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DISAGGREGATING DATA FOR DEVELOPMENT: A COST-EFFECTIVE APPROACH TO SDG INDICATORS 2.1.2, 2.3.1 AND 2.3.2 IN LATIN AMERICA USING SMALL AREA ESTIMATION

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Abstract

This paper presents the experience of the Food and Agriculture Organization of the United Nations (FAO) in providing technical assistance to four countries in Latin America – Brazil, Chile, Colombia and Ecuador – to produce small area estimates for three Sustainable Development Goal (SDG) indicators: SDG Indicator 2.1.2, on the prevalence of moderate and severe food insecurity in the population based on the Food Insecurity Experience Scale (FIES); SDG Indicator 2.3.1, measuring the average value of agricultural production per labour unit; and SDG Indicator 2.3.2, on the average income of small-scale food producers.

The paper describes the methodological details and results of the case studies developed, showing how small area estimation can be used to increase the precision of estimates at the subnational level and produce predictions in estimation domains excluded from the sample. It discusses the policy implications of having SDG estimates at the subnational level, and how countries can use this information to formulate programmes and allocate funds. The paper concludes with recommendations on how small area estimation can be incorporated in the processes implemented at the national level to produce agriculture and food security statistics.

Contents

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Abbreviations

AIC	Akaike information criteria
CASEN	National Socioeconomic Characterization Survey (Chile)
CML	conditional maximum likelihood
CV	coefficient of variation
DANE	National Administrative Department of Statistics (Colombia)
DF	degree of freedom
EBLUP	empirical best linear unbiased predictor
ECLAC	United Nations Economic Commission for Latin America and the Caribbean
ECV	National Survey on the Quality of Life (Colombia)
ESPAC	Annual Agricultural Area and Production Survey (Ecuador)
FAO	Food and Agriculture Organization of the United Nations
FH	Fay-Herriot model
FIES	Food Insecurity Experience Scale
FIES-SM	Food Insecurity Experience Scale – Survey Module
GWP	Gallup© World Poll
INEC	National Institute of Statistics and Census (Ecuador)
LNOB	leave no one behind
MDG	Millennium Development Goal
MSDF	Ministry of Social Development and Family (Chile)
MSE	mean square error
NSO	National Statistical Office
NSS	national statistical system
PSU	primary sampling unit
SAE	small area estimation
SDG	Sustainable Development Goal

1 Introduction

Building on lessons of the Millennium Development Goals (MDGs), the 2030 Agenda for Sustainable Development puts at its heart the commitment to leave no one behind (LNOB) and reach those who are furthest behind first. The LNOB principle is not merely a rhetorical flourish but serves as the guiding ethos permeating the 2030 Agenda's definitions of goals and targets. Its essence underscores the overarching aspiration for the benefits of global development to reach every stratum of society. This steadfast commitment underscores the imperative of inclusivity, particularly for vulnerable and marginalized groups, in the pursuit of development that is both equitable and sustainable.

Furthermore, the 2030 Agenda introduces an ambitious monitoring framework comprising over 230 Sustainable Development Goal (SDG) indicators distributed across the 17 goals. Each indicator, where applicable, includes a disaggregation list aimed at tracking disparities in progress among various social and demographic groups. While this reflects a laudable aspiration and an idealistic objective, it imposes significant financial and technical burdens on national data providers, such as National Statistical Offices (NSOs) and line ministries.

In this regard, building on various attempts to estimate the cost of monitoring the SDG indicators, Open Data Watch estimated in 2016 a total price tag of USD 33.5–45.3 billion to adequately expand survey, census and administrative data systems in 144 low- and middle-income countries. Considering national budgets and donor expenditures at the time of the study, the paper concluded that to measure only Tier 1 and 2 indicators (those with available data), an additional yearly investment of USD 635–685 million would be needed from donors and national governments to close the gap (Open Data Watch, 2016).

Notably, this price tag likely underestimates the cost of measuring SDG indicators at the disaggregated level required by the LNOB principle. In fact, the 2030 Agenda indicator framework recommends disaggregating by income, sex, age, race, ethnicity, migration status, disability, geographic location and other relevant dimensions. Having reliable data disaggregated by these dimensions would facilitate better targeted decision-making, as it enables identifying certain sociodemographic groups that may not be benefiting from positive developments or specific projects and policies. However, generating reliable estimates for each of these subpopulation groups, in the context of statistics generated through sample surveys, would place a large financial burden on data providers since substantial increases in sample sizes would be needed (Asian Development Bank, 2020).

Typical survey operations use sampling strategies to obtain the most precise estimates possible for a key set of target variables in planned estimation domains given a predefined budget constraint. This produces very accurate and precise estimates at the national level or in other broad disaggregation domains identified at the sampling design stage. However, any further disaggregation may reduce the precision of the estimates and the reliability of the results. A traditional approach to improve the precision of these estimates is to increase the number of sampling units in the considered disaggregation domain. However, many data producers do not have the financial resources to increase sample sizes, and trying to optimize for very specific domains can complicate survey implementation. Finally, some important disaggregation requirement may not be known at the sample design stage, only to be identified after the survey is implemented.

One possible solution proposed by international development agencies and national statistical offices to produce disaggregated indicators without increasing sample sizes is the adoption of indirect estimation techniques, such as small area estimation (SAE). In a nutshell, SAE is a model-based estimation approach that combines data from multiple sources to increase the precision and reliability of survey estimates in “small areas”, which are any disaggregation dimensions (i.e. domains identified by geographical areas or specific population groups) where direct estimators do not reach a prespecified level of precision due to limited sampling size. SAE combines the data from the survey with auxiliary data at the individual or area level. Auxiliary data can come from any source that is not affected by sampling error, such as censuses, administrative records, geographic information systems, and any other data source providing variables for the entire target population. SAE is therefore more cost-effective than increasing sample sizes.

Recent efforts by international organizations to support countries in applying SAE techniques include technical assistance and research efforts by the United Nations Economic Commission for Latin America and the Caribbean (ECLAC) to generate detailed poverty statistics and maps (Molina, 2022). The World Bank also developed SAE models using auxiliary data sources, such as census data, mobile/smartphone/ connectivity data, call records and night-time light intensity to develop granular poverty data (Ziulu *et al.*, 2022). The National Agricultural Statistics Service of the United States Department of Agriculture (USDA) applied SAE models to generate county level estimates for farm labour, crop area and other variables (Young and Chen, 2022).

The objective of this paper is to share FAO’s experience in Latin America supporting four countries (Brazil, Chile, Colombia and Ecuador) in applying SAE techniques to produce disaggregated data for three SDG indicators: SDG Indicator 2.1.2, on the prevalence of moderate or severe food insecurity in the population based on the Food Insecurity Experience Scale (FIES); SDG Indicator 2.3.1, measuring the average value of production per labour unit; and SDG Indicator 2.3.2, on the average income of small-scale food producers. The aim is not only to explain the methodological aspects and lessons learned, but also to describe the policy application and use of more granular data in the targeted countries.

This paper is divided into three further chapters. Chapter 2 focuses on SDG Indicator 2.1.2, its methodology and the adaptations made to calculate its variance that were needed for the SAE model, and describes the methodological process, the results and lessons learned in Chile and Colombia. Chapter 3 looks at SDG Indicators 2.3.1 and 2.3.2 and describes the examples of Ecuador (which developed an SAE model) and Brazil (based on an agricultural census using direct estimation), their methodological processes, results and lessons learned. Finally, Chapter 4 provides a summary of this paper’s findings and recommendations.

2 SDG Indicator 2.1.2: prevalence of moderate and severe food insecurity in the population

2.1 Introduction

Target 2.1 of the 2030 Agenda for Sustainable Development seeks to end hunger and ensure access by all, in particular the poor and people in vulnerable situations, to safe, nutritious, and sufficient food all year round. The target is monitored by two indicators under FAO custodianship, providing complementary information on the difficulties that households and individuals face in accessing food: SDG Indicator 2.1.1, measuring the prevalence of undernourishment, and SDG Indicator 2.1.2, monitoring the prevalence of moderate and severe food insecurity. Notably, SDG Indicator 2.1.2 provides a measure of the physical and economic access to food as experienced by individuals or households.

The severity of food insecurity is measured using data collected with the Food Insecurity Experience Scale Survey Module (FIES-SM), which is a set of eight questions asking respondents to self-report conditions and experiences typically associated with limited access to food (Figure 1). The module can be included in nationally representative household or individual surveys. For annual monitoring, the questions refer to the 12 months preceding the interview (but other reference periods can be used for different purposes).[1] The analytical protocol of FIES data involves statistical techniques based on the Rasch measurement model (Rasch, 1980): the information obtained with the FIES-SM is validated for internal consistency and converted into a quantitative measure along a scale of severity ranging from low to high. Based on their responses, interviewed households or individuals are assigned a probability of being either moderately or severely food insecure, as defined by two globally set thresholds.

Figure 1. Food Insecurity Experience Scale survey module (FIES-SM) at the individual level, using a 12-month reference period, for SDG monitoring

Q1. During the last 12 months, was there a time when you were worried you would not have enough food to eat because of a lack of money or other resources?	0 No 1 Yes	98 Don’t know 99 Refused
Q2. Still thinking about the last 12 months, was there a time when you were unable to eat healthy and nutritious food because of a lack of money or other resources?	0 No 1 Yes	98 Don’t know 99 Refused
Q3. During the last 12 months, was there a time when you ate only a few kinds of foods because of a lack of money or other resources?	0 No 1 Yes	98 Don’t know 99 Refused
Q4. During the last 12 months, was there a time when you had to skip a meal because there was not enough money or other resources to get food?	0 No 1 Yes	98 Don’t know 99 Refused
Q5. Still thinking about the last 12 months, was there a time when you ate less than you thought you should because of a lack of money or other resources?	0 No 1 Yes	98 Don’t know 99 Refused
Q6. In the past 12 months, was there a time when your household ran out of food because of a lack of money or other resources?	0 No 1 Yes	98 Don’t know 99 Refused
Q7. In the past 12 months, was there a time when you were hungry but did not eat because of a lack of money or other resources for food?	0 No 1 Yes	98 Don’t know 99 Refused
Q8. During the last 12 months, was there a time when you went without eating for a whole day because of a lack of money or other resources?	0 No 1 Yes	98 Don’t know 99 Refused

Source: FAO. 2016. *Global Food Insecurity Experience Scale Survey Modules*. Rome. https://openknowledge.fao.org/handle/20.500.14283/bl404e

[1] For examples of FIES modules with different recall periods, see https://openknowledge.fao.org/handle/20.500.14283/bl404e

2.1.1 Preferred data sources for SDG monitoring

By proposing the FIES as the basis to monitor progress toward SDG Target 2.1, FAO expects that national values for the prevalence of food insecurity will eventually be based on data from national surveys conducted by NSOs, in accordance with the principles that govern the definition of the global SDG indicator framework by the United Nations Statistical Commission.

So far, survey data from national governments were used to calculate the food insecurity prevalence estimates for 70 countries covering one-third of the world population. In Latin America and the Caribbean only, the official food insecurity assessment is informed by data collected by national institutions in 15 countries.

To ensure that the results are comparable across countries, however, it was necessary to process data obtained from as large a set of countries as possible while controlling for the survey vehicle used. To that aim, FAO contracted the Gallup Organization as service provider for data collection in 2013. The FIES-SM was then added as a client module to the Gallup© World Poll (GWP) and data have been collected in 153 countries and territories since 2014.[2] FIES data collected by FAO through the GWP, along with other data service providers, are used to inform the official food insecurity statistics when no other data are available from the countries, and in agreement with national institutions.[3]

2.1.2 Methodology used for direct estimation

The FIES data collected are validated and used to build a scale of food insecurity severity based on the Rasch model, which postulates that the probability of observing an positive answer (coded as 1) by respondent h to question j is a logistic function of the distance, on an underlying scale of severity, between the position a_h of the respondent and that of the item, b_j. In symbols:

$$Prob\left(X_{h,j} = 1\right) = \frac{exp\left(a_h - b_j\right)}{1 + exp\left(a_h - b_j\right)} \tag{2.1}$$

Testing adherence of the data to the Rasch model assumptions is essential, as only measures obtained with data that do not reject the Rasch model's assumption can be considered invariant with respect to the specific sample of respondents used to estimate the parameters of the model, which is an important feature of a globally valid measurement tool (Cafiero *et al.*, 2017).

Conditional maximum likelihood methods (CML) (Fischer and Molenaar, 1995) are used to estimate the severity of each item and the severity experienced by each respondent, and calculate item- and respondent-fit statistics, conditional correlations across items, and the measurement reliability of the scale. A customized R-package (Viviani *et al.*, 2018) implements Rasch model estimation and also allows for complex survey design, producing several additional statistics that are useful to analyse FIES data. The package produces estimates of item severity parameters by maximizing the likelihood function conditional on the raw score, and using, in the estimating process, only cases with non-extreme response patterns (that is, with the raw score between 1 and 7). Respondent severity parameters are then estimated by

[2] The GWP is a worldwide survey conducted annually since 2006 in about 150 countries, interviewing nationally representative samples of the adult population (aged 15 and older). It covers a range of topics, including family economics, employment, human development and well-being.

[3] FIES microdata files collected through the GWP are disseminated by FAO as licensed files through the Food and Agriculture Microdata Catalogue.

maximizing the likelihood function given the item parameters. Finally, the standard error of the respondents' severity parameters is measured as the square root of the inverse of the slope of the test characteristic curve at the point corresponding to the raw score parameter (or the inverse of the square root of the Fisher information matrix).

Because of the CML estimation method for the item parameters, each respondent h with the same raw score k $(k = 0, \dots, 8)$ is located on the latent trait in the same position, given by the estimate of the raw score parameter.

However, to account for possible misclassification[4] and measurement errors, an additional assumption is included, leading to the "probabilistic assignment". Specifically, it is assumed that the true severity Y_k of a respondent with raw score k and position $\hat{a}_k$ is given by:

$$Y_k \sim N(\hat{a}_k; se(\hat{a}_k))$$

This probability distribution is used to assign – to all n_k respondents h with raw score k – the same probability $\hat{y}_{h,L}$ of being food insecure above a certain threshold L.

After the application of the Rasch model to the FIES data, it is possible to estimate the cross-country comparable probability of being food insecure at each level of severity of food insecurity $\hat{\bar{Y}}_L$, i.e. at moderate or severe, or severe only, for each respondent h.

In this context, the prevalence of food insecurity at each level of severity ($\bar{Y}_L$) in the population can be estimated through the Hájek estimator, given by:

$$\hat{\bar{Y}}_L = \frac{\sum_{h \in s} w_h \hat{y}_{hL}}{\sum_{h \in s} w_h} \tag{2.2}$$

where w_h are sampling weights that indicate the proportion of individuals or households in the national population represented by each record in the sample.

This estimator includes two separate sources of variability: one due to the sample (V_1) and the other due to the Rasch model (V_2). Both should be considered in the small area estimation process. A detailed description of the functional form of V_1 and V_2, and that of their estimators, is provided in FAO (2024).

Producing comparable measures over time, and across different populations, requires establishing a common scale to use as a reference, and finding the formula needed to convert measures across different scales. This requires the identification of a set number of "anchoring" points. In the FIES methodology, these anchoring points are the severity levels associated with the items whose relative position on the scale of severity can be considered equal to that of the corresponding items on the global reference scale. The mapping of the measures from one scale to the other is then obtained by finding the formula that equates the mean and standard deviation of the common items' severity levels.

