Disaggregating the Hidden: Small Area Estimates of Child Labor in Bali Province

A N Al Agung[1], A D Firlanasari[1], C Azarine[1], L Oktaviana[1], Z A Al Aqsha[1], and N Istiana[1,*]

[1] Politeknik Statistika STIS, Jakarta, Indonesia

*Corresponding author's email: nofita@stis.ac.id

Abstract. Child labor remains a critical concern in Indonesia, including in Bali Province, which exhibits a higher prevalence than the national average. However, efforts to formulate effective local policies are often hindered by the unreliability of child labor statistics at the regency/municipality level, primarily due to high Relative Standard Error (RSE) values. This study seeks to estimate more reliable proportion of child labor at the regency level in Bali through the application of Small Area Estimation (SAE). The analysis utilizes data from the August 2024 Sakernas survey, supplemented with contextual variables from the 2024 PODES dataset. The SAE approach employed was the Hierarchical Bayes method with a Beta distribution (HB-Beta). The findings indicate that the HB-Beta model yields better accurate estimates, as evidenced by RSE values below 25% across all regencies. This demonstrates the potential of the HB-Beta model produces more accurate estimates than direct estimates, as it can better reflect differences between regency and help design more effective local policies to reduce child labor.
Keyword: Child labor, Hierarchical Bayes Beta, Small Area Estimation.

1. Introduction

Children represent the future generation of a nation and are entitled to optimal growth and development, both physically, mentally, and socially. Nevertheless, various social and economic challenges, such as poverty and limited access to education, compel some children to enter the workforce in order to support their families financially [1]. Furthermore, inadequate enforcement of child labor regulations contributes to the vulnerability of children being engaged in work that is inappropriate for their age and detrimental to their physical and psychological well-being [2-3].

Child labor remains a critical issue of concern. Efforts to eradicate child labor have become a shared commitment at both global and national levels. At the international level, this initiative is reflected in the Sustainable Development Goals (SDGs), particularly Goal 8.7, which aims to eliminate the worst forms of child labor, including the recruitment and employment of children, and to end all forms of child labor by 2025. At the national level, the Government of Indonesia has adopted the policy framework of a "Child-Friendly Indonesia" as part of the 2020–2024 National Medium-Term Development Plan

(RPJMN). A key focus of this policy is to strengthen a child protection system that is responsive to regional characteristics and diversity, ensuring that all children can fully exercise their rights.To fulfil its commitment to eliminating child labor, the Indonesian government has enacted regulatory measures through Law No. 13 of 2003 concerning Employment. This law prohibits and restricts the involvement of children in the labor force. However, despite being codified in legal instruments, the implementation of these regulations continues to face numerous obstacles. The issue of child labor persists annually and, in some cases, has progressed into more severe forms of exploitation that pose significant threats to children's physical, mental, moral, and intellectual development [3].

The proportion of child labor in Indonesia experienced a significant increase from 1.58 percent in 2019 to 2.30 percent in 2020, which represents the highest rate within the period from 2019 to 2023 (Figure 1). This rise was most likely driven by the socioeconomic impacts of the COVID-19 pandemic on households [4]. In the years that followed, the percentage of child labor gradually declined and reached 1.72 percent in 2023. Nevertheless, despite this downward trend, the figure remains above the target set by the Sustainable Development Goals (SDGs), particularly Target 8.7, which emphasizes the global commitment to eliminate all forms of child labor by the year 2025. In fact, the percentage recorded in 2023 is still higher than that of 2019.

One of the provinces that continues to face this issue is Bali Province. When compared with the national level, Bali has consistently shown a higher proportion of child labor throughout the 2019 to 2023 period (Figure 1). Similar to national trends, the percentage in Bali increased significantly due to the COVID-19 pandemic, rising from 2.03 percent in 2019 to 2.95 percent in 2020. Although a slight decline occurred in 2021 to 2.70 percent, the percentage rose again in 2022 and 2023. By the year 2023, the child labor rate in Bali had reached 3.06 percent, the highest recorded during the 2019-2023 period.

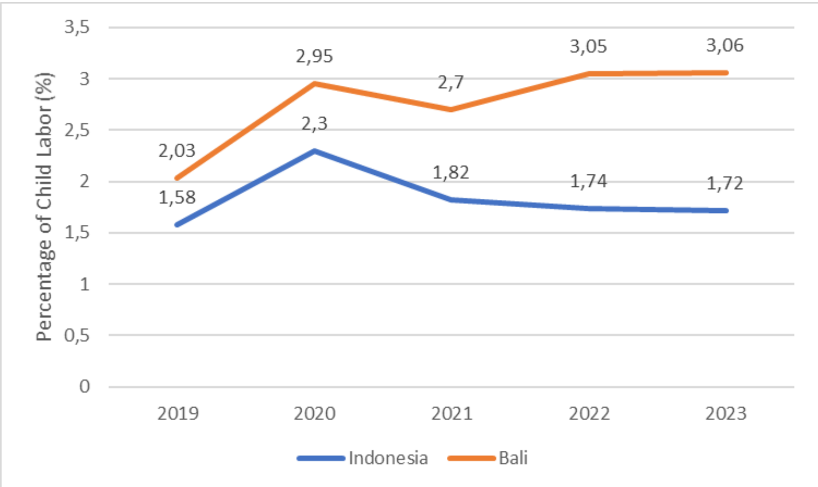


Figure 1. Percentage of Child Labor in Indonesia and Bali Province in 2019-2023.

Bali Province is one of the most popular tourist destinations in the world and has become a tourism icon in Indonesia with its natural beauty, culture, and hospitality. As a result, tourism serves as the primary economic driver in the region, contributing substantially to local income generation and employment. This sector encompasses a wide spectrum of job types, ranging from low-skilled, low value-added work to high-skilled, high value-added occupations [5]. The broad range of employment opportunities available in the tourism industry not only attracts adult workers but also creates openings for child labor, particularly in roles characterized by a high demand for unskilled manual work [6].

