, value of nearby locality is assumed.

Source: [15]