2.1.3 Methodology considerations and adaptations for applying small area estimation to the FIES

The estimation of SDG Indicator 2.1.2 at the country level is based on FIES microdata collected through representative national surveys, which allows the production of reliable estimates at the national level

[4] For example, the probability of being food insecure at a given level is expected to be similar for respondents with similar raw scores (e.g. 1 and 2).

and for other broad disaggregation domains. To ensure that direct disaggregated estimates are reliable, the sample at the disaggregated level must be large enough to yield adequate precision, in other terms a small variance. Otherwise, this is a case of "small areas", i.e. disaggregation domains where too few or no sampling observations are available.

In most situations, the sample size is not large enough to guarantee enough observations for every possible disaggregation domain. Therefore, the use of indirect estimation techniques, such as SAE models, to borrow information from auxiliary data on the population of interest is often necessary.

The literature classifies SAE models into two broad categories identified as **area-level** and **unit-level** models, depending on the level of aggregation of auxiliary variables included in the model. While area-level approaches relate a small area direct estimator to area-specific auxiliary information and can also be adopted when unit-level data are not available, unit-level models require access to microdata at the unit level, as they relate the unit values of the variable of interest to unit-specific covariates (Rao and Molina, 2015).

The two SAE case studies related to SDG Indicator 2.1.2 that are discussed in the remainder of this chapter were based on the generalization of the classic area-level model, also known as the Fay-Herriot (FH) model (Fay and Herriot, 1979).

To describe the FH model, let U_d represent the d-th disaggregation domain of a target population U. The FH model combines a sampling model, assuming that the unknown parameter $\bar{Y}_d$ and the direct estimate $\hat{\bar{Y}}_d^{dir}$ differ by a sampling error e_d, and a linking model specifying a relationship between the population value $\bar{Y}_d$ and a set of domain-level auxiliary information.

The sampling model can be formulated as:

$$\hat{\bar{Y}}_d^{dir} = \bar{Y}_d + e_d, \qquad d = 1, \dots, D \tag{2.3}$$

where $\hat{\bar{Y}}_d^{dir}$ is a design-unbiased direct estimator (such as the one in equation 2.2 for the prevalence of moderate or severe food insecurity) and the sampling error e_d has mean 0 and variance $\sigma_{e_d}^2$.

On the other hand, the linking model can be expressed as:

$$\bar{Y}_d = x_d^T \beta + u_d, \;\; d = 1, \dots, D \tag{2.4}$$

where $\bar{Y}_d$ is the parameter of interest, $\beta = (\beta_1, \dots, \beta_P)$ is the vector of unknown regression parameters, and u_d are area-specific random effects, which are supposed to be independent and identically normally distributed with mean 0 and variance σ_u^2.

In the context of the estimation of SDG Indicator 2.1.2 based on the FIES, an extension of the sampling model reported in equation 2.3 should be considered, to account for the additional uncertainty induced by the Rasch model. In particular, the sampling model in the context of a response variable generated through an item response theory model can be formalized as in equation 2.3, but in this case the sampling error follows the normal distribution specified below:

$$e_d \sim N(0, \sigma_{e_d}^2 = V_1 + V_2)$$

where V_1 is the variance of the direct estimator due to the sample and V_2 is that due to the Rasch model.

The combination of the sampling model in equation 2.3 and the linking model in equation 2.4 leads to an extension of the original FH model, which can be formalized as:

$$\hat{\hat{Y}}_d^{dir} = x_d^T\beta + u_d + e_d, \qquad d = 1, \dots, D \tag{2.5}$$

The unknown parameters of equation 2.5 to be estimated are the fixed-effects parameters β and the variance of the random effects σ_u^2.

Although under the FH model we assume V_1 and V_2 to be known, in practical applications they also need to be estimated with standard techniques. Under the frequentist paradigm, the common approach used to estimate the unknown parameters β and σ_u^2 is the empirical best linear unbiased prediction (EBLUP), which results in the following SAE estimator:

$$\hat{\hat{Y}}_d^{EBLUP} = \hat{\gamma}_d\hat{\hat{Y}}_d^{dir} + (1 - \hat{\gamma}_d)x_d^T\hat{\beta} \tag{2.6}$$

where $\hat{\beta}$ is the weighted least squares estimator of the regression parameter, and $\hat{\gamma}_d = \frac{\hat{\sigma}_u^2}{\hat{\sigma}_u^2+\sigma_{e_d}^2} = \frac{\hat{\sigma}_u^2}{\hat{\sigma}_u^2+\hat{V}_1+\hat{V}_2}$ is the shrinkage factor for domain d, which weights the direct estimate and the regression synthetic component, and decreases when the global variance of direct estimates increases. When $n_d = 0$ (i.e. for out-of-sample domains), $\hat{\gamma}_d$ is set to 0, and the corresponding SAE estimates are produced using only the regression synthetic component $x_d^T\hat{\beta}$ of $\hat{\hat{Y}}_d^{EBLUP}$.

The basic, or traditional, FH model is given by the combination of a linear sampling model for direct survey estimates, and a linear linking model for the parameter of interest. As a result of this linear combination, the output of the model (the prediction) may take values outside the admissible range for the parameter of interest, which in this case is expressed as a proportion taking values in [0,1]. For this reason, with small area parameters expressed as percentages or proportions, non-linear transformations of the parameter of interest or non-linear linking models are often more suitable. Several transformations of the target variable and non-linear linking models were considered in applications discussed in the next sections, and the arc-sin transformation provided the best performance for the case studies of Chile and Colombia.

2.2 Small area estimation of SDG Indicator 2.1.2 in Chile at the municipal level

The Ministry of Social Development and Family (MSDF) of Chile has implemented the National Socioeconomic Characterization Survey (CASEN) since 1987. Undertaken every two or three years, the CASEN is used to estimate the level of poverty in the country and the distribution of income among Chilean households and individuals. The survey also provides information on households' access to adequate housing, jobs, healthcare, education and other basic services. Since 2017, the CASEN includes a FIES module at the household level, allowing the estimation of progress towards SDG Indicator 2.1.2 in Chile.[5] For the study discussed here, the MSDF and FAO used FIES microdata collected through CASEN 2020 and, at the time of writing, the Ministry already completed the replication of the exercise for the 2022 survey.

A two-stage stratified random sample was used for the CASEN 2020, with strata defined by the combination of municipality and area type.[6] The sample size (62 911 households and 185 437 individuals) was selected to produce representative estimates of income poverty rates at the national and regional

[5] The CASEN includes a simplified FIES module that skips the last four questions if a respondent reports that they had not faced experiences described by the first four FIES questions.
[6] Areas classified as rural or urban.

level, and for the national–urban and national–rural disaggregation. Although it covers most municipalities in the country (324 of 346 municipalities), the selected sample was not intended to be representative at the municipal level. This, combined with the need for municipal estimates for various national policies and programmes led to the consideration of SAE approaches discussed in the previous section to produce estimates of SDG Indicator 2.1.2 at the municipal level.

2.2.1 Implementation of small area estimation

Direct estimation and weights trimming

The FIES microdata collected with the CASEN were used in conjunction with sampling weights to estimate the prevalence of moderate and severe food insecurity at the national level and in other planned estimation domains. The sampling weights had previously been adjusted to correct for issues that occurred during data collection, specifically non-response and low coverage of the sampling frame, and calibrated at the regional, provincial, and municipal level.[7] These operations resulted in a vector of sampling weights with a few very large values in some of the municipalities, which could have a negative impact on the estimation of the variance component due to the sampling.

Hence, before implementing direct estimation, a sampling weight trimming procedure based on the Potter approach (Potter, 1993) was implemented as described in FAO (2024): the original sampling weights are iteratively compared to a cut-off value K, minimizing the mean square error (MSE) of the variable of interest, which in this case is the household probability of being moderately or severely food insecure. Sampling weights above the considered threshold are set equal to K. In all other cases, the original weight is used. Finally, the vector of trimmed weights is adjusted to obtain the same estimate of the national population size resulting from the summation of original sampling weights.

Importantly, the variable of interest must be available for the sample's units in order to trim sampling weights. However, in the case of SDG Indicator 2.1.2, the probability of interest is not observed for sampled households, but instead is measured with the Rasch model using the sampling weights. To overcome this apparent vicious circle, the following strategy was adopted and is suggested for future applications:

1) The variable of interest is generated applying the Rasch model using a weight equal to 1 for each household in the sample.

2) Then, the Potter method is implemented to trim sampling weights, using the probabilities generated at step 1 as a response variable for the optimization of the MSE.

3) The Rasch model is implemented again, using the trimmed sampling weights, to generate the probabilities to be used for direct and small area estimation.

More details on trimming operations are provided in FAO (2024).

Selection of direct estimates based on predefined quality criteria

As illustrated in Section 2.1.3, the FH SAE estimator in equation 2.6 can be defined as a convex linear combination of a direct estimator and a synthetic estimator, with the weight of the first component

[7] The calibration was performed to reconcile estimates obtained with the survey with projections obtained from the 2017 Population and Housing Census (MDSF-ECLAC, 2021).

decreasing when the variability of direct estimates increases. One of the main practical characteristics of direct estimators is that their variance should be estimated with the observed data. When the sample size is very small, the variance estimates are no longer unbiased and lack precision. The magnitude coefficient of variation (CV) of direct estimates, which is the most common measure of precision used for survey estimates, is not only affected by the sampling size in the considered estimation domain. Other elements may affect the accuracy of obtained small area estimates that should be assessed before implementing SAE.[8] For studies discussed in this paper, hierarchical quality criteria have been set to identify direct estimates of sufficient quality to be included in the SAE estimator. In other terms, in those small areas where direct estimates met the established quality criteria, the direct estimator was considered in the calculation of the FH estimator. In all other cases, small areas have been treated as out of sample, and the indirect estimates were produced using the synthetic estimator. In the case of Chile, the following parameters have been considered to set quality criteria at the municipality level:

- **Degrees of freedom (DF):** Difference between the number of primary sampling units (PSU) and the number of strata in each municipality.

- **Design effect ($Deff$):** Ratio between the variance of the estimator obtained under the complex sampling design of the survey, and the variance resulting from a simple random sampling without replacement.

$$Deff = \frac{Var_s(\hat{\theta})}{Var_{srswor}(\hat{\theta})}$$

- **Intra-class correlation (ρ):** Describing how strongly units in the same PSU share similar characteristics.

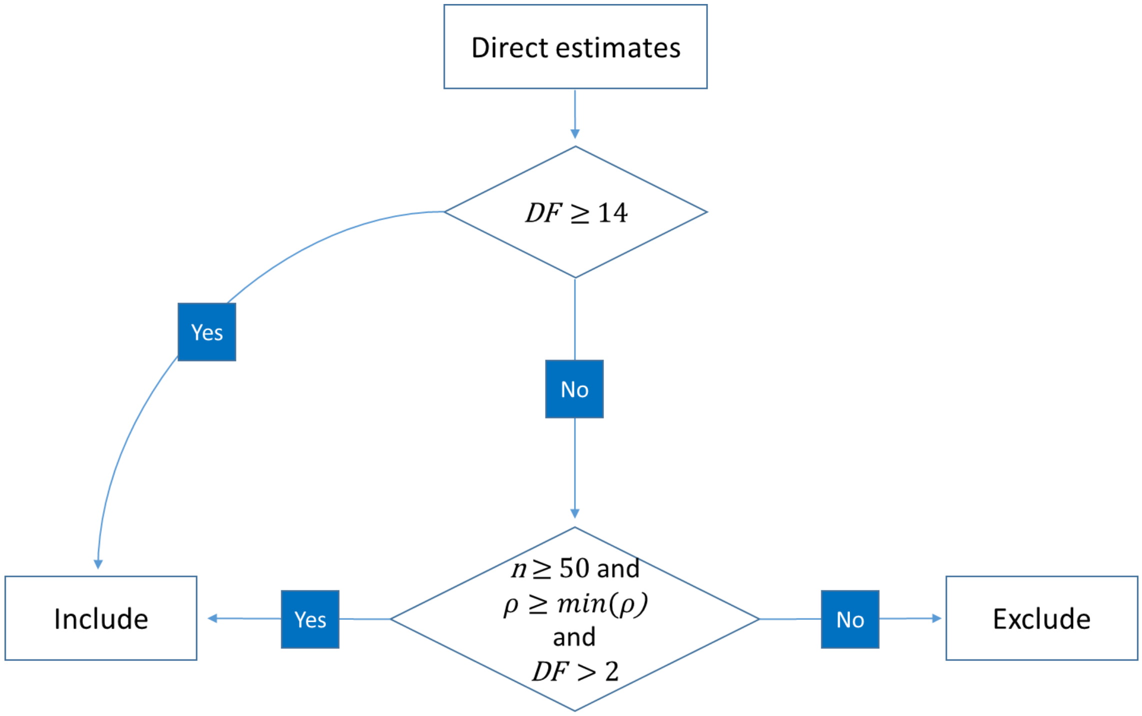
$$\rho = \frac{Deff - 1}{\frac{n}{n_{psu}} - 1}$$

- **Sampling size (n):** Number of sampling observations in the municipality.

Figure 2 illustrates the operational rules set for the selection of municipalities based on the criteria mentioned above.

[8] See Gutiérrez *et al.* (2020) for a detailed review of quality criteria to be considered when estimating indicators with survey data.

Figure 2. Quality criteria for the selection of municipalities



Source: Adapted from FAO. 2024. *Estimation of the prevalence of moderate and severe food insecurity in Chilean municipalities using small area estimation methods*. Santiago. https://doi.org/10.4060/cd1350en

After implementation, 41 out of 324 municipalities failed the quality criteria and were considered as out of sample. In all these municipalities the estimation has relied exclusively on the synthetic estimator.

Variance smoothing

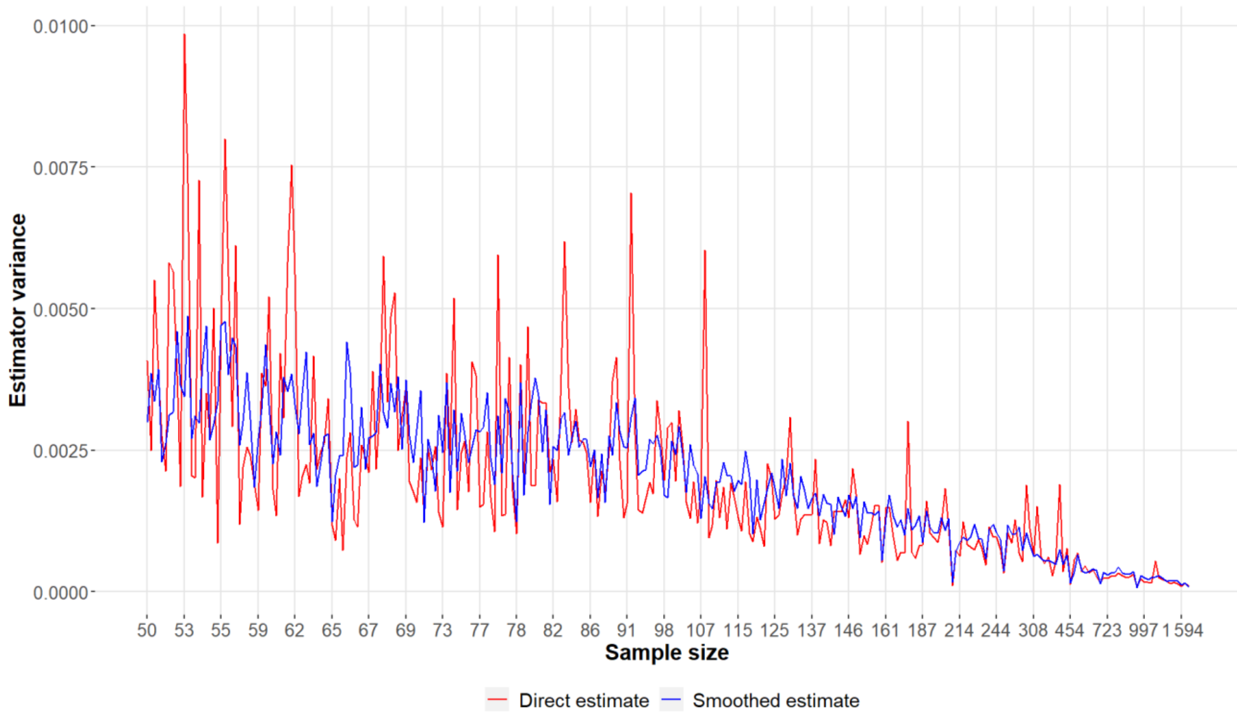
Although one of the fundamental assumptions of the FH model is the known variances $\sigma^2_{e_d}$, in practical applications, the variance of direct estimates is unknown and needs to be estimated through a design-unbiased estimator $\hat{\sigma}^2_d$. However, for very small domain sampling sizes, $\hat{\sigma}^2_d$ may need to be stabilized using suitable smoothing techniques. To this end, the following smoothing model (Rivest and Belmonte, 2000) was adopted:

$$log\ \hat{\sigma}^2_d = z_d^T \alpha + e_d$$

where z_d is a vector of explanatory variables,[9] α is a vector of unknown model parameters, and e_d is a random error assumed to be identically distributed conditionally on z_d with mean 0 and constant variance. Figure 3 compares the direct estimate and the smoothed estimate of the estimator variance and shows, as expected, that the variance decreases with increasing sampling sizes. In addition, the variance-smoothing model induces greater variance stability across municipalities.