As of 2023, most jobs in Bali are concentrated in production, operational, and manual labor sectors, totaling approximately 888,128 workers [7]. This labor structure suggests the existence of potential entry points for children to be involved in informal or casual work arrangements. One illustrative example, as reported by [8], is the involvement of children in economic activities around Kuta Beach, where they may work up to 16 hours a day engaging in activities such as selling small items, offering entertainment services, or renting out tourist equipment like mats. Although such tasks may be categorized as light work, the extended hours can have adverse effects on children's well-being.

Engagement in labor from a young age can lead to detrimental consequences for children's education, health, psychological development, and the fulfilment of their basic rights [9]. The use of child labor is widely regarded as a violation of human rights, as it exposes children to economic exploitation and hazardous work that interferes with their educational attainment, health, physical and mental development, and moral and social growth [10]. Accordingly, collective efforts from governments, international bodies, and civil society are crucial in preventing child labor, protecting affected children, and supporting their rehabilitation.

The formulation of effective child labor policies requires reliable and granular data, particularly at the sub-provincial level. Such detailed data are essential for capturing the geographic distribution and socio-demographic characteristics of child laborers, especially in areas with heterogeneous economic and social conditions. Without localized data, patterns of child labor vulnerability may be obscured in aggregate provincial or national statistics, resulting in poorly targeted interventions. Currently, direct estimates of child labor using data from the National Labor Force Survey (SAKERNAS) are only statistically valid at the provincial level due to limitations in sample size. Estimating figures at the regency/municipality level would require significantly larger samples, leading to increased costs, time consumption, logistical complexity, and a higher risk of non-sampling errors.

To overcome these limitations, indirect estimation techniques such as Small Area Estimation (SAE) offer a viable alternative for producing reliable regency/municipality level estimates [11]. This method integrates survey data with auxiliary information from sources free sampling error, including censuses and administrative records. By leveraging these combined data sources, SAE enhances estimation efficiency and allows for more precise and cost-effective analysis of child labor prevalence at smaller geographic scales.

A number of prior studies have examined child labor in Indonesia by exploring its driving factors [12-15], assessing its consequences on educational outcomes for child workers [1], and evaluating the effectiveness of policy interventions aimed at its elimination [16]. However, these studies primarily rely on data aggregated at the national or provincial levels, limiting their ability to reflect conditions at more localized scales, such as regency/municipality. Moreover, direct estimation approaches based on sample survey data, such as those from SAKERNAS, often lack the statistical power to generate reliable estimates at the regency or municipality level due to sample size constraints.

To address this limitation, the Small Area Estimation (SAE) technique has been widely applied to produce more precise estimates of various socioeconomic indicators at regency/municipality levels [17-20]. Despite its broad application, the SAE method has not yet been utilized to estimate the proportion of child labor at the regency/municipality level within Bali Province. Therefore, this study seeks to present direct estimates and their relative standard errors (RSEs) for the proportion of child labor aged 5–17 in each regency/municipality of Bali Province in 2024; generate indirect estimates using the SAE approach; compare the results of direct and indirect estimation; and develop a spatial map of the estimated child labor proportions at the regency/municipality level in Bali Province based on the most robust model.

2. Research Method

3.1 Theoretical Foundation

Child Labor. The United Nations Convention on the Rights of the Child define a child as any individual below the age of 18. This definition has been adopted by the Government of Indonesia under the Law No. 35 of 2014 Article 1, which further includes unborn children within this classification. In alignment with the 1945 Constitution of the Republic of Indonesia, children are entitled to the right to survival, growth, and development, as well as protection from violence and discrimination. Nevertheless, the inadequate fulfilment of these fundamental rights often gives rise to the persistence of child labor in society. Child labor refers to work undertaken by children who are under the minimum age for employment and/or work that, due to its nature or the conditions under which it is carried out, poses risks to their health, safety, or moral development [4].

To operationalize legal standards into measurable statistical indicators, the percentage of child labor is used as a key metric. This indicator estimates the prevalence of child labor by using the number of working hours as a proxy for hazardous work conditions. The use of working hours as a proxy is deemed appropriate for assessing exposure to harmful labor practices among children [21]. Based on the classification system adopted by Statistics Indonesia (BPS), child labor is categorized into three groups: (i) children aged 5–12 years who are engaged in any form of work; (ii) children aged 13–14 years who work more than 15 hours per week; and (iii) children aged 15–17 years who work more than 40 hours per week. The proportion of child labor is calculated as the number of children engaged in labor divided by the total population of children aged 5–17 years.

Webbink proposed a theoretical framework to understand the determinants of child labor, particularly within the context of developing countries [6]. This framework is conceptualized as a comprehensive multilevel model, illustrated in Figure 2 using concentric circles, where factors at the innermost levels are nested within and influenced by broader contextual layers. At the core of the model is the child, situated within an interconnected structure comprising household and local environments. The household level, where decisions concerning a child's involvement in labor or education are primarily made, is central to the model, while external environmental factors exert additional influence. The determinants of child labor are categorized into three overarching dimensions: resources, structural conditions, and cultural factors.

ICDSOS The 3rd International Conference on Data Science and Official Statistics November 27 - 28, 2025

Figure 2. Theoretical Framework for Children's Involvement in Child Labor.

Resource-related factors pertain to the capacity of individuals, households, and regions to fulfil basic needs. These include children's demographic attributes, parents' levels of education and occupational status, household socioeconomic conditions, and the degree of regional development. Structural factors encompass family composition—such as parental presence and the number of siblings—as well as broader regional characteristics, including labor market dynamics and the availability of educational infrastructure. In contexts where access to education is limited and labor markets are dominated by low-skilled or manual employment. children are more likely to engage in work. Cultural factors, on the other hand, reflect prevailing social norms and value systems that influence public attitudes toward children's involvement in the workforce, gender roles, and the acceptance of modern societal values. These cultural dimensions collectively contribute to societal tolerance or endorsement of child labor practices.