[9] The implemented variance-smoothing model included the following list variables, plus and intercept term: $\hat{\theta}_d$; n_d; n_d^2; $\hat{\theta}_d \times n_d$; $\sqrt{\hat{\theta}_d}$; $\sqrt{n_d}$; and $\sqrt{\hat{\theta}_d \times n_d}$ with $\hat{\theta}_d$ denoting the direct estimator and n the sampling size.

Figure 3. Original versus smoothed variance for SDG Indicator 2.1.2 in Chile



Source: Adapted from FAO. 2024. *Estimation of the prevalence of moderate and severe food insecurity in Chilean municipalities using small area estimation methods*. Santiago. https://doi.org/10.4060/cd1350en

Selection of auxiliary variables and model implementation

The selection of auxiliary variables to be included in the model is a fundamental step of the SAE implementation process. In the case of Chile, the initial 73 municipal-level auxiliary variables considered for the model were retrieved from administrative records provided by the MSDF, the 2017 Population and Housing Census, and Google Earth Engine.[10] This initial set was reduced to 49 variables as highly correlated statistics were removed to avoid multicollinearity issues. Variables were then further reduced using a stepwise regression implemented to select the most significant regressors, resulting in the following list of auxiliary variables based on the Akaike information criteria (AIC):

- Affiliation to private health system,
- Affiliation to public health system,
- Percentage of formal wage earners with taxable income below 50 percent of the median income,
- Permanent income per capita,
- Elderly and child nutritional status rate,
- Aging index,

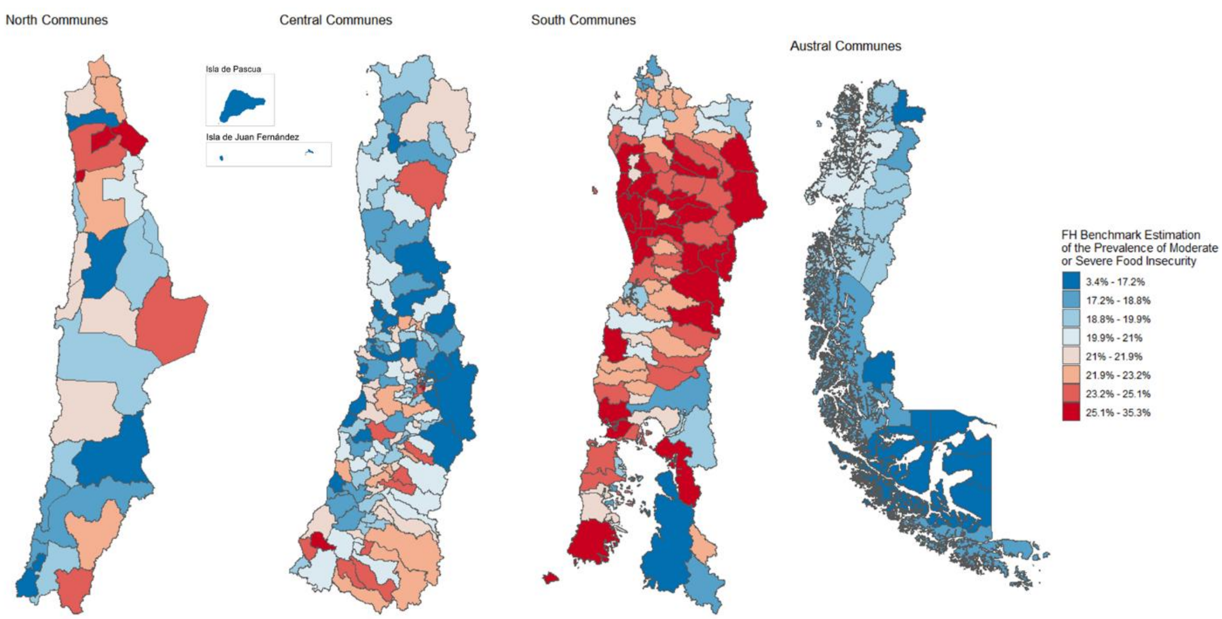
[10] A full description of auxiliary variables that were reviewed and tested is provided in FAO (2024).

- Victimization rate,
- Proportion of dwellings with quantitative deficit by type,
- Proportion of dwellings by water source,
- Infant mortality rate,
- Night-time light intensity,
- Accessibility of hospitals, and
- Regional dummies.

The SAE model resulting from the use of auxiliary variables listed above and arc-sin transformation of the response variable achieved an R^2 equal to 0.76, indicating a satisfactory model fit. The additional tests implemented to assess and validate the model and its results are presented in Section 2.2.2.

Finally, the SAE model has been used to obtain predictions of the prevalence of moderate and severe food insecurity in Chilean municipalities. These small area estimates were then benchmarked to ensure consistency between the model-based estimates at the municipal level and direct estimates at the regional and national level.[11]

Figure 4. Small area estimates of SDG Indicator 2.1.2 in Chilean municipalities



Note: Refer to the disclaimer on the copyright page for the names and boundaries used in this map.
Source: Adapted from FAO. 2024. *Estimation of the prevalence of moderate and severe food insecurity in Chilean municipalities using small area estimation methods*. Santiago. https://doi.org/10.4060/cd1350en

The indirect estimates of the prevalence of moderate and severe food insecurity presented in Figure 4 show the disparities in the prevalence of food insecurity across the country. While many municipalities of

[11] See FAO (2024) for details.

the Santiago Metropolitan Region, such as Vitacura, Las Condes, Providencia, La Reina, Lo Barnechea and Ñuñoa have a prevalence of food insecurity well below 10 percent, it exceeds 30 percent in municipalities such as San Juan de la Costa, Alto Biobío, Teodoro Schmidt, La Pintana and Ercilla. On average, most of the municipalities in the south communes had a prevalence of moderate and severe food insecurity above 20 percent.

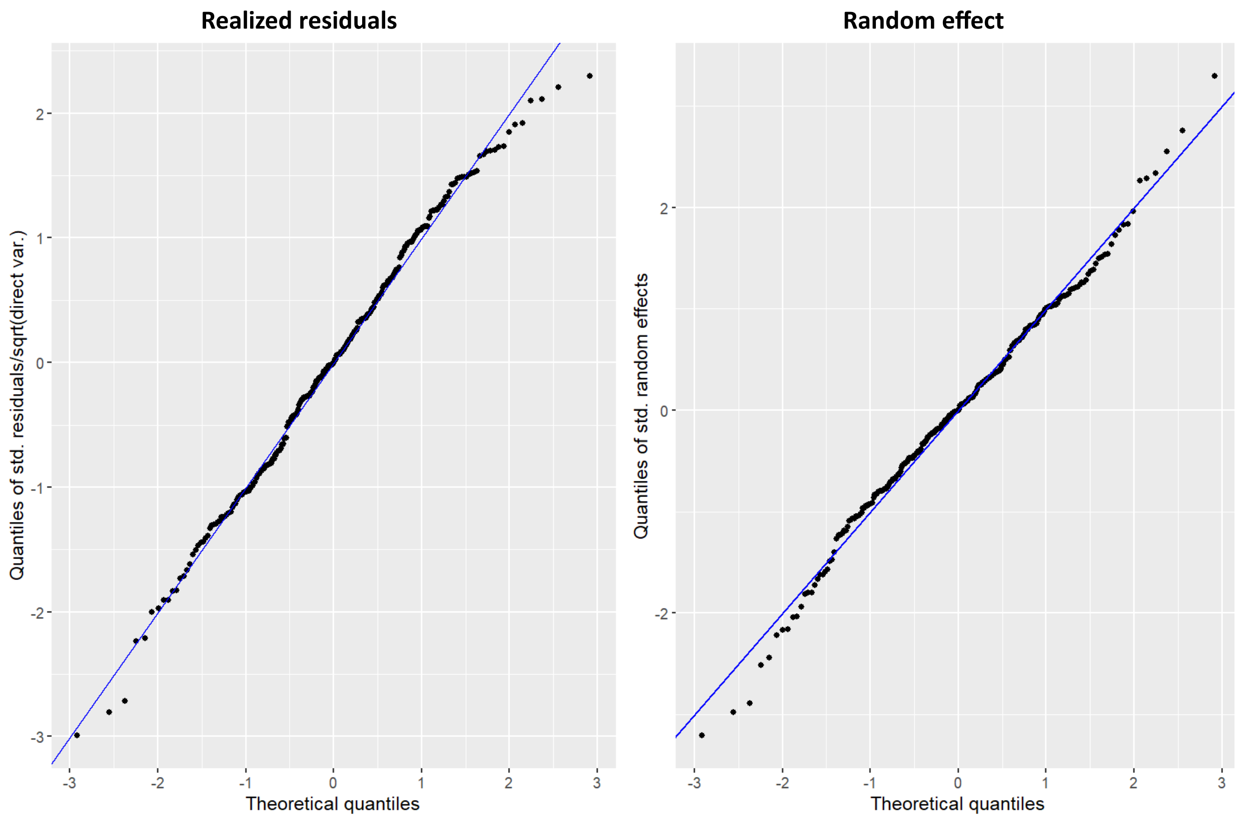
2.2.2 Assessment and validation of results

After implementation, the fundamental assumptions of the FH model were validated, and the MSE of estimates was assessed. A full presentation of all the validation tests and analysis implemented is provided in FAO (2024).

Normality of residuals and random effects

The FH model assumes the normality of both the residuals and the random effects, which can be validated with QQ-plots or specific tests, such as the Shapiro-Wilk test. Figure 5 shows that both the error term and the random effects do not deviate significantly from the normal distribution, which is confirmed by the Shapiro-Wilk test. Indeed, the tests resulted in p-values above 0.05 for both the residuals and the random effects, leading to acceptance of the null hypothesis of normality.

Figure 5. QQ-plots of residuals and random effects for SDG Indicator 2.1.2 in Chile

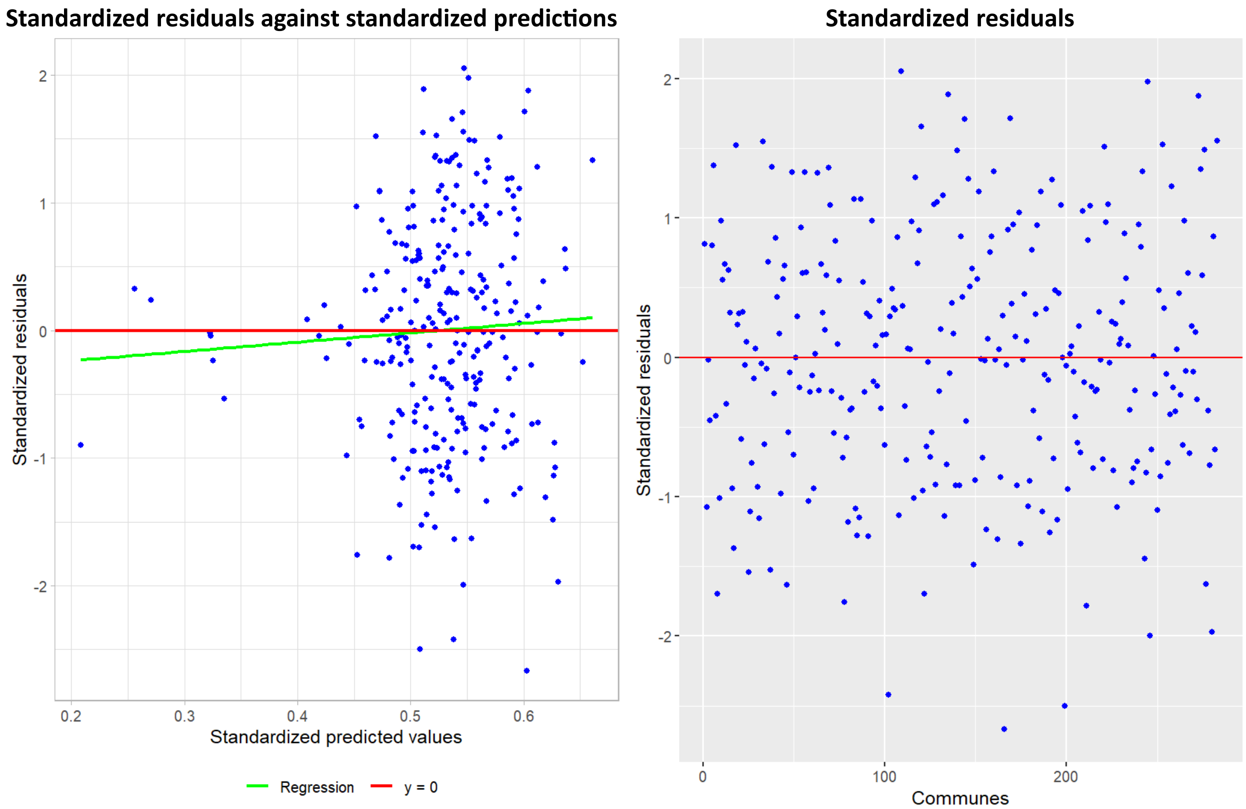


Source: Adapted from FAO. 2024. *Estimation of the prevalence of moderate and severe food insecurity in Chilean municipalities using small area estimation methods*. Santiago. https://doi.org/10.4060/cd1350en

Homoscedasticity

The FH model also assumes homoscedasticity of residuals, i.e. that residuals have constant variance in all the small areas and that this variance is independent of the value of auxiliary variables. Figure 6, which shows the standardised residuals against the sampled municipalities (right side) and against the predicted values (left side), confirms that the distribution of residuals does not follow a specific pattern, highlighting that the model assumptions and specification are appropriate. In addition, the variability of residuals does not change substantially across different municipalities, confirming the hypothesis of homoscedasticity.

Figure 6. Homoscedasticity and independence of residuals

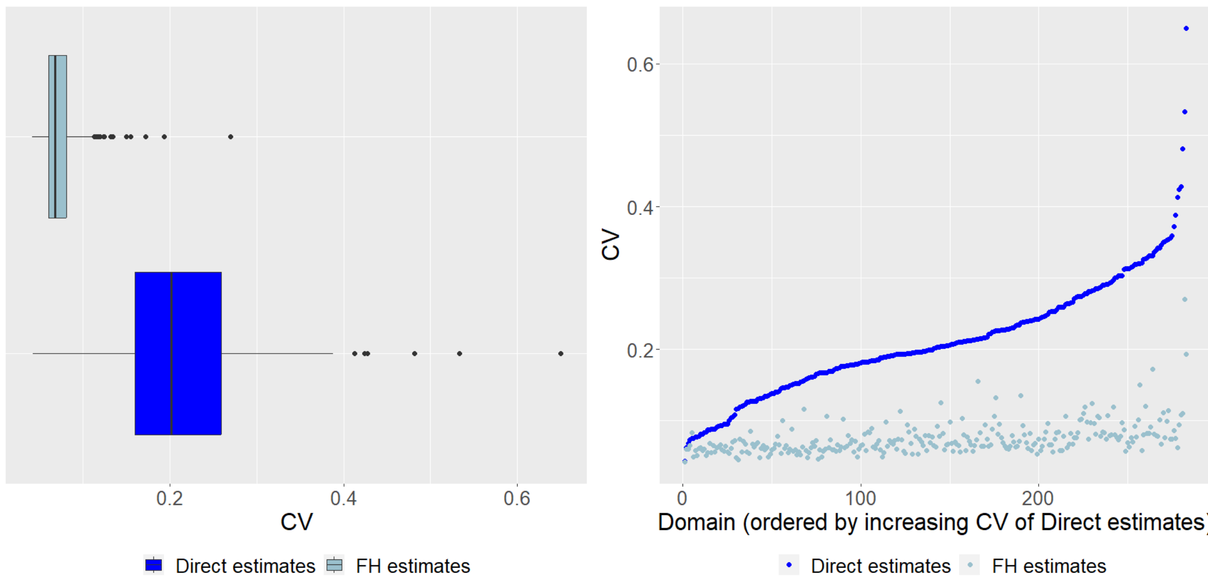


Source: Adapted from FAO. 2024. *Estimation of the prevalence of moderate and severe food insecurity in Chilean municipalities using small area estimation methods*. Santiago. https://doi.org/10.4060/cd1350en

Mean square error and coefficient of variation

The estimation of the MSE adopted in this application is extensively discussed in FAO (2024). The CV, which is obtained as $\frac{\sqrt{MSE}}{\hat{\theta}}$, is normally used to assess the quality of model-based estimates, as it is easier to interpret and compare. The efficiency gain obtained through SAE can be assessed by looking at the CV of direct estimates against that of FH estimates. In this respect, Figure 7 shows that FH estimates are more precise in all in-sample municipalities, resulting in a substantial gain. While direct estimates had a mean CV of 21.21 percent and a maximum CV of 64.99 percent, SAE reduced the average variability to 8.56 percent and the maximum to 27.02 percent.

Figure 7. Coefficient of variation of direct estimates and Fay-Herriot estimates



Source: Adapted from FAO. 2024. *Estimation of the prevalence of moderate and severe food insecurity in Chilean municipalities using small area estimation methods*. Santiago. https://doi.org/10.4060/cd1350en

2.2.3 Key messages and use of results

With the area-level FH model, the SDG Indicator 2.1.2 estimates had a CV below the 30 percent threshold in most Chilean municipalities (340 out of the 345 for which an estimate could be produced), and below 36 percent in all cases. All of the auxiliary variables used to build the model were available free of charge from administrative records, the 2017 Population and Housing Census, and Google Earth Engine. As a result, reliable estimates for food insecurity were produced for 99 percent of municipalities without increasing the budget of the CASEN survey. These results will help optimize the allocation of government resources across several programmes.

One concrete example is the Municipal Common Fund,[12] which is operated by the Subsecretary of Regional Development (Subdere). This fund is the main source of financing at the municipal level to carry out governmental development initiatives. Accordingly, municipal-level data on food security will help Subdere allocate these resources more efficiently.

Another example is the Preferential School Subsidy Law, which is implemented by the Ministry of Education.[13] This subsidy programme aims to provide additional resources to the schools or municipalities with higher levels of students facing socioeconomic challenges that affect their capacity to learn. Accordingly, food security data at the municipal level will provide an important input for resource allocation of this programme, ensuring that funds are allocated to schools where they are needed most.

Finally, many other funding sources and programmes, such as the Regional Support and Innovations funds, will be able to make better decisions thanks to more granular data on food insecurity.

[12] See https://www.subdere.gov.cl/programas/divisi%C3%B3n-municipalidades/fondo-com%C3%BAn-municipal-fcm
[13] See https://www.ayudamineduc.cl/ficha/antecedentes-generales-sep-12

2.3 Small area estimation of SDG Indicator 2.1.2 in Colombia at the municipal level

Colombia's National Administrative Department of Statistics (DANE) implements the National Quality of Life Survey (ECV), which that is a key instrument to assess and compare the socioeconomic status of households in the country. The ECV, which includes the household-level FIES-SM since 2022, is based on a stratified multistage sampling design and is meant to be representative at the national, regional and departmental level, as well as in urban and rural areas.

Despite the large size of the sample (88 328 households in 2022), the adopted sampling design does not allow the production of representative direct estimates at the municipal level, which could inform the planning of assistance interventions and allocation of national and regional resources. Hence DANE, with the support of FAO, used the area-level FH model discussed in Section 2.1 to produce small area estimates of SDG Indicator 2.1.2 at the municipal level. The adopted methodology and the results of this exercise are fully described in DANE (2024), while key elements of this experience are presented below.

2.3.1 Implementation of small area estimation

Direct estimation

The first step of this exercise was to produce direct estimates for all municipalities included in the ECV sample through the approaches discussed in Section 2.1. Colombia is divided into 1 122 municipalities, of which only 640 had at least one segment included in the sample. The remaining 482 municipalities were treated as out of sample. After careful evaluation and comparison of results, it was decided to not perform any trimming operation on the sampling weights, and the original vector of weights was used for estimation.

Selection of direct estimates based on predefined quality criteria

Similar to the Chilean case study, quality rules for selecting the municipalities with direct estimates that will be used to produce small area estimates were implemented. Only the 458 municipalities that satisfied the following five operational rules were included in the EBLUP estimator:

- Effective sample size in the municipality equal to or greater than 40: $neff = n/deff \geq 40$;
- At least two degrees of freedom in each municipality: $DF = PSU - n_{strata} \geq 2$;
- Logarithmic CV equal to or below 30 percent: $logCV = \log(CV) \leq 30$;
- Design effect[14] equal to or greater than 1: $Deff \geq 1$; and
- Exclusion of all municipalities with only one zone (urban or rural) in the sample and with a share of the population in the out-of-sample zone above 50 percent.

Variance smoothing

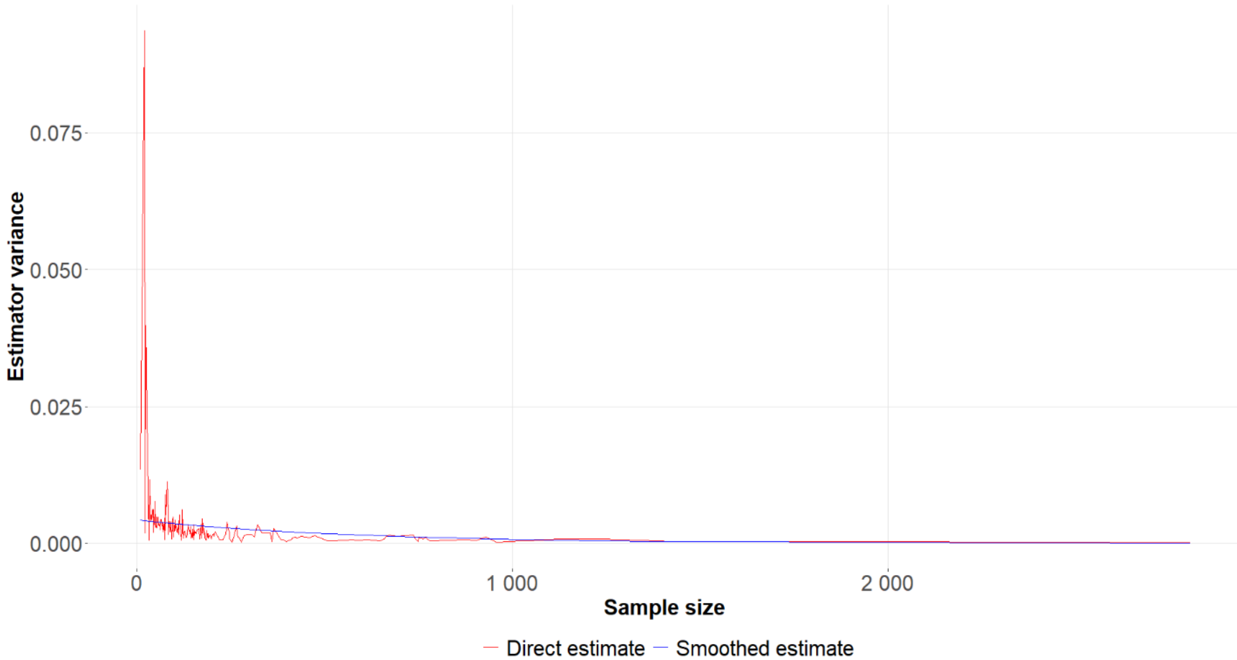
Before implementing the FH model, the variance of direct estimates was smoothed with the following log-linear model and ordinary least square estimation:

$$log(\hat{V}_i) = \beta_0 + \beta_1 \frac{n_i}{N_i} + \beta_2 n_i + e_i$$

[14] The definition of the design effect ($Deff$) is provided in Section 2.2.1.

where $\hat{V}_i$ is the estimate of the variance of the estimator based on the sampling design and the Rasch model, n_i is the sampling size in the i-th municipality, and N_i is the total population in i. Figure 8 shows that both the original variance of direct estimates and the smoothed variance decrease as the sampling size increases, with a significant stabilization of the variance introduced by the smoothing model.

Figure 8. Original versus smoothed variance for SDG Indicator 2.1.2 in Colombia



Source: DANE. 2024. Estimation of the prevalence of moderate or severe food insecurity in Colombia at the municipal level in 2022. In: *DANE*. [Cited March 2025]. https://www.dane.gov.co/index.php/estadisticas-por-tema/estadisticas-experimentales#sociedad-5

Selection of auxiliary variables and model implementation

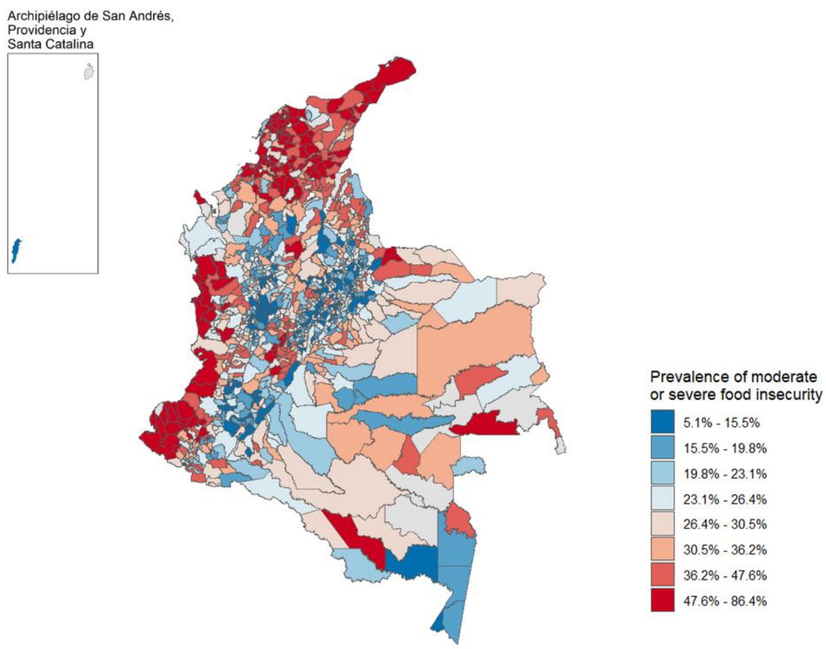
Many potential auxiliary variables for the implementation of the area-level SAE model were considered, including:

- Vital statistics produced by DANE, providing information on mortality rates, causes of deaths and other life-cycle information at the municipality level;
- Municipal aggregates extracted by DANE from the population and housing census indicating the number of households by specific sociodemographic groups or dwelling with certain characteristics;
- Municipal aggregates extracted from the agriculture census concerning agricultural production and the main characteristics of agricultural households;
- Wholesale prices by municipality of origin extracted by DANE's price information system;
- Statistics on formal education produced by DANE using information provided by public and private institutes in the country;
- Municipal value added by economic activity;

- Municipal-level indicators on social protection coverage, results of assistance, and infrastructure retrieved from the information system of the Ministry of Health and Social Protection (SISPRO);
- Administrative data from the Rural Agricultural Planning Information System (SIPRA); and
- Information on planning, finance, risk management, and municipal performance from the National Planning Department (NDP).

As in the case of Chile, the Colombian example was based on the generalization of the FH model discussed in Section 2.1.3 using the arc-sin transformation of the probability of moderate or severe food insecurity to ensure that predictions fall in the interval [0,1]. Starting from the transformed probabilities, the initial set of 215 area-level auxiliary variables was reduced with a stepwise regression based on the AIC. This led to the selection of 30 auxiliary variables for the implementation of the SAE model. The municipal-level predictions obtained with the model had to be benchmarked to ensure consistency with direct estimates at the departmental, regional and national level (DANE, 2024).

Figure 9. Small area estimates of SDG Indicator 2.1.2 in Colombian municipalities



Note: Refer to the disclaimer on the copyright page for the names and boundaries used in this map.
Source: Adapted from DANE. 2024. Estimation of the prevalence of moderate or severe food insecurity in Colombia at the municipal level in 2022. In: *DANE*. [Cited March 2025]. https://www.dane.gov.co/index.php/estadisticas-por-tema/estadisticas-experimentales#sociedad-5

Figure 9 shows a significantly heterogeneous situation in the country. Except for a few municipalities, the prevalence of moderate or severe food insecurity is relatively low in the central area of the country, while it appears to be higher (above 40 percent) in the northern and western areas of Colombia. This heterogeneity in the prevalence of food insecurity reinforces the need for municipal-level statistics.