Small Area Estimation (SAE). SAE is a method used to estimate parameters for which direct estimation is difficult to obtain good accuracy. This is because subpopulations have small samples so that the parameters generated by direct estimation do not represent the entire population [11]. SAE borrows strengths across related small areas through additional information from census or administrative records called auxiliary variables through statistical model equations. SAE modelling is divided into two types, namely models with an area level approach and models with a unit level approach. In practice, SAE modelling can be done with various methods that can be adjusted to the data conditions and the suitability of the results to achieve the research objectives.

SAE Hierarchical Bayes Beta. The Bayesian method considers a parameter as a random variable. The Bayesian model includes three components, namely the prior distribution, likelihood, and posterior distribution. The relationship between the three components is illustrated by the following equation.

$$Posterior\ distribution \propto Likelihood \times Prior\ Distribution \tag{1}$$

One of the data distributions that can be used in SAE HB is the Beta distribution. The use of beta distribution is based on the nature of the proportion that has a range between 0 to 1 and is able to overcome asymmetric data [22]. In its application, in accommodating the asymmetric or non-normal sampling distribution on the proportion parameter, the Beta distribution assumption is used at the sampling level of the model as follows.

$$\text{Level 1. } Sampling\ model:\ \hat{\theta}_i|\theta_i \sim Beta(a_i, b_i) \tag{2}$$

$$\text{Level 2. } Linking\ model:\ logit\left(\frac{a_i}{a_i+b_i}\right)|\,\boldsymbol{\beta}, \sigma_v^2 \sim N\left(\boldsymbol{x}_i^T\boldsymbol{\beta}, \sigma_v^2\right) \tag{3}$$

$$logit(\theta_i)|\,\boldsymbol{\beta}, \sigma_v^2 \sim N\left(\boldsymbol{x}_i^T\boldsymbol{\beta}, \sigma_v^2\right) \tag{4}$$

$$logit(\theta_i) = \boldsymbol{x}_i^T\boldsymbol{\beta} + v_i \tag{5}$$

Where $i = 1, \dots, m$ is the small area (domain), θ_i is the proportion parameter, and $\hat{\theta}$ is the proportion estimator for the small area i. Where $a_i = \theta_{ik}$ and $b_i = (1 - \theta_i)k$ are the parameters of the beta distribution, so that $E(\hat{\theta}_i) = \theta_i = \frac{a_i}{a_i+b_i}$. With k is the beta distribution parameter, a constant which is assumed to be gamma distributed $k \sim Gamma(g_1, g_2)$. Equation (5) is a simple form of equations (3) and (4). Where $v_i \sim N(0, \sigma_v^2)$ with initial $\sigma_v^2 = 1$, and $\sigma_v^2 \sim Inversed\ Gamma(c_1, c_2)$. $\boldsymbol{\beta}$ and σ_v^2 are mutually independent with $\boldsymbol{\beta} \sim N(\mu_\beta, \sigma_\beta^2)$, initial $\mu_\beta = 0$ dan $\sigma_\beta^2 = 1$. Where $\boldsymbol{\beta}$ is the vector of fixed effects or regression coefficients, and σ_v^2 is the variance of random effect area. It is assumed that $g_1, g_2, c_1, c_2, \mu_\beta$, and σ_β^2 predetermined or constant in value.

The Bayesian theorem is based on the posterior distribution which is a combination of the prior distribution (past information before observation) and the observation data used to compile the Likelihood function [23]. In Bayesian theorem, if there is a parameter θ given by the observation data $\hat{\theta}$, then the probability distribution for the posterior θ on the data $\hat{\theta}$ will be proportional to the product of the prior distribution θ and the likelihood function θ given by the data $\hat{\theta}$. Mathematically it can be written as follows.

$$f(\theta|\hat{\theta}) \propto f(\theta) \cdot f(\hat{\theta}|\theta) \quad (7)$$

where $f(\theta|\hat{\theta})$ is the posterior distribution which proportional to the product of the likelihood function $f(\hat{\theta}|\theta)$ and the prior distribution $f(\theta)$.

The estimator of the HB model and its variance are obtained from its posterior formula, where the estimated values are obtained from the posterior mean [21]. The value is obtained by the Markov Chain Monte Carlo (MCMC) numerical method. The MCMC approach is very effective for reducing the computational burden in solving complex integration equations [23]. MCMC generates samples from the posterior density function $f(\theta|\hat{\theta})$. If the MCMC algorithm has converged, the Markov chain will follow the posterior distribution [24]. The converged MCMC sample is used to calculate the expected value of the posterior parameter of interest $\phi = h(\theta)$. The posterior mean $\phi^{HB} = E[h(\theta)|\hat{\theta}]$ in the HB approach is used as the point estimate and the posterior variance $Var(\phi^{HB}) = V[h(\theta)|\hat{\theta}]$ as the variability measure [24].

3.2 Data and Data Sources

This study estimates the proportion of child labor at the regency level in Bali Province in August 2024 with 9 regencies observation units. Data on the proportion of child labor was obtained from the August 2024 National Labor Force Survey (SAKERNAS). Meanwhile, the auxiliary variables used were obtained from the 2024 Village Potential data collection (PODES). The candidate auxiliary variables used can be seen in Table 1.

Table 1. Auxiliary variables.

Variable Notation	Variable Name
X1	Number of private boarding schools
X2	Number of health centers with inpatient care
X3	Number of micro and small industries of wood, woven bamboo, rattan, and similar products
X4	Number of kindergartens (TK)
X5	Number of junior high schools (SMP)
X6	Number of families with non-electric main source of lighting
X7	Number of families whose main cooking fuel is kerosene/charcoal/firewood

Analysis Method

The methods used in this research are descriptive and inferential analysis. The descriptive analysis used were bar charts, histograms, summary statistics, and boxplots. The inferential analysis used in this research is SAE HB Beta. This research uses R and QGIS software in descriptive and inferential analysis. The stages of analysis carried out in this study are as follows.

1) Conduct descriptive analysis on the direct estimate of the proportion of child labor and its RSE
2) Conducting a normality test on the direct estimate of the proportion of child labor
3) Performing correlation between the dependent variable and the auxiliary variables
4) Performing stepwise regression
5) Checking multicollinearity among the auxiliary variables using VIF
6) Performing indirect estimation using SAE HB Beta
7) Comparing the estimation results and RSE of direct estimation and SAE HB Beta
8) Checking the consistency of estimation results
9) Mapping the estimation results

3. Result and Discussion

Overview the Proportion of Child Labor in Bali Province

The proportion of child labor by region was estimated directly using the 2024 National Labor Force Survey or Survei Angkatan Kerja Nasional (SAKERNAS) data. The following figure shows the proportion of child labor from direct estimation in nine regencies of Bali Province in 2024.

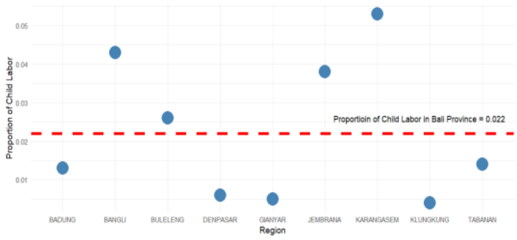


Figure 3. Direct Estimation of the Proportion of Child Labor by Regency/ Municipality in Bali.

On average, the proportion of child labor by regency in Bali Province is 0.022 with a variation of 0.0003. It can be seen from Figure 3 that Karangasem, Bangli, Jembrana, and Buleleng regency have a higher proportion of child labor than the proportion of child labor in Bali Province, while Tabanan, Badung, Klungkung, Gianyar, and Denpasar have a lower proportion of child labor than the proportion of child labor in Bali Province. The lowest proportion is found in Klungkung Regency, which is 0.004, while the highest proportion is found in Karangasem Regency, which is 0.053. Based on the highest and lowest values, the range of the proportion of child labor is 0.049, indicating that there is considerable variation between regencies in Bali Province.

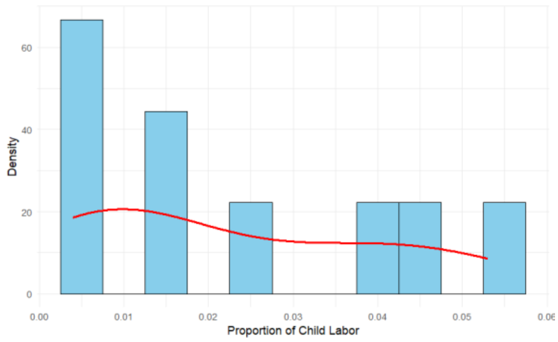
The quality of the estimation results can be seen from the resulting RSE. On average, the RSE of direct estimation is 51.4%. Klungkung Regency has the highest RSE of 98.8% and Karangasem Regency has the lowest RSE of 30.3%. According to Statistics Indonesia, RSE can be categorized into three categories, RSE ≤ 25% which indicates that the estimation results are accurate, 25-50% indicates that the estimation results need to be cautious in their use, and RSE > 50% indicates that the estimation results are not worth presenting.

Table 2. Number of Regencies/Municipalities for Each RSE Group on Direct Estimation Method.

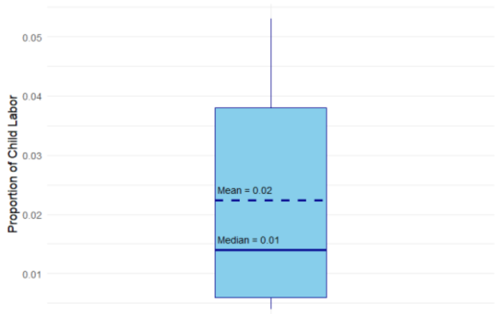
ICDSOS
The 3rd International Conference on Data Science and Official Statistics
November 27 - 28, 2025

Category	Number of regencies/municipalities
0% < RSE ≤ 25%	0
25% < RSE ≤ 50%	6
RSE > 50%	3

Based on these categories, there are no regencies that have a direct estimation RSE ≤ 25%, there are 6 regencies with an RSE of 25%-50%, which are Tabanan, Badung, Jembrana, Buleleng, Bangli, and Karangasem. Then, there are 3 regencies/municipalities with RSE above 50%, which are Klungkung Regency, Denpasar, and Gianyar Regency.



(a) Histogram



(b) Boxplot

Figure 4. Distribution of Directly Estimated Data on the Proportion of Child Labor in Bali Province.

Based on the histogram in Figure 4a, the distribution of the directly estimated data tends to be positively skewed, which means that most areas have a relatively low proportion of child labor, but there are some areas with much higher values. In addition, the boxplot in Figure 4b shows that the median value (0.01) is lower than the mean value (0.02), indicating a distribution that is not symmetrical and tends to right skewed.

Normality Test of Direct Estimation Results of Child Labor Proportion in Bali Province

Before SAE modelling, it is necessary to test the normality of the data from the direct estimation of the proportion of child labor.