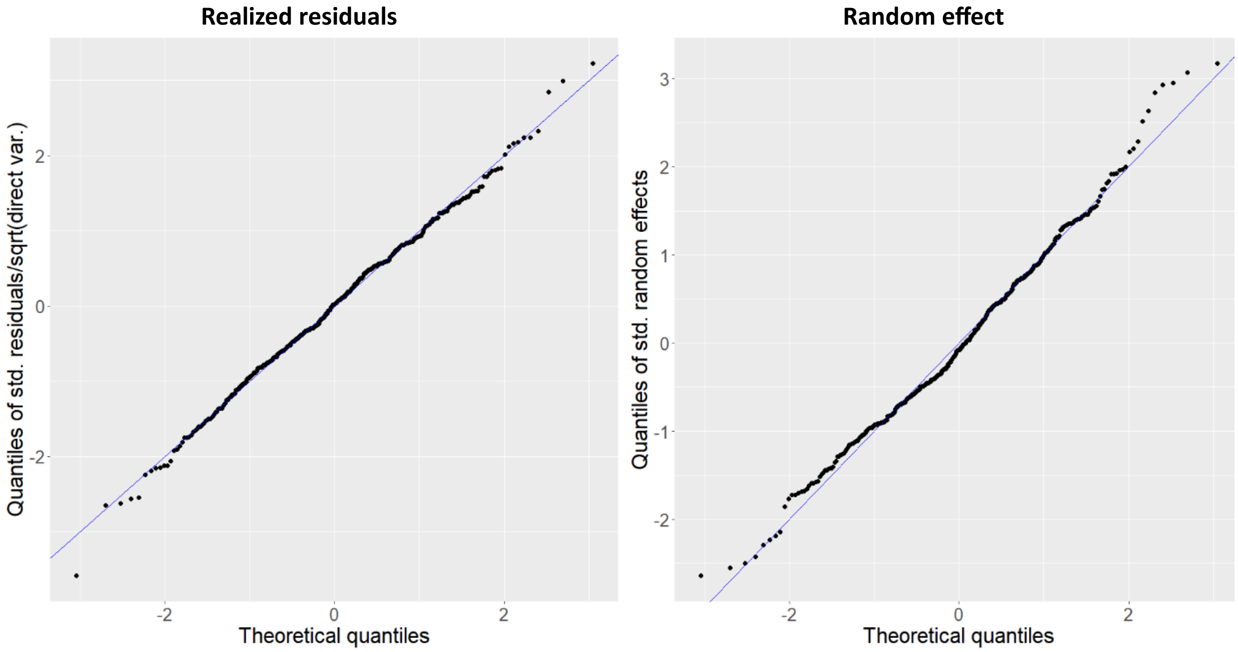
2.3.2 Assessment and validation of results

As in the case of Chile, the fundamental assumptions of the FH model have been validated, and the CV of estimates has been assessed to evaluate the quality improvement induced through SAE.

Normality of residuals and random effects

The QQ-plots of the error term and the random effects (Figure 10) did not show any significant deviation from normality. This was also confirmed by the Shapiro-Wilk test, which resulted in p-values above 0.05 for both the residuals and the random effects (0.662 for the residuals and 0.173 for the random effects), leading to acceptance of the null hypothesis of normality.

Figure 10. QQ-plots of residuals and random effects for SDG Indicator 2.1.2 in Chile



Source: Adapted from DANE. 2024. Estimation of the prevalence of moderate or severe food insecurity in Colombia at the municipal level in 2022. In: *DANE*. [Cited March 2025]. https://www.dane.gov.co/index.php/estadisticas-por-tema/estadisticas-experimentales#sociedad-5

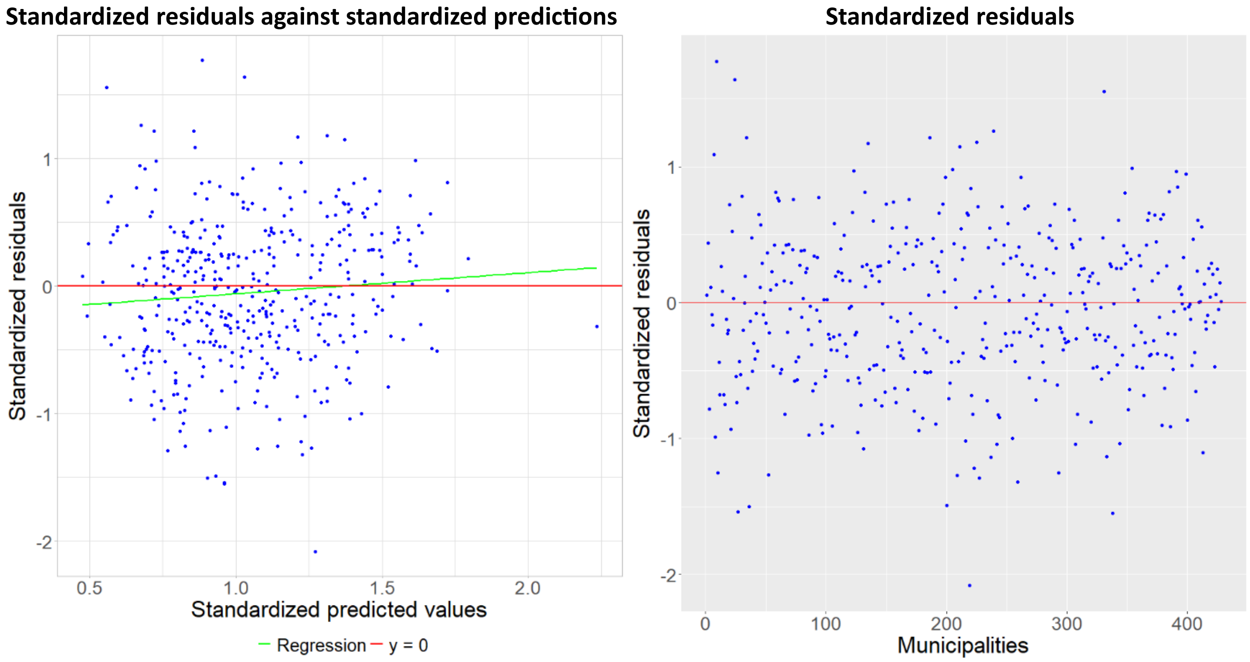
Homoscedasticity

The left panel of Figure 11 confirms that the distribution of residuals does not follow a specific pattern, highlighting that the model assumptions and specification are appropriate; it also confirms the hypothesis of residuals with a mean equal to zero. The right panel shows that the variability of residuals does not change substantially across different municipalities, which confirms the hypothesis of homoscedasticity.

Mean square error and coefficient of variation

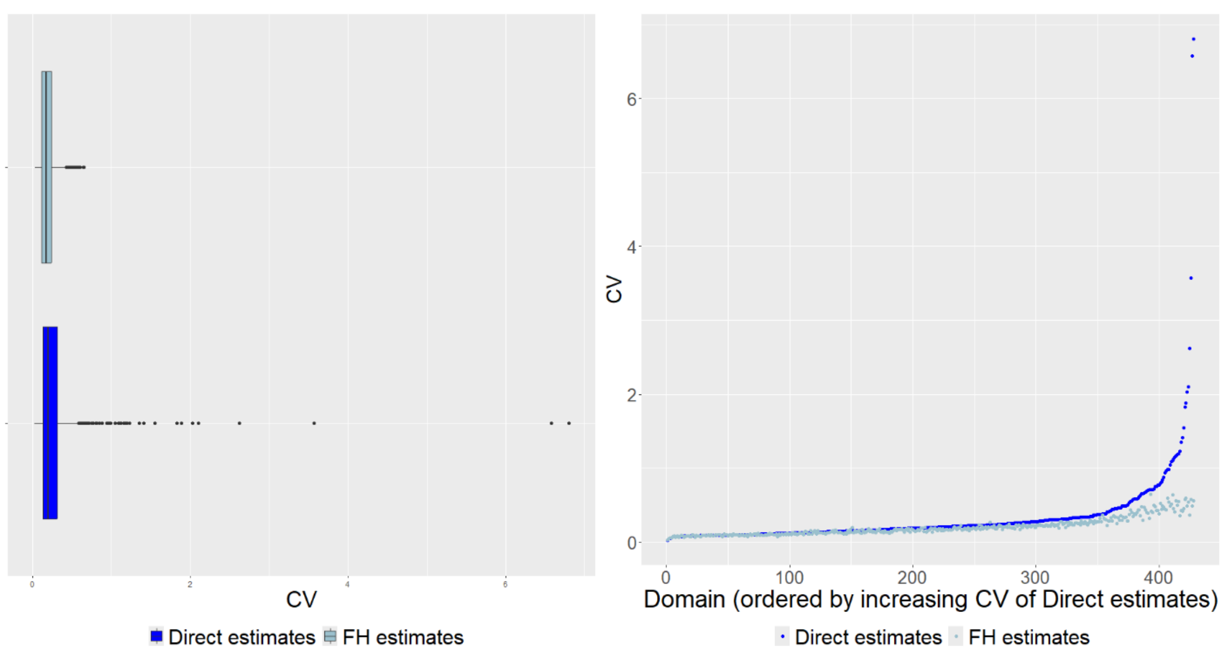
The implementation of SAE reduced the CVs of the estimates. However, the improvement achieved in Colombia was lower than in Chile.

Figure 11. Homoscedasticity and independence of residuals



Source: Adapted from DANE. 2024. Estimation of the prevalence of moderate or severe food insecurity in Colombia at the municipal level in 2022. In: *DANE*. [Cited March 2025]. https://www.dane.gov.co/index.php/estadisticas-por-tema/estadisticas-experimentales#sociedad-5

Figure 12. Coefficient of variation of direct and Fay-Herriot estimates



Source: Adapted from DANE. 2024. Estimation of the prevalence of moderate or severe food insecurity in Colombia at the municipal level in 2022. In: *DANE*. [Cited March 2025]. https://www.dane.gov.co/index.php/estadisticas-por-tema/estadisticas-experimentales#sociedad-5

Also in this case, the implementation of SAE allowed reducing the CVs of the estimates. However, the reliability improvement achieved in Colombia was lower than in Chile.

2.3.3 Key messages and use of results

DANE produces poverty and food insecurity estimates at the national and departmental level, as well as by urban or rural locations, on an annual basis with the ECV. However, the level of disaggregation that can be achieved through direct estimation with the current sample sizes is not sufficient to effectively inform policy programmes and interventions aimed at eradicating poverty and hunger in the most problematic areas of the country.

The 33 departments and 1 122 municipalities of Colombia have very different population densities, income levels and food insecurity status: estimates at the department level may hide or minimize food insecurity in some municipalities. The use of SAE to estimate food insecurity is crucial to produce statistics for evidence-based policymaking in the context, for example, of the Zero Hunger policy of the Vice-Presidency of the Republic.

3 SDG Indicators 2.3.1 and 2.3.2: labour productivity and income of small-scale food producers

3.1 Introduction

SDG Target 2.3 is to double the productivity and incomes of small-scale food producers, in particular women, Indigenous Peoples, family farmers, pastoralists and fishers.[15] Progress towards this target is monitored by two SDG indicators under FAO custodianship: SDG Indicator 2.3.1, measuring the value of agricultural production of small-scale food producers per labour unit, and SDG Indicator 2.3.2, on the average agricultural income of small-scale food producers.

Given the focus on a specific category of producers – i.e. those that can be considered as small-scale producers – both indicators need to be disaggregated by holding size. In addition, other specific disaggregation dimensions have been established for the two indicators. In particular, SDG Indicator 2.3.1 should be estimated by type of product (farming, pastoral, forestry and fishery), while SDG Indicator 2.3.2 by the indigenous status of the holder or household head. The Inter-Agency and Expert Group on SDG indicators (IAEG-SDGs) has also identified future desirable disaggregation dimensions for the two indicators, including the urban and rural location of the holding, the agroecological zones and the subnational level.[16]

3.1.1 Preferred data sources for SDG monitoring

The ideal data source for SDG indicators related to Target 2.3 is a national agricultural sample survey with all the data required to estimate them. Although SDG Indicators 2.3.1 and 2.3.2 could also be measured using information collected through the agricultural census, the World Programme for the Census of Agriculture 2030 guidelines do not recommend the inclusion of many of the requested data items in the census questionnaire as they are not considered structural variables and are thus better collected using sample surveys.

Due to the heavy data demands of the considered indicators and the relative scarcity of agricultural survey samples in Latin America and the Caribbean, the reporting rate of SDG Indicators 2.3.1 and 2.3.2 remains very low: only three and nine countries in the region have official data on SDG Indicators 2.3.1 and 2.3.2, respectively, at the time of writing.

3.1.2 Methodology used for direct estimation

Both indicators are measured based on a unified methodology for identifying smallholders proposed by FAO (FAO, 2019) and endorsed by the IAEG-SDGs. This approach relies on an internationally agreed definition of small-scale food producers proposed by FAO in 2017, considering the combination of two criteria: 1) the physical size of the farm, expressed as the area of operated land and the number of livestock heads; and 2) the economic size of the holding, measured as the total value of agricultural production (Figure 3.1). Both criteria are applied in relative terms to enhance international comparability. In practice, small-scale food producers are holders who:

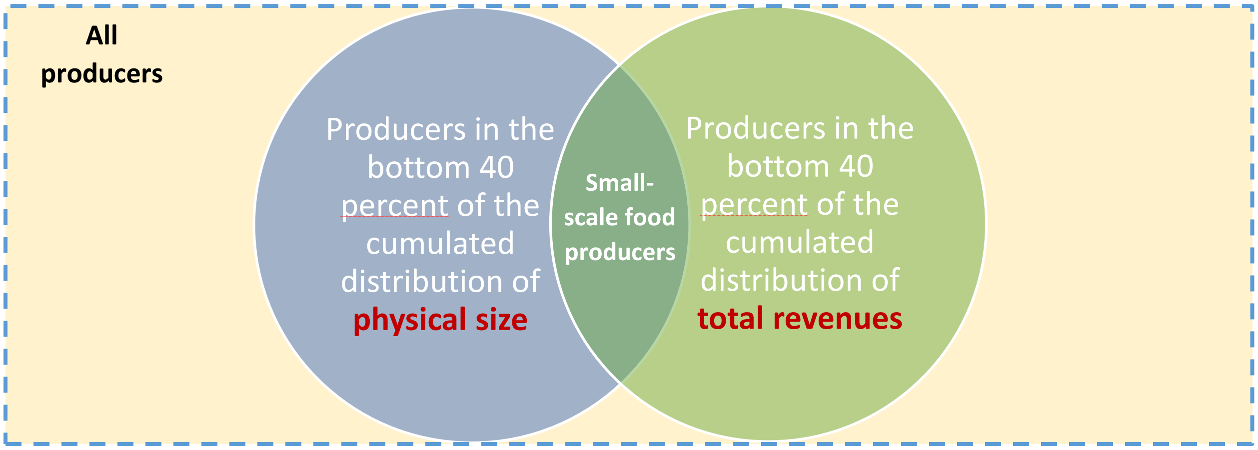
[15] See https://sdgs.un.org/goals/goal2#targets_and_indicators

[16] Khalil and di Candia (2023) discuss the main challenges encountered in measuring the indicators of Target 2.3 according to each of these dimensions.

- operate an area of land falling in the bottom 40 percent of the cumulative distribution of households' land area at the national level, as measured in hectares;
- manage a number of heads of livestock falling in the bottom 40 percent of the cumulative distribution of the number of animals per household at the national level, as measured in tropical livestock units (TLUs); and
- obtain total annual revenues from agricultural activities falling in the bottom 40 percent of the cumulative distribution of agricultural revenues per household at the national level, as measured in purchasing power parity (PPP) USD.

Finally, the resulting set of producers identified by these criteria is filtered, setting an additional absolute cap to exclude producers earning a revenue higher than USD 34 387 PPP per year.[17]

Figure 13. Identification of small-scale food producers



Source: FAO. 2019. *Methodology for computing and monitoring the Sustainable Development Goal Indicators 2.3.1 and 2.3.2*. FAO Statistics Working Paper Series, No. 18–14. Rome. http://www.fao.org/documents/card/en/c/ca3043en

After identifying the population of N_s small-scale food producers among the N food producers ($N_s < N$) of a country, SDG Indicators 2.3.1 and 2.3.2 can, respectively, be expressed as:

$$SDG\ 2.3.1 = I_{2.3.1}^{t} = \frac{\sum_{j=1}^{N_s}\left(\frac{\sum_i V_{ij}^{t}\, p_{ij}^{t}}{L_j^{t}}\right)}{N_s} = \frac{\sum_{j=1}^{N_s} y_{2.3.1,j}}{N_s} \quad (3.1)$$

$$SDG\ 2.3.2 = I_{2.3.2}^{t} = \frac{\sum_{j=1}^{N_s}\left(\sum_i V_{ij}^{t}\, p_{ij}^{t} - C_{ij}^{t}\right)}{N_s} = \frac{\sum_{j=1}^{N_s} y_{2.3.2,j}}{N_s} \quad (3.2)$$

where:

- V_{ij}^{t} is the physical volume of agricultural product i sold or used by small-scale food producer j (with $j = 1, \dots, N_s$) during year t;

[17] The addition of this threshold was one of the recommendations FAO received from a consultation of IAEG-SDGs on the international definition of small-scale food producers.