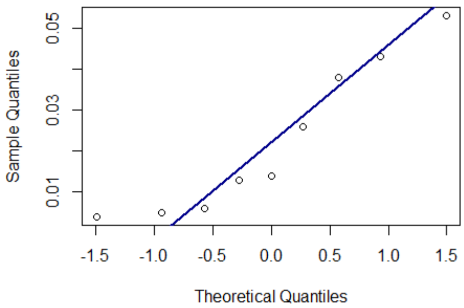


Figure 5. QQ Plot of Normality Test of Proportion of Child Labor in Bali Province.

Based on Figure 5, the direct estimate of the proportion of child labor is close to the line on the QQ Plot which indicates that the data follows a normal distribution. In addition, the results of the normality test using Shapiro-Wilk which can be seen in Table 3 show a p-value of 0.1752 which is greater than the significance level of 0.05. Thus, it can be concluded that the direct estimate of the proportion of child labor follows a normal distribution.

Table 3. Normality Test Results of Direct Estimation Results of Child Labor Proportion.

Test	Test Statistics Value (W)	P-Value
Normality (Shapiro-Wilk)	0.8845	0.1752

Exploration of Auxiliary Variables

The construction of the SAE model begins with the selection process of auxiliary variables that will be used in modelling. This selection process is carried out by considering the existence of a causal relationship between the auxiliary variables and the response variable indicated by a high correlation value. Based on the correlation value of all candidates auxiliary variables, seven variables were obtained with a high absolute correlation value, which is more than 0.65.

Table 4. Pearson Correlation Values.

Variable	Correlation	Description
X1	0.9291	Number of private boarding schools
X2	0.6517	Number of health centers with inpatient care
X3	0.7282	Number of micro and small industries of wood, woven bamboo, rattan and similar products
X4	-0.7554	Number of kindergartens (TK)
X5	-0.7165	Number of junior high schools (SMP)
X6	0.7619	Number of families with non-electric main source of lighting
X7	0.7007	Number of families whose main cooking fuel is kerosene/charcoal/ firewood

To obtain the best combination of auxiliary variables, a variable selection process was carried out using stepwise regression and checking the non-multicollinearity assumption using the Variance Inflation Factor (VIF) indicator. The selection results produced the four best auxiliary variables with VIF as follows.

Table 5. VIF of Selected Auxiliary Variables Stepwise Results.

Variable	VIF
Number of health centers with inpatient care (X2)	3.5466
Number of micro and small industries of wood, woven bamboo, rattan and similar products (X3)	3.4699
Number of kindergartens (X4)	4.2144
Number of families with non-electric main source of lighting (X6)	4.3819

Based on Table 5, the four auxiliary variables have VIF less than 10, which indicates that there is no violation of the assumption of non-multicollinearity, thus confirming that all variables are appropriate to be used as auxiliary variables in the SAE modelling.

Indirect Estimation Results with SAE HB-Beta

Estimation with the SAE HB-Beta method is carried out because the proportion of child labor is a proportion data that is in the open range of 0 to 1 (0,1) so that it is in accordance with the SAE HB Beta model which assumes that the response variable follows the Beta distribution. Modelling with SAE HB Beta uses the four auxiliary variables, which are X2, X3, X4, and X6.

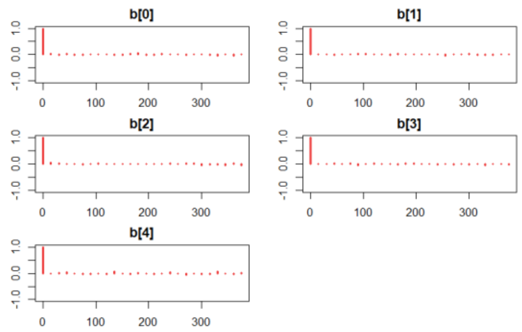


Figure 6. Autocorrelation Plot on SAE HB Beta Model.

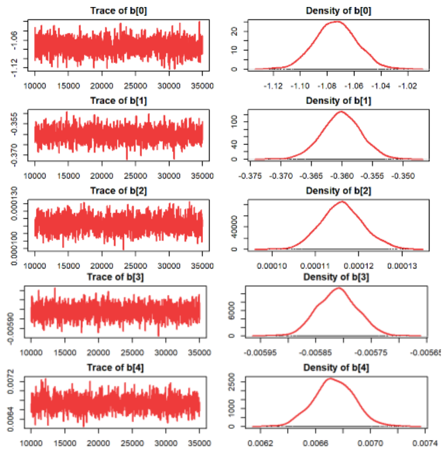


Figure 7. Trace Plot and Density Plot on SAE HB Beta Model.

Based on Figure 6 and Figure 7, the iteration process in the SAE HB Beta model with update of 75, MCMC iterations of 35,000, and thin of 15, has shown a convergent condition. This indicates that the assumed distribution has matched the data on the proportion of child labor by regency/municipality in Bali Province. The autocorrelation plot only shows significant autocorrelation at lag 0 which decreases sharply to zero at the next lag, the trace plot is stable without trend, and the density plot forms a symmetric posterior distribution for all parameters. The results of SAE HB Beta modelling are presented in Table 6.

Table 6. Estimated Parameter Coefficients of the SAE HB Beta Model.

Variable	Mean	SD	2,5%	97,5%
Intercept	-1.07363	0.015543	-1.08393	-1.04366
X2	-0.36008	0.003186	-0.36219	-0.35382
X3	0.000116	$4.81 \text{x} 10^{-6}$	0.000113	0.000126
X4	-0.00581	$3.53 \text{x} 10^{-5}$	-0.00584	-0.00574
X6	0.006735	0.000147	0.006641	0.007024

Based on Table 6, the four auxiliary variables have a significant effect on the proportion of child labor in Bali Province, which can be seen from the credible interval range that does not include zero value between the 2.5% and 97.5% quantiles in each auxiliary variable used.

The variable number of health centers with inpatient care has a negative effect on the proportion of child labor. This implies that as the number of health centers with inpatient care increases, the proportion of child labor tends to decrease. Health centers are often the most accessible health facilities in many areas. One of the key drivers of child labor is the limited access to basic services, such as health care and social protection [23]. [24] also emphasized that improved access to public services, including health and education, can contribute to a reduction in child labor. Therefore, when parents fall ill, timely and affordable treatment can reduce the likelihood of children entering the labor force to compensate for lost household income.

The variable number of Micro and Small Industries (IMK) of wood, woven goods from bamboo, rattan, and similar sectors has a positive effect on the proportion of child labor. This suggests that an increase in the number of such labor-intensive industries is associated with a higher prevalence of child labor. According to [6], regional labor market conditions and education infrastructure significantly influence the incidence of child labor. Child labor is typically concentrated in low-skilled, manual occupations, as children generally lack education and work experience. As a result, children are more likely to be employed in areas where there is greater demand for unskilled labor, such as in small-scale timber and craft industries. This is also in line with [14] which states that micro and small industries have a positive effect on child labor.

The variable number of kindergartens has a negative effect on the proportion of child labor. This implies that an increase in the number of kindergartens tends to reduce the proportion of child labor. According to [6], the availability of educational facilities is a key structural factor influencing child labor. When no school is available in a given area, children are more likely to be forced into labor or remain idle [25]. Similarly, [26] explain that the level of education is a key factor in enhancing individual capabilities. In areas where educational facilities are lacking or inaccessible, children are more likely to enter the labor force at an early age to support their families financially.

The variable number of households with non-electric lighting has a positive influence on the proportion of child labor. This suggests that as the number of such households increases, so does the incidence of child labor. Households without access to electricity are generally indicative of poverty or low-income conditions. According to [14], low household income is a strong determinant of child labor, as families often rely on their children's labor to supplement their earnings. [27] also notes that most child laborers are compelled to work to support their families financially, especially when parental income is small and unstable.

The RSE with SAE HB Beta method is in the range of 6.51% to 20.71%, with an average of 12.59%. This shows a significant decrease from the average RSE of direct estimation (51.4%). The highest RSE in the estimation results with SAE HB Beta was found in Klungkung Regency, while the lowest RSE was obtained in Karangasem Regency.

Model Evaluation

A summary of the Relative Standard Error (RSE) values from the direct estimation methods and indirect estimation method with SAE HB Beta is presented in Table 7. Among these methods, the highest average RSE was observed in the direct estimation method (51.4%), while the lowest average RSE was produced by the SAE HB Beta method (12.59%).

Table 7. Number of Regencies/Municipalities for Each RSE Group on Direct Estimation and SAE HB Beta.

Category	**Number of regencies/municipalities**	
	Direct	**SAE HB Beta**
0% < RSE ≤ 25%	0	9
25% < RSE ≤ 50%	6	0
RSE > 50%	3	0

Based on Table 7, the use of SAE HB Beta method resulted RSE values of less than 25% in all regencies/municipalities. Furthermore, Figure 8 shows the comparison of RSE between direct estimation and SAE HB Beta using boxplot.

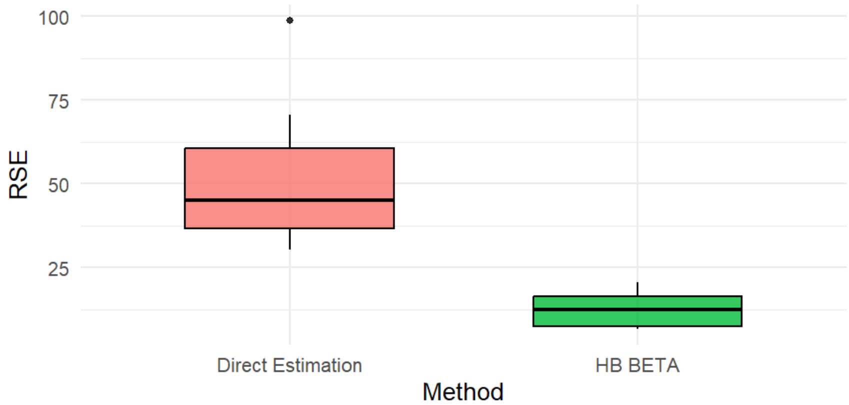


Figure 8. Comparison of RSE.

Based on Figure 8, the SAE HB Beta method not only has the lower RSE but also has a low mean value and small variation between regencies/municipalities. Thus, it can be concluded that the HB Beta estimation method can produce precise estimation of the proportion of child labor at the regency/municipality level in Bali Province and is able to reduce the RSE value optimally.

Consistency of SAE HB-Beta model

In the last stage, a consistency check was conducted on the results of indirect estimation with the SAE HB Beta method. Based on Table 8, the HB Beta estimation value does not differ much from the direct estimation value. The maximum value in both methods is in Karangasem Regency and the minimum value is in Gianyar Regency.

Table 8. Comparison of the Estimation Results of the Proportion of Child Labor in Direct and SAE HB Beta Estimation Beta by Regency/Municipality.

Regency/municipality	Direct Estimation	SAE HB BETA
Jembrana	0.038	0.03833
Tabanan	0.014	0.01258
Badung	0.013	0.01261
Gianyar	0.005	0.00492
Klungkung	0.004	0.00510
Bangli	0.043	0.04345
Karangasem	0.053	0.05309
Buleleng	0.026	0.02560
Denpasar	0.006	0.00640

The boxplot in Figure 9 illustrates the distribution of child labor proportions obtained from both direct estimation and the SAE HB Beta method. The two distribution patterns appear similar, and the proportion of child labor in Bali Province (0.022) falls within the range of estimates produced by the

SAE HB Beta method. This shows that the SAE HB Beta results are consistent for estimation at the regency/municipality level.