- p_{ij}^{t} is the constant sale price received by small-scale food producer j during year t for product i;
- L_{j}^{t} is the number of labour days (full time equivalent) worked by small-scale food producer j during year t; and
- C_{ij}^{t} is the production cost of agricultural product i for small-scale food producer j during year t.

Equations 3.1 and 3.2 can only be used for actual computation when census data for the entire target population are available. On the other hand, when the estimation is based on microdata collected through representative surveys, the adopted sampling design needs to be taken into account through the sampling weights in the estimation process. In this context, a generalized expression of the Horvitz–Thompson (HT) estimator of both indicators can be written as:

$$\hat{\bar{y}}_{l}^{dir} = \frac{\sum_{j \in s} w_j y_{l,j}}{\sum_{j \in s} w_j} \qquad \text{with } l = 2.3.1 \text{ or } 2.3.2 \text{ and } j = 1, \dots, n \qquad (3.3)$$

where $y_{2.3.1,j}$ and $y_{2.3.2,j}$ have been defined in expressions 3.1 and 3.2, respectively.

3.1.3 Methodology used for small area estimation

While the measurement of SDG Indicator 2.1.2 in Chile and Colombia used the same approach, the disaggregated estimates of SDG Indicators 2.3.1 and 2.3.2 at the subnational level in Brazil and Ecuador were measured with different approaches: using agricultural census microdata in Brazil, and survey data integrated with additional data sources through SAE in Ecuador.

In the case of Brazil, a simple direct estimation based on expressions 3.1 and 3.2 was possible. However, in the case of Ecuador, the construction of a suitable SAE model was necessary. In particular, SAE was implemented with the traditional area-level FH model for linear parameters.

The area-level SAE approach was based on the FH combining a sampling model, which assumes that the unknown parameter and the direct estimate difference can be summarized in a sampling error, and a linking model, specifying the relationship between the population value and a set of auxiliary data at the domain level. In symbols, direct estimates were modelled as:

$$\hat{\bar{y}}_{l}^{dir} = x_{l,d}^{T}\,\beta_l + \mu_{l,d} + e_{l,d} \qquad \text{with } l = 2.3.1 \text{ or } 2.3.2 \text{ and } d = 1, \dots, D \qquad (3.4)$$

where:

- The unknown parameters are the fixed effects β and random effects variance $\sigma_{\mu_l}^{2}$; and
- $e_{l,d}$ and $\mu_{l,d}$, respectively, denote the error term and the random effects in the d-th disaggregation domain.

In this context, the small area estimates of the two indicators can be derived with the EBLUP estimator, which is given by a weighted average between the direct estimator and a synthetic regression component:

$$\hat{\bar{y}}_{l,d}^{EBLUP} = \hat{\gamma}_{l,d}\,\hat{\bar{y}}_{l,d}^{dir} + \left(1 - \hat{\gamma}_{l,d}\right) x_{l,d}^{T}\,\hat{\beta}_l \qquad (3.5)$$

where:

$\hat{\beta}_l$ is the weighted least squares estimator of the regression parameters and $\hat{\gamma}_{l,d}$ is the shrinkage factor for the estimator ($l = 2.3.1$ or $2.3.2$) expressed as:

$$\hat{\gamma}_{l,d} = \frac{\hat{\sigma}^2_{u_l}}{\hat{\sigma}^2_{u_l} + \sigma^2_{e_{l.d}}}$$

In order to improve the performance of the model, a logarithmic transformation of both dependent variables $y_{2.3.1}$ and $y_{2.3.2}$ was used.

3.2 Small area estimation of SDG Indicators 2.3.1 and 2.3.2 in Ecuador at the canton level

The National Institute of Statistics and Censuses of Ecuador (INEC) implements the Annual Agricultural Area and Production Survey (ESPAC). This survey is the main source of crop and livestock information in the country and collects all the microdata needed to identify small-scale food producers and estimate the two SDG indicators monitoring Target 2.3. The ESPAC is designed to be representative at the national and provincial level. However, when adding the disaggregation by small-scale and non-small-scale producers the sampling size may not be large enough for producing representative estimates. This is even more true when geographic disaggregation at a more granular level is considered, such as the cantonal level (the second administrative unit of Ecuador). Only 211 of the 221 cantons in Ecuador were included in the sample. To fill the data gap resulting from the lack of reliable information at the canton level, SAE techniques were considered as a valid tool to produce disaggregated subnational estimates to inform targeted policies on Ecuador's smallholder population. ESPAC microdata were integrated, with auxiliary variables retrieved by administrative and geospatial information systems.

3.2.1 Implementation of small area estimation

Production of direct estimates and implementation of quality criteria

Direct estimates of SDG Indicators 2.3.1 and 2.3.2 for 2022, specifically targeting smallholder producers, were produced using the HT estimator in expression 3.3. The estimation process was implemented with the ReGenesees[18] package in R, which produces direct estimates along with their coefficient of variation and standard error, taking the sampling design into account (Zardetto, 2015).

Subsequently, basic quality criteria were implemented to select direct estimates to be included in the EBLUP estimator. These consisted of:

- Having a CV of cantonal direct estimates between 0.001 and 80 percent;[19] and
- Having a sampling size at the canton level greater than 5 small-scale food producers for SDG Indicator 2.3.1 and greater than 1 small-scale food producer for SDG Indicator 2.3.2.

The results achieved with several different quality criteria were compared, and those producing the better fit of the final SAE model were retained.

All the cantons that passed both quality criteria mentioned above were retained, and the others were considered as out of sample. As a result, the EBLUP estimator could be implemented in 195 cantons for SDG Indicator 2.3.1 and 198 cantons for SDG Indicator 2.3.2. In all other cases, the estimation was based on the synthetic component of the estimator in equation 3.5.

[18] https://www.istat.it/en/methods-and-tools/methods-and-it-tools/process/processing-tools/regenesees

[19] The shrinkage factor in the EBLUP estimator minimized the contribution of direct estimates with high CVs.

Smoothed variance calculation

As mentioned in Chapter 2, the FH model assumes that sample variances are known. However, in practice they must be estimated using direct estimators, which may be affected by the same limited sample size that prevents the accurate and precise estimation of the indicators. To overcome this issue, a variance smoothing approach was also used to stabilize the sampling variance estimates. Given that in this case the parameters of interest for both indicators monitoring Target 2.3 can be expressed as a ratio, a linearization approach of the variance is adopted. Indicating with $\bar{R} = \frac{\bar{X}}{\bar{Y}}$ the ratio estimator, the Taylor series estimator of the variance of $\bar{R}$ is:

$$v(\bar{R}) = \frac{1}{\bar{Y}^2}\left(v(\bar{X}) + \bar{R}^2 v(\bar{Y}) - 2\bar{R}\rho xy \times \sqrt{v(\bar{X})}\,\sqrt{v(\bar{Y})}\right)$$

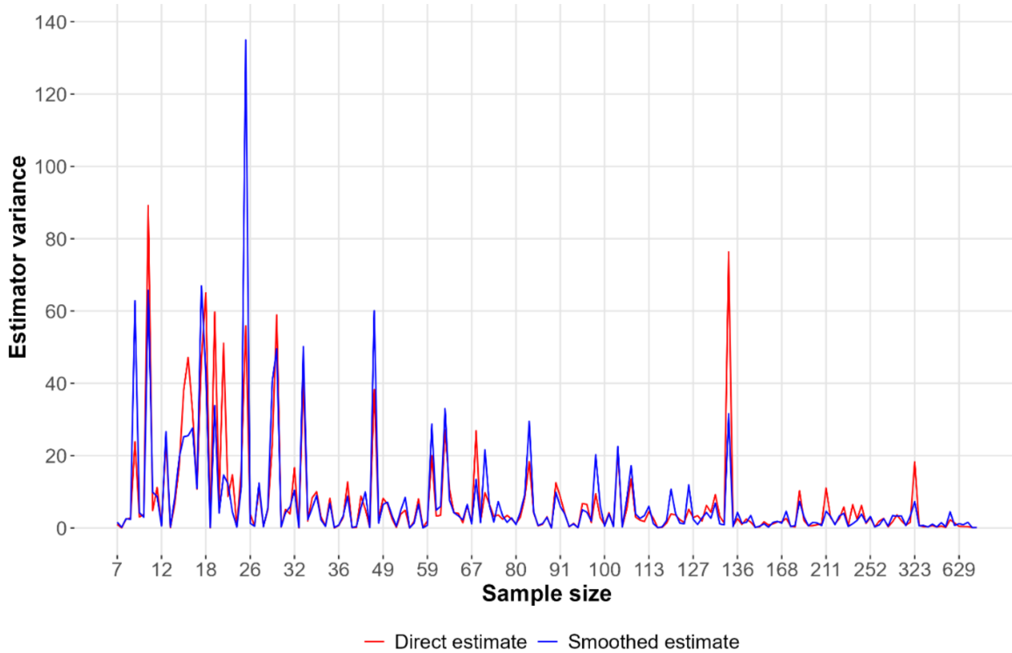
where $v(\bar{X}), v(\bar{Y})$ and ρxy denote estimators of the variance of $\bar{X}$, the variance of $\bar{Y}$ and the linear correlation between $\bar{X}$ and $\bar{Y}$, respectively. The smoothed variance of $\bar{R}$ is obtained by replacing $v(\bar{X})$ and $v(\bar{Y})$ with their smoothed versions $\tilde{v}(\bar{X})$ and $\tilde{v}(\bar{Y})$. The smoothing models chosen for $v(\bar{X}), v(\bar{Y})$ were the following:

$$log\, v(\bar{X}) = log\ \bar{X}^T \alpha + e$$

$$log\, v(\bar{Y}) = log\ \bar{Y}^T \alpha + e$$

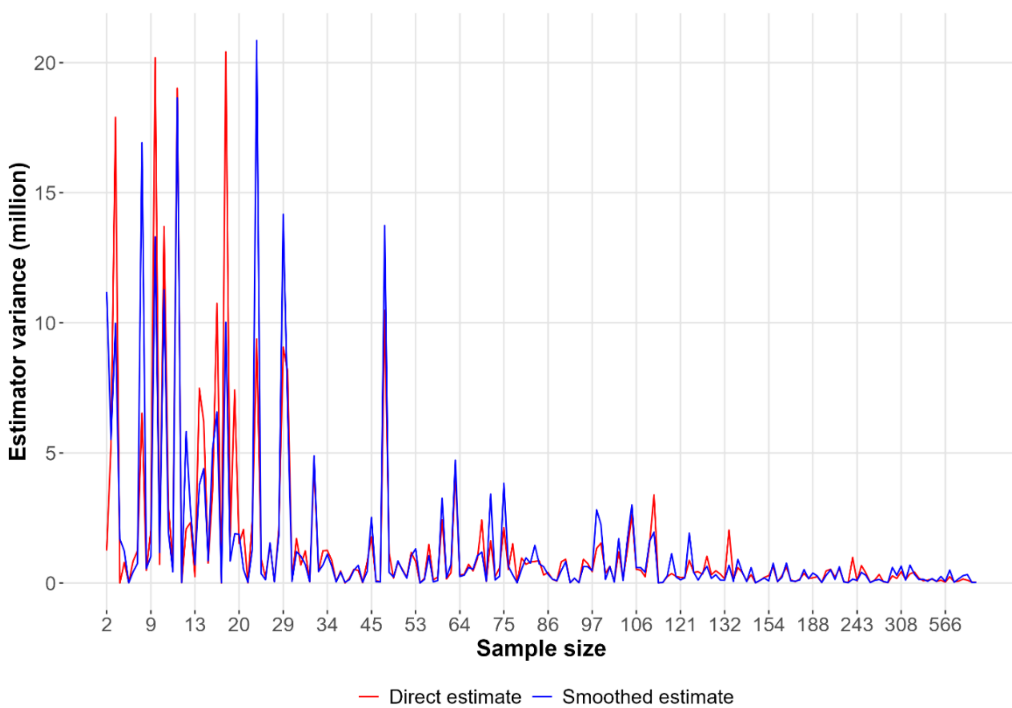
Figure 14 shows that the variance decreases significantly with as the sample size increases. The direct estimates exhibit high volatility, especially in small samples (n < 50), where pronounced peaks can be observed. The smoothing model tends to reduce the variance. For sample sizes greater than 100, both the original and smoothed variance estimates tend to stabilize around zero.

Figure 14. Original versus smoothed variance for SDG Indicator 2.3.1 in Ecuador



Source: Authors' own elaboration.

Figure 15. Original versus smoothed variance for SDG indicator 2.3.2 in Ecuador



Source: Authors' own elaboration.

Selection of auxiliary variable and implementation of SAE

Several sources of auxiliary variables were considered for this application:

- **Satellite data:** A large set of topographic, taxonomic, soil, climate and production variables were extracted from Google Earth Engine**;**
- **Administrative records:** data from the administrative register on the management of solid waste maintained by INEC. In addition, colleagues from INEC provided FAO with administrative records retrieved from INEC's registry on cattle; and
- **Census data:** aggregates from the population and housing census of 2022, and the census on drinking water and sanitation of 2021.

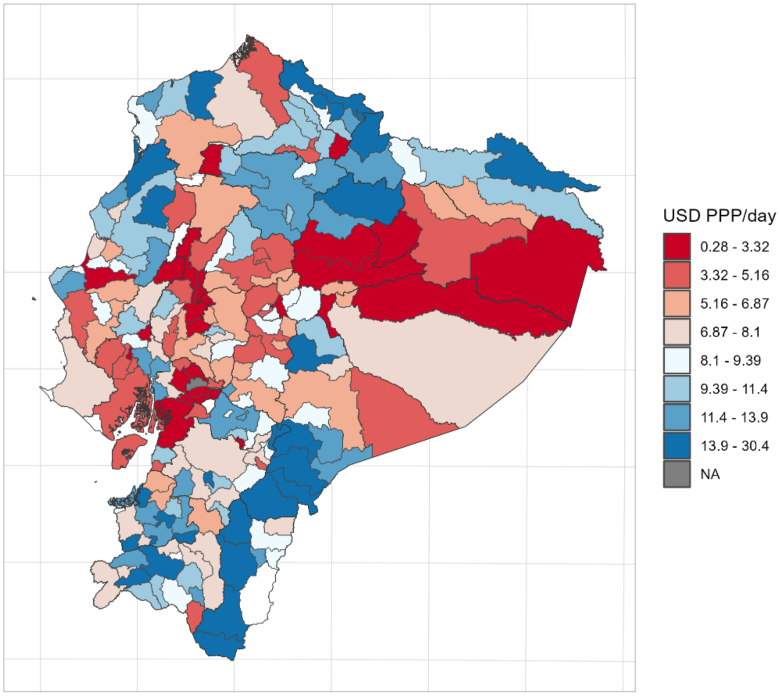
The large list of covariates identified were cleaned, eliminating those affected by a high number of missing values. Subsequently, the best sets of predictors for SDG Indicators 2.3.1 and 2.3.2 were identified with a stepwise regression (forward and backward). The absence of multicollinearity of selected auxiliary variables was ascertained looking at the variance inflation factor (VIF).