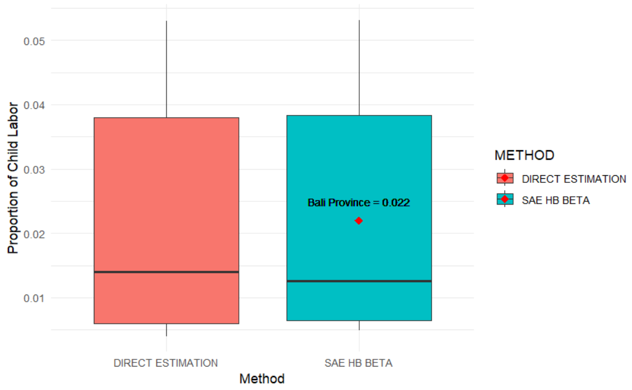


Figure 9. Comparison of Estimation Results and SAE HB Beta.

SAE HB-Beta Estimation Mapping

Based on the analysis results, the most appropriate method employed is indirect estimation using the Small Area Estimation (SAE) approach with a Hierarchical Bayesian (HB) Beta model. This method produced estimates of the proportion of child laborers, which were then visualized in a map to provide a more detailed depiction of their distribution at the regency/municipality level.

The estimated proportions of child laborers across nine regencies/municipalities in Bali Province are presented in Figure 10. Karangasem Regency recorded the highest estimated proportion of child laborers at 0.05309. In contrast, Gianyar Regency had the lowest estimated proportion, at 0.00492. Other areas such as Tabanan (0.01258), Badung (0.01261), Buleleng (0.02561), Jembrana (0.03833), and Bangli (0.04345) showed relatively high proportions. Meanwhile, Denpasar (0.0064) and Klungkung Regency (0.00509) were identified as having relatively low proportions of child labor compared to other regency in Bali Province.

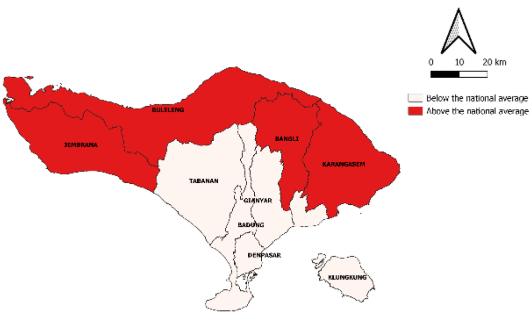


Figure 10. Thematic Map of Proportion of Child Laborers by Regency/Municipality in Bali Province Based on SAE HB-Beta Estimates.

4. Conclusion

The estimation results indicate that the average proportion of child laborers in Bali Province stands at 0.022. Karangasem Regency recorded the highest proportion, whereas Klungkung Regency had the lowest. Six out of the nine regencies/municipalities exhibit proportions exceeding the provincial average, while the remaining three fall below it. Regarding the reliability of the estimates, all regencies/municipalities show relative standard errors (RSE) above 25% under the direct estimation approach, with Klungkung, Denpasar, and Gianyar exceeding 50%, rendering direct estimates unsuitable for dissemination. Compared to the direct method, the SAE-HB Beta model substantially reduces estimation error, lowering the maximum RSE from 98.8% under the direct method to just 20.7%. Notably, the SAE-HB Beta method achieves RSE values ≤ 25% across all regencies/municipalities in Bali, signifying its superior performance and reliability in estimating the proportion of child labor. SAE-HB Beta demonstrates higher level of precision, effectively minimizing RSE and enhancing the quality of the estimates. In 2024, Karangasem emerges as the regency with the lowest RSE under the SAE-HB Beta approach, indicating the most accurate estimate in the province. The SAE-HB Beta estimation also reveals that all four predictor variables significantly influence the proportion of child labor in Bali. The availability of inpatient health centers and the number of kindergartens are negatively associated with child labor prevalence. In contrast, the number of micro and small-scale wood-based industries, along with the number of households without access to electricity, show a positive association. Thematic mapping based on these estimates highlights spatial disparities in the distribution of child labor within the province. Higher concentrations are observed in Karangasem, Bangli, and Jembrana, while lower proportions are found in Denpasar, Klungkung, and Badung.

Acknowledgement
The author acknowledges all parties who provided assistance and feedback during the writing of this article.

References
[1] L. Nursita and B. S. E. P, “PENDIDIKAN PEKERJA ANAK: DAMPAK KEMISKINAN PADA PENDIDIKAN,” *JAMBURA ECONOMIC EDUCATION JOURNAL*, vol. 4, no. 1, 2022.
[2] M. I. Azwar, “PERLINDUNGAN PEKERJA ANAK: TANTANGAN DAN UPAYA DARI SUDUT PANDANG HAK ASASI MANUSIA,” *Triwikrama: Jurnal Ilmu Sosial* , vol. 1, no. 3, pp. 110–120, 2023.
[3] E. D. Setiamandani, “PERLINDUNGAN HUKUM BAGI PEKERJA ANAK DAN UPAYA PENANGGULANGANNYA,” *Jurnal Reformasi*, vol. 2, no. 2, pp. 74–81, 2012.
[4] Internationales Arbeitsamt and UNICEF, Eds., *Child labour: Global estimates 2020, trends and the road forward*. International Labour Office, 2021.
[5] ILO, *Mengukur Lapangan Kerja dalam Industri Kepariwisataan lebih dari Neraca Satelit Pariwisata: Studi Kasus Indonesia*. ILO, 2011.
[6] E. Webbink, J. Smits, and E. de Jong, “Household and Context Determinants of Child Labor in 221 Districts of 18 Developing Countries,” *Soc Indic Res*, vol. 110, no. 2, pp. 819–836, Jan. 2013, doi: 10.1007/s11205-011-9960-0.
[7] Disnaker ESDM Bali, *Data Ketenagakerjaan, Transmigrasi, dan Energi Sumber Daya Mineral di Provinsi Bali*. 2023.
[8] F. Chandra, K. S. M. Parwati, and F. L. Amir, “ANALISIS FENOMENA SOSIAL PEKERJA ANAK DI DESTINASI WISATA PANTAI KUTA BALI,” *Majority Science Journal (MSJ)* , vol. 1, no. 3, pp. 64–68, 2023.
[9] A. Pungkasari, “Problematika Ketenagakerjaan Anak Di Indonesia Dan Cara Menanggulanginya,” *INNOVATIVE: Journal Of Social Science Research*, vol. 3, no. 2, 2023.
[10] S. Faridah and L. Afiyani, “Isu Pekerja Anak dan Hubungan dengan Hak Asasi Manusia,” *Lex Scientia Law Review*, vol. 2, no. 2, pp. 163–176, 2019, [Online]. Available: https://journal.unnes.ac.id/sju/index.php/lslr/
[11] J. N. K. Rao and I. Molina, *Small area estimation*, 2nd ed. John Wiley & Sons, Inc., 2015.
[12] I. M. J. Ardana, “PELUANG ANAK-ANAK BEKERJA MENURUT KARAKTERISTIK ANAK, RUMAH TANGGA, DAN KEPALA RUMAH TANGGA DI BALI,” *Jurnal Ilmu Sosial dan Humaniora*, vol. 10, no. 2, pp. 309–321, Aug. 2021, doi: 10.23887/jish-undiksha.v10i2.35042.

[13] H. D. Raharja and E. Suwandana, “KARAKTERISTIK SOSIAL EKONOMI KEPALA RUMAH TANGGA DAN MUNCULNYA PEKERJA ANAK DI NTT 2022,” *JSTAR*, vol. 3, no. 2, pp. 13–22, 2023, doi: 10.5300/JSTAR.V3I02.52.

[14] R. S. Utama and D. Handayani, “Pekerja Anak di Indonesia: Peran Penawaran dan Permintaan Ketenagakerjaan,” *JURNAL EKONOMI KUANTITATIF TERAPAN*, vol. 13, no. 1, pp. 145–157, 2020, [Online]. Available: https://www.researchgate.net/publication/346644761

[15] L. O. Wardana and L. K. Sari, “ANALISIS FAKTOR-FAKTOR YANG MEMENGARUHI EKSPLOITASI PEKERJA ANAK DI INDONESIA MENGGUNAKAN REGRESI LOGISTIK BINER,” 2020.

[16] M. M. Ibrahim and I. D. G. K. Wisana, “Apakah Program Keluarga Harapan Mampu Mengurangi Pekerja Anak di Masa Pandemi COVID-19?,” *Jurnal Ekonomi Dan Statistik Indonesia*, vol. 3, no. 1, pp. 37–52, May 2023, doi: 10.11594/jesi.03.01.04.

[17] W. R. Eliezer *et al.*, “Small Area Estimation for Percentage of Out-of-School Children Aged 7-17 Years in Sumatera Island, 2023,” *Jurnal Matematika, Statistika dan Komputasi*, vol. 21, no. 1, pp. 215–233, Sep. 2024, doi: 10.20956/j.v21i1.36043.

[18] B. R. Niashinta, D. Ispriyanti, and A. Hoyyi, “PENDUGAAN AREA KECIL TERHADAP PENGELUARAN PER KAPITA DI KABUPATEN SRAGEN DENGAN PENDEKATAN KERNEL,” *JURNAL GAUSSIAN*, vol. 5, no. 1, pp. 71–80, 2016, [Online]. Available: http://ejournal-s1.undip.ac.id/index.php/gaussian

[19] Priatmadani, P. P. Sari, E. N. Rahmat, P. B. Aji, F. A. Nafiis, and N. Istiana, “Small Area Estimation of Maluku and Papua Island Child Poverty Levels in 2023,” *Jurnal Matematika, Statistika dan Komputasi*, vol. 21, no. 1, pp. 46–61, Sep. 2024, doi: 10.20956/j.v21i1.35293.

[20] P. Septianingsih and I. Y. Wulansari, “Small Area Estimation Using Empirical Bayes Poisson Gamma on Adolescent Fertility Rate in Indonesia,” *Indonesian Journal of Statistics and Its Applications*, vol. 7, no. 2, pp. 114–129, Dec. 2023, doi: 10.29244/ijsa.v7i2p114-129.

[21] Krismawati and A. Sukroni, *Pekerja anak di Indonesia 2009*. Jakarta: Badan Pusat Statistik; Organisasi Perburuhan Internasional (ILO), 2010.

[22] B. Liu, “HIERARCHICAL BAYES ESTIMATION AND EMPIRICAL BEST PREDICTION OF SMALL-AREA PROPORTIONS,” 2009.

[23] ILO, *Global Estimates of Child Labour*. 2017.

[24] E. V. Edmonds and C. Theoharides, *Child Labor and Economic Development*. 2020.

[25] F. Kondylis and M. Manacorda, “School Proximity and Child Labor: Evidence from Rural Tanzania,” 2012.

[26] N. L. P. A. Artini, A. Daeng, and E. Agustiani, “FAKTOR-FAKTOR PENYEBAB ADANYA PEKERJA ANAK DIBAWAH UMUR DI KOTA MATARAM,” *Jurnal Oportunitas Ekonomi Pembangunan*, vol. 2, no. 1, 2023.

[27] N. Endrawati, “FAKTOR PENYEBAB ANAK BEKERJA DAN UPAYA PENCEGAHANNYA (Study Pada Pekerja Anak Sektor Informal di Kota Kediri),” *Jurnal Ilmu Hukum*, 2011.

ICDSOS
The 3rd International Conference on Data Science and Official Statistics
November 27 - 28, 2025