The model applied had an R^2 adjusted to the number of independent variables of 70 percent for SDG Indicator 2.3.1 and 79.2 percent for SDG Indicator 2.3.2. This implies that in both cases the model explains at least 70 percent of the variance, which can be considered acceptable.

For SDG Indicator 2.3.1, the direct and small area estimates at the canton level reached a correlation of 95.6 percent, with an average productivity of USD 8.57 per day worked estimated with the direct estimator, and of USD 8.77 per day with the EBLUP. Figure 16 shows that the southeastern cantons of Ecuador present, on average, a higher labour productivity than the rest of the country.

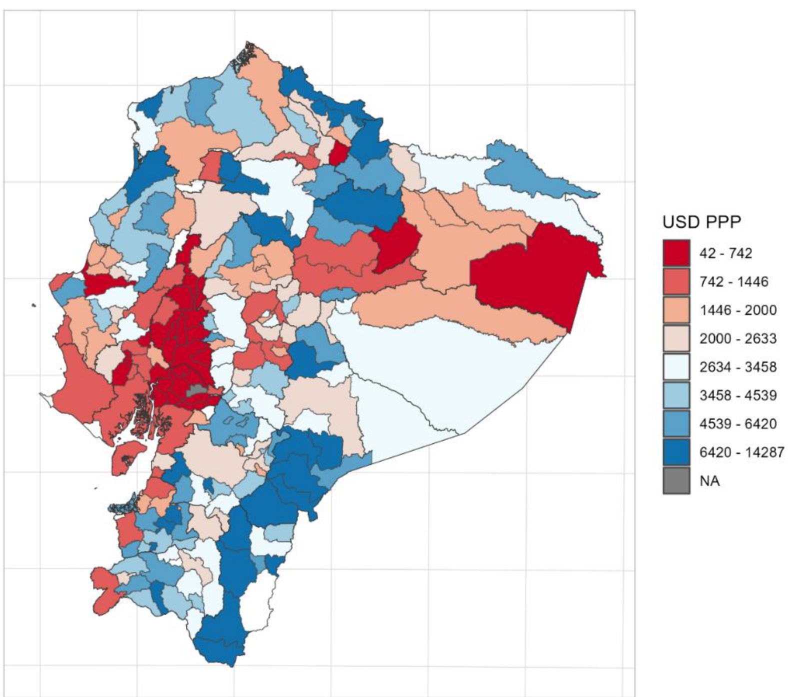
The correlation between direct and indirect estimates for SDG Indicator 2.3.2 reached 97 percent, denoting a good behaviour of the selected model. Using the direct estimator, the mean value of estimates obtained was USD 3 372 excluding 13 of the sample cantons for which the estimation was not possible. On the other hand, the use of the FH model led to a mean of USD 3 347 and included all cantons. Figure 17 shows that small-scale food producers in the southeastern cantons also have, on average, a higher income than those in the rest of the country.

Figure 16. Small area estimates of SDG Indicator 2.3.1 in Ecuador



Note: Refer to the disclaimer on the copyright page for the names and boundaries used in this map.
Source: Authors' own elaboration based on 2022 ESPAC-INEC microdata.

Figure 17. Small area estimates of SDG Indicator 2.3.2 in Ecuador



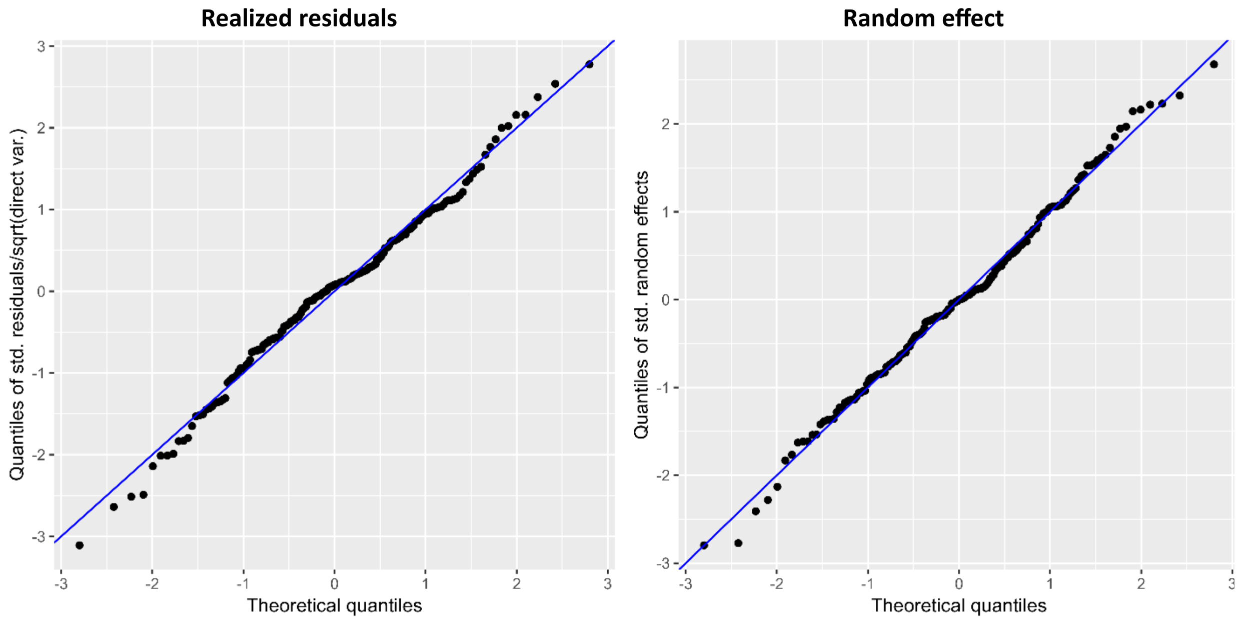
Note: Refer to the disclaimer on the copyright page for the names and boundaries used in this map.
Source: Authors' own elaboration based on 2022 ESPAC-INEC microdata.

3.2.2 Assessment and validation of results

Normality of errors and random effects

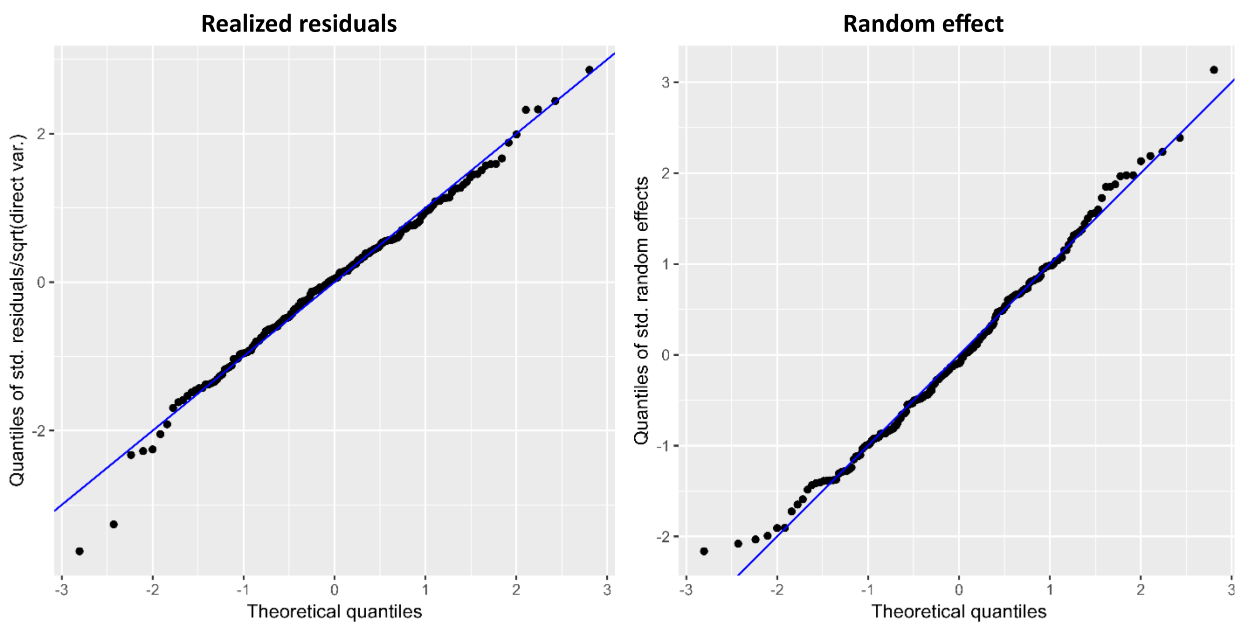
The normality of residuals and random effects for both SDG Indicators 2.3.1 and 2.3.2 was verified (Figures 18 and 19). In particular, since the p-value of the Shapiro Wilk test was above 0.05 in all cases, the null hypothesis of normality was accepted.

Figure 18. QQ-plots of residuals and random effects for SDG Indicator 2.3.1 in Ecuador



Source: Authors' own elaboration based on 2022 ESPAC-INEC microdata.

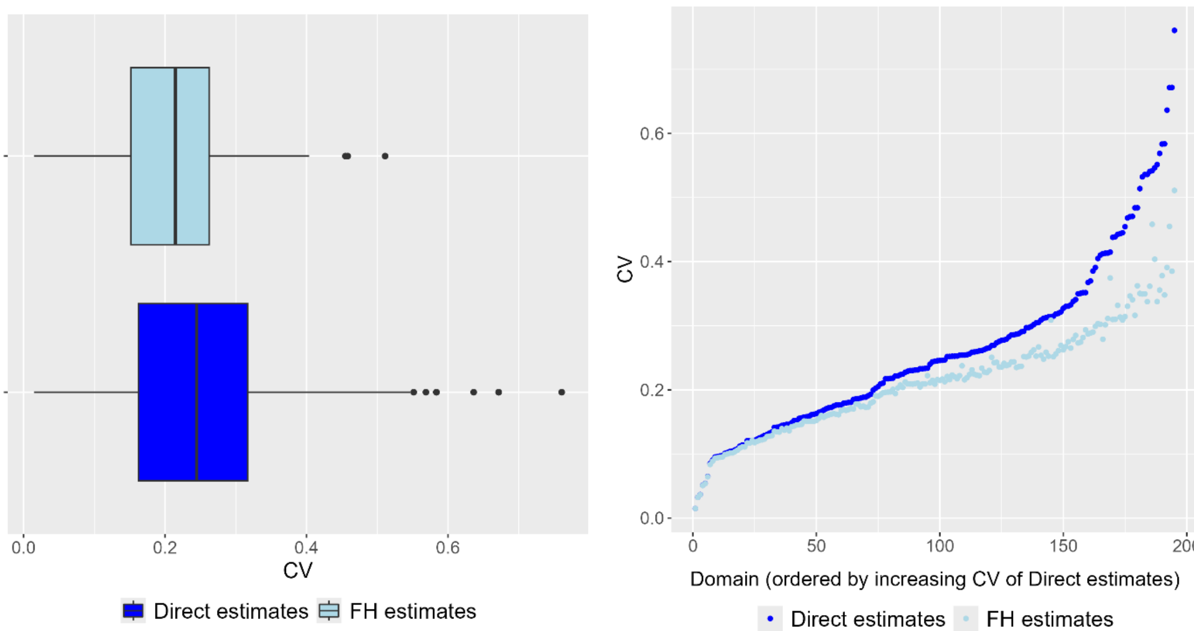
Figure 19. QQ-plots of residuals and random effects for SDG Indicator 2.3.2 in Ecuador



Source: Authors' own elaboration based on 2022 ESPAC-INEC microdata.

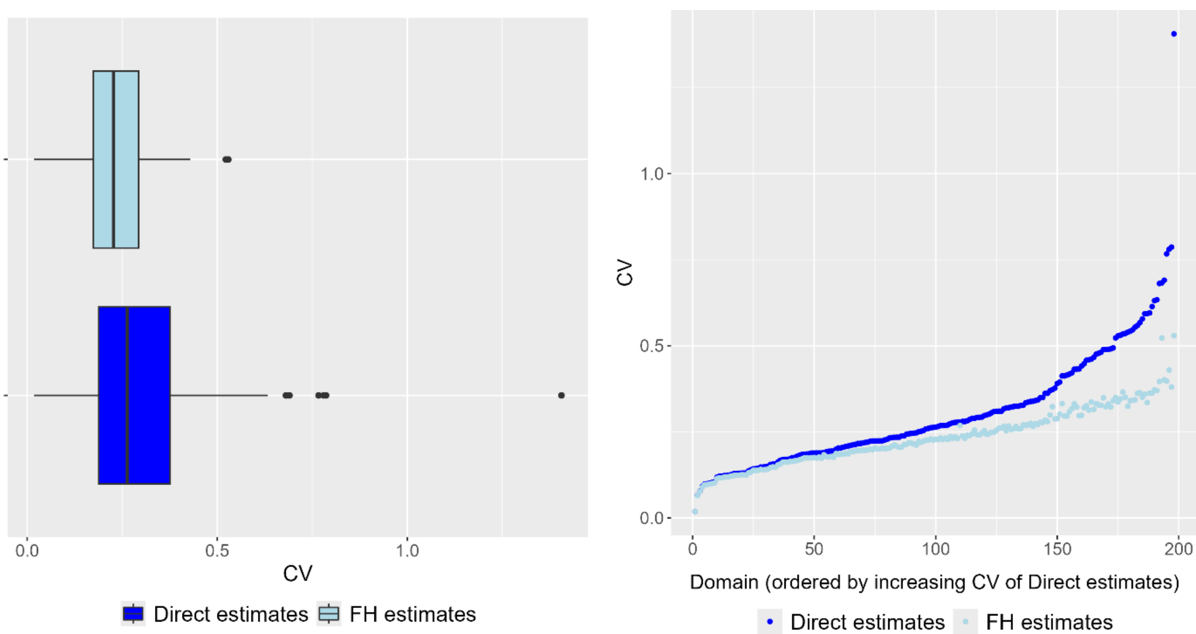
Figures 20 and 21 show that the adoption of the FH model led to a substantial reduction in the CV of the estimates of both indicators.

Figure 20. Coefficient of variation of direct and Fay-Herriot estimates for SDG Indicator 2.3.1



Source: Authors' own elaboration based on 2022 ESPAC-INEC microdata.

Figure 21. Coefficient of variation of direct and Fay-Herriot estimates for SDG Indicator 2.3.2



Source: Authors' own elaboration based on 2022 ESPAC-INEC microdata.

In the case of SDG Indicator 2.3.1, the direct estimates had a mean CV of 26.17 percent, with a maximum value of 76 percent while the mean CV of FH estimates was 21.4 percent, with a maximum value reduced to 51.1 percent. Hence, although the error measures obtained after the implementation of SAE were medium, the reliability of SDG Indicator 2.3.1 estimates was improved as 92 percent of cantons had a CV of indirect estimates below 33 percent.

Similarly, for SDG Indicator 2.3.2, the average CV of cantonal estimates was reduced from the 30.4 percent based on the direct estimator to 23.3 percent using the FH estimator. In this case, 81 percent of small area estimates based on the FH had a CV below 16.6 percent.

3.2.3 Key messages and use of results

The development and application of the small area estimation (SAE) model to generate canton-level estimates for SDG Indicators 2.3.1 and 2.3.2 in Ecuador using ESPAC microdata illustrates the feasibility and cost-effectiveness of such approaches to address critical data gaps. The current ESPAC sample design produces representative estimates at the national and provincial levels, despite requests from key stakeholders for statistics at the canton level. For instance, the Ministry of Agriculture and Livestock needs canton-level estimates for agricultural production and land area. Similarly, the Secretariat for Risk Management requires data disaggregated below the provincial level to identify productive areas and assess potential disaster impacts. Additionally, the Central Bank requires canton-level agricultural data for national accounts, and the National Planning Secretariat needs this level of detail for the formulation of development and territorial planning strategies.

Traditionally, meeting these demands would require a budget increase for ESPAC to accommodate larger sample sizes, which may not be financially viable. However, the SAE model developed in this study demonstrates that reliable canton-level estimates can be produced without increasing the cost of ESPAC by integrating ESPAC data with existing administrative data.

3.3 Direct estimation of SDG Indicators 2.3.1 and 2.3.2 in Brazil at the municipal level

In 2023, FAO collaborated with the Brazilian Institute of Geography and Statistics (IBGE) to compute SDG Indicators 2.3.1 and 2.3.2 at the municipal level using the microdata collected by the census of agriculture, forestry and aquaculture. This exercise was necessary not only for SDG monitoring purposes, but also to improve the quality of Brazil's statistical records and inform public policies focused on small-scale food producers in priority municipalities.

3.3.1 Implementation of direct estimation

As opposed to building an SAE model as presented in previous sections, the approach for Brazil was to use the agricultural census data covering all farms. As a result, the calculation was made directly based on the 5 073 324 farm records included in the census. Notably, the scope of the census questionnaire was unusually wide, capturing detailed data on the demographic characteristics of farmers, as well as the farm, income, expenses, labour, production, fishing, and agro-industry, thus meeting the data requirements for SDG Indicators 2.3.1 and 2.3.2.

To prepare the dataset for analysis, first the records that did not contain data were excluded, resulting in a total number of 5 056 411 farms. From these records, thresholds were established to define small farms. The thresholds were set at 184.8 ha for the agricultural area, 159.7 TLU for the livestock herd, and USD 303 737 for the value of production in purchasing power parity.

Given that Brazil has the highest GDP in Latin America and considering the importance of the agricultural sector in its economy, the threshold production value at the national level (close to USD 304 000) is nearly nine times higher than the recommended value of USD 34 387. This is reflected in Table 1, where the percentage of smallholder farms varies by almost 10 percentage points between the two thresholds. To avoid bias in the distribution of production value, it was decided to follow FAO recommendations and use the recommended USD 34 387 value as the economic size threshold.

There is significant inequality, not just in terms of geographical distribution but also between large- and small-scale producers. Nearly 60 percent of crop areas, animal ownership and production value are concentrated in only 0.8, 3.1, and 1.5 percent of farms, respectively. This highlights the disproportionate influence of large farms in the overall agricultural landscape.

Table 1. Cut-off points of selected variables for the identification of small-scale food producers at the national level in Brazil (2017)

Variable	Cut-off point	Establishments below the cut-off point	
		Number	Percent
Agricultural area	184.8 ha	5 016 879	99.2
Livestock herd	159.7 TLU	4 898 878	96.9
Value of production	USD 303 737.6	4 978 706	98.5
Value of production	USD 34 387	4 463 887	88.3
Small-scale producers		**4 427 072**	**87.6**

Source: Based on IBGE. n.d. Census of Agriculture. In: *IBGE*. [Cited March 2025]. https://www.ibge.gov.br/en/statistics/economic/agriculture-forestry-and-fishing/21929-2017-2017-censo-agropecuario-en.html?=&t=sobre

The number of small-scale food producers (establishments below each of the three thresholds) is 4 427 072, representing 87.6 percent of the total number of farms in Brazil. Once the study population was identified, the indicators of interest were calculated using equations 3.1 and 3.2 above.

3.3.2 Assessment and validation of results

The disaggregation at the municipal level for both indicators shows the marked inequality existing in the country, not only at the territorial level, but also within producer groups (medium/large vs small), as well as the indigenous status and gender of the producer. At the national level, the average net income (SDG Indicator 2.3.2) of small-scale food producers amounts to USD 2 790.55, while medium and large producers had an average net income 75.9 times higher. Men had an average net income 3.1 times higher than women. Meanwhile, the Indigenous small-scale food producers had an average net income that was 6.6 percent higher than non-Indigenous small-scale food producers; this can be attributed to the lower expenses recorded for Indigenous producers in the agricultural establishment, which implies a higher average net income. However, when analysing the average productivity (SDG Indicator 2.3.1), Indigenous small-scale food producers have a productivity of USD 4.3/day, while for non-Indigenous small-scale food producers it amounts to USD 7.9/day, or 1.84 times more than their Indigenous counterparts (Table 2).

Table 2. Number of establishments, labour productivity and average income by farm size, sex and indigenous status of the producer at the federal level in Brazil (2017)

Type of producer	Disaggregation dimensions		Establishments		Average productivity (SDG Indicator 2.3.1)	Average income (SDG Indicator 2.3.2)
	Sex	Indigenous	Number	Percent	USD PPP/day	USD PPP
All	Total	Total	5 056 411	100.00	25.67	18 053.47
All	Man	Total	4 110 336	81.30	29.28	20 605.66
All	Woman	Total	946 075	18.70	9.99	6 965.19
All	Total	Yes	56 447	1.10	5.88	4 990.17
All	Total	No	4 999 964	98.90	25.89	18 200.95
Small	Total	Total	4 427 072	87.60	7.85	2 790.55
Small	Man	Total	3 524 264	69.70	8.74	3 044.41
Small	Woman	Total	902 808	17.90	4.34	1 799.56
Small	Total	Yes	55 171	1.10	4.30	2 971.30
Small	Total	No	4 371 901	86.50	7.89	2 788.27
Small	Man	Yes	40 720	0.80	4.67	3 210.63
Small	Man	No	3 483 544	68.90	8.79	3 042.47
Small	Woman	Yes	14 451	0.30	3.27	2 296.91
Small	Woman	No	888 357	17.60	4.35	1 791.47
Medium and large	Total	Total	629 339	12.40	151.03	125 420.18
Medium and large	Man	Total	586 072	11.60	152.74	126 207.84
Medium and large	Woman	Total	43 267	0.90	127.87	114 750.96
Medium and large	Total	Yes	1 276	0.00	74.01	92 281.20
Medium and large	Total	No	628 063	12.40	151.19	125 487.51
Medium and large	Man	Yes	1 110	0.00	75.90	96 363.93
Medium and large	Man	No	584 962	11.60	152.89	126 264.47
Medium and large	Woman	Yes	166	0.00	61.38	64 981.04
Medium and large	Woman	No	43 101	0.90	128.13	114 942.64

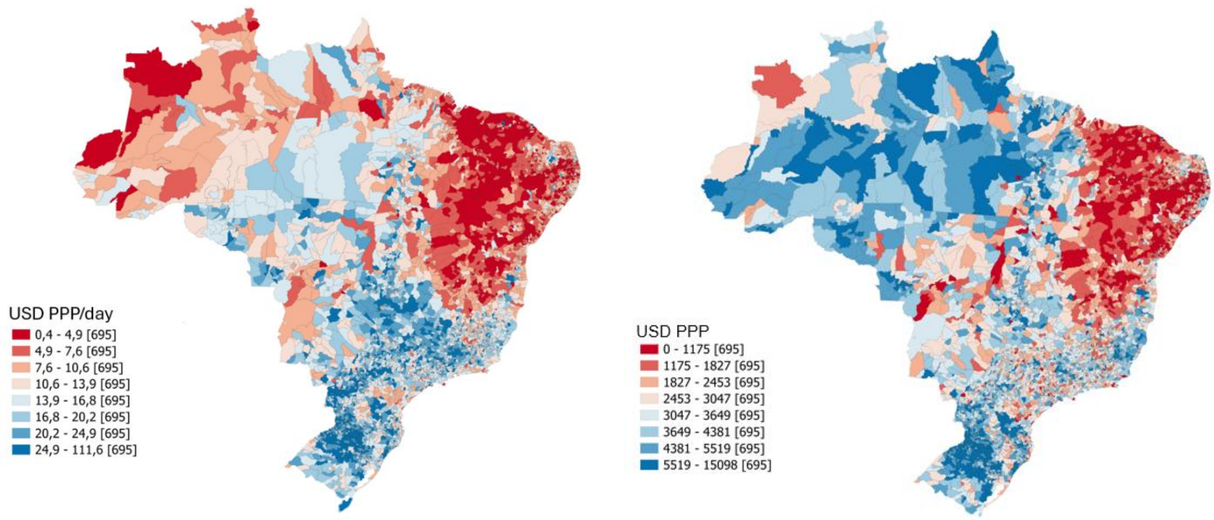
Source: Based on IBGE. n.d. Census of Agriculture. In: *IBGE*. [Cited March 2025]. https://www.ibge.gov.br/en/statistics/economic/agriculture-forestry-and-fishing/21929-2017-2017-censo-agropecuario-en.html?=&t=sobre

The territorial distribution shows that the municipalities in the south and southeast regions, composed of the states of Paraná, Santa Catarina, Rio Grande do Sul, Espírito Santo, Minas Gerais, Rio de Janeiro and São Paulo, are those with the highest average productivity per day worked (above USD 20/day). On the other hand, the municipalities in the northeastern region have values below USD 10/day worked and are the most vulnerable.

Municipalities in the south and southeast regions have the highest average income (above USD 6 000), and municipalities in the north region, which includes the states of Acre, Amazonas, Pará, Rondônia, Roraima, Amapá and Tocantins, stand out. The municipality with the highest average income is Barra de Santo Antônio. The municipalities of Taboão da Serra, Porteirão, Santa Cruz de Minas and Alumínio had the lowest agricultural average income, with incomes below USD 1 700 per year.

Figure 22. Small area estimates of SDG indicators 2.3.1 and 2.3.2 in Brazilian municipalities (2017)

Productivity of small-scale food producers **Average income of small-scale food producers**



Note: Refer to the disclaimer on the copyright page for the names and boundaries used in this map.
Source: Based on IBGE. n.d. Census of Agriculture. In: *IBGE*. [Cited March 2025]. https://www.ibge.gov.br/en/statistics/economic/agriculture-forestry-and-fishing/21929-2017-2017-censo-agropecuario-en.html?=&t=sobre

3.3.3 Key messages and use of results

The results of this study highlight the wide disparities in labour productivity and incomes of smallholder farms across demographics and geographic areas in Brazil. This disaggregated data can be a fundamental input to better target government policies aiming to benefit smallholders.

The Family Farming Law[20] establishes an official definition of family farms so that policies aiming to support them apply consistent criteria. These family farms do not coincide with smallholders as defined by the methodologies of SDG Indicators 2.3.1 and 2.3.2. Nonetheless, it can be argued that there is significant overlap between family farms and smallholders since (as seen above) approximately 88 percent of the census' population are considered smallholders.

The National Programme for Food Acquisition (PAA) was launched in 2003 to reduce food and nutrition insecurity and strengthen family farming.[21] In 2023, the PAA was revamped, further prioritizing family production by Indigenous Peoples, *quilombola* and traditional communities, agrarian reform settlers, African descendants, women and rural youth. Disaggregated data showing the disparities between these groups, as well as their geographic location, can help ensure food is purchased from the family farms where the resources are most needed.

[20] See https://www.planalto.gov.br/ccivil_03/_ato2004-2006/2006/lei/l11326.htm
[21] See https://www.gov.br/secom/pt-br/acesso-a-informacao/comunicabr/lista-de-acoes-e-programas/programa-de-aquisicao-de-alimentos-paa

4 Findings and recommendations for incorporating small area estimation methods into agricultural and food security statistics production

Detailed agricultural and food security statistics are needed for better policy implementation and resource allocation.

In all four countries, specific government policies or initiatives were identified, which need detailed geographic statistics for improving their programming and implementation. In Chile for example, multiple national institutions allocate financial resources at the municipal level rather than the regional level, which is the level of the results of the CASEN survey. The municipal-level estimates developed with the SAE model will result in a more efficient allocation of resources. In Brazil, municipal-level estimates will support the implementation of the National Food Acquisition Plan, which requires the government to purchase farming products from smallholder farmers.

SAE is a cost-effective technique for producing reliable municipal-level estimates.

The estimated cost for monitoring SDG indicators under Target 2.3 exceeds the budget of most National Statistical Offices (NSOs) and is even underestimated if the costs generated by data disaggregation based on increased sample sizes and direct estimation are considered. SAE techniques offer an alternative to increasing sample sizes by combining survey data with auxiliary information retrieved from other existing data sources that are not affected by sampling error to increase the precision, and eventually the accuracy, of SDG estimates for detailed disaggregation dimensions.

Ample auxiliary data for constructing effective SAE models can be sourced from both national and international databases.

SAE is cost-effective because it leverages existing survey data and administrative datasets rather than relying on larger sample sizes. The success of any small area estimation exercise depends heavily on the availability of high-quality auxiliary variables related to the target phenomena, and preparing these variables is typically the most time-consuming aspect of the process. However, these studies demonstrate that, by collaborating with NSOs, the combination of national administrative data and open datasets provides sufficient auxiliary data to build functional SAE models. For food security, data from population and housing censuses, along with administrative records on health, education, economic activity, and nighttime light intensity, proved to be adequate. In Ecuador, for SDG Indicators 2.3.1 and 2.3.2, the auxiliary data also included environmental data from Google Earth Engine and administrative data on livestock.

NSOs lack experience in applying SAE models to food security and agricultural data, which underscores the need for greater support from FAO.

Despite the pressing demand for more detailed statistics on food and agriculture, many NSOs face challenges due to limited experience. While organizations such as the World Bank and ECLAC have been assisting Latin American countries in applying SAE to poverty statistics, making many NSOs familiar with these approaches, SDG Indicator 2.1.2 – measured with the FIES – requires additional training and adaptation due to its unique methodology, particularly the use of the Rasch model. For agricultural indicators, such as SDG Indicators 2.3.1 and 2.3.2, the auxiliary variables required differ from those used in poverty estimation, incorporating more environmental data such as soil quality, topography, land cover and precipitation. Therefore, targeted support from FAO is essential to equip countries with the necessary skills to apply SAE methods to agricultural and food security data.

With minimal technical assistance, countries can successfully integrate SAE models into their statistical production processes to fill data gaps.

Throughout the project, FAO experts collaborated closely with technical staff in national institutions. Rather than traditional technical assistance, the process was more collaborative, with FAO offering foundational guidance while national officers took the lead in identifying and acquiring auxiliary datasets. Together, FAO and national partners developed scripts and conducted analyses through regular meetings and remote support, without the need for any in-country missions, which kept project costs low. Importantly, all participating countries reported that they would continue applying the SAE models, effectively incorporating the approach into their statistical production processes to generate municipal-level estimates in the future.

FAO's support could be expanded to assist additional countries.

The techniques discussed in this study can be replicated in virtually any country by leveraging a nationally representative sample survey and reliable sources of auxiliary variables related to the indicator of interest. For example, small area estimation of SDG Indicator 2.1.2 could be implemented in countries such as Chile, the Dominican Republic, Paraguay, Peru and Uruguay, all of which have integrated the FIES into their national surveys. While replicating the efforts for SDG Indicators 2.3.1 and 2.3.2, as demonstrated in Ecuador, may be more challenging due to low reporting rates, this approach can still be applied to disaggregate other crucial indicators, such as agricultural production and yield, in countries with national agricultural surveys, including Chile, Colombia, Costa Rica, El Salvador, Mexico, Paraguay and Peru.

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