JSDS: JOURNAL OF STATISTICS AND DATA SCIENCE
VOLUME 3, No 1, March 2024
e-ISSN: 2828-9986
https://ejournal.unib.ac.id/index.php/jsds/index

Application of Small Area Estimation for Estimation of Sub-District Level Poverty in Bengkulu Province: Comparison of Empirical Best Linear Unbiased Prediction (EBLUP) and Hierarchical Bayesian (HB) Methods

Auliya Yudha Pratama[1*]
[1] Statistics Indonesia of Bengkulu Province, Indonesia

* Corresponding Author: aypratama@bps.go.id

Article Info

Article History:
Submitted: October 18, 2023
Accepted: March 27, 2024
Available Online: March 30, 2024

Key Words:
Small Area Estimation
Poverty
EBLUP
Bayesian
Hierarchical Bayesian

Abstract

Poverty is an important problem facing the world. Various ways are done to eradicate poverty. In planning poverty alleviation, policy makers need detailed information down to the smallest area level that can be produced. Currently, the demand for estimation at the small area level is increasing, while the success of estimation using the indirect method in reducing the Relative Standard Error (RSE) is very dependent on data conditions and the selection of the right method. This study aims to compare the results of estimating the percentage of poor people using direct estimates with indirect estimates using the Small Area Estimation (SAE) technique such as Empirical Best Linear Unbiased Predictor (EBLUP) and Hierarchical Bayesian (HB) method using a case study of poverty data at the sub-district level of Bengkulu Province. The data used are from the Social and Economic Survey (Susenas) in March 2022 and the 2021 Village Potential Data Collection (Podes). There is one sub-district that was not sampled in the March 2022 Susenas. The average RSE value of the direct estimator is 47.014 and the average RSE of the EBLUP estimator is 39.40 and the HB estimator is 15.318. In addition, the SAE EBLUP and HB methods can reduce the mean and median values of RSE estimation results when compared with direct estimates. The RSE of the direct estimator is greater than the RSE of the indirect estimator.

1. INTRODUCTION

Poverty is a complex problem that is the number one focus in all regions of Indonesia, without exception in Bengkulu Province. Bengkulu Province is a province with fairly good natural resources (SDA) on the island of Sumatra, but in reality Bengkulu Province is one of the provinces with the highest percentage of poor people on the island of Sumatra. Statistics Indonesia (BPS) recorded that the percentage of poor people in Bengkulu Province in March 2022 was 14.62% (BPS Bengkulu Province, 2022). This value makes Bengkulu Province the province with the second highest percentage of poor people on Sumatra Island in March 2022, not far from Aceh Province with the highest percentage of poor people on Sumatra Island (14.64%).

In general, poverty is a condition where a person or group of people is unable to fulfill their basic needs in order to maintain and develop a decent and dignified life. Poverty is a multidimensional problem so it is very difficult to measure poverty and agreement is needed to determine the measurement approach used. In calculating poverty, BPS uses the concept of meeting basic needs (basic needs approach). Poverty is seen as an economic inability to meet basic needs in the form of food and non-food as measured in terms of expenditure. The expenditure approach is used because it is very difficult to obtain accurate individual and household income information. So, what is meant by poor people is people whose average monthly expenditure is below the poverty line (BPS, 2012).

At the district level, the highest poverty percentage in March 2022 occurred in Seluma Regency (18.36%), followed by Kaur Regency (18.10%) and South Bengkulu Regency (17.86%). Meanwhile, the lowest percentage occurred in Central Bengkulu Regency (9.76%), Mukomuko Regency (11.44%) and North Bengkulu Regency (11.48%). There are only five districts that record a percentage of poor people below the Bengkulu Province figure of 14.62%. Something that deserves special attention is that there are no districts/cities in Bengkulu Province that have a poverty percentage below the national figure (9.54%). Therefore, the relatively high level of poverty in Bengkulu Province is a problem that must be addressed immediately.

The poverty level figures produced from the March Susenas can only provide information up to the district/city level, while the September Susenas can only produce poverty information up to the provincial level. The limited estimation level is because the number of samples used is only sufficient to provide estimates up to that level. If used for estimation at a lower level, it will produce a high standard error due to the lack of samples needed to obtain estimates for a smaller area, so that analyzes based on these conditions become unreliable (Ubaidillah, 2014). The relative standard error (RSE) value that is considered accurate is RSE≤25%. Meanwhile, estimates with a value of 25%<RSE≤50% need to be used with caution if they want to be used, while RSE>50% is considered very unreliable (Mulia et al, 2007).

There is an alternative solution that makes it possible to estimate in a smaller area without increasing the sample size, namely by using a combination of existing survey data and other supporting data (Rao, 2003). On this basis, it is necessary to calculate the estimated poverty percentage using an indirect method, namely the Small Area Estimation (SAE) method. The SAE method is relatively capable of reducing the high standard error resulting from direct estimation in a small area due to the small number of samples (Hidroglou, 2007).

Indirect parameter estimation based on the SAE model consists of two approaches, namely explicit models and implicit models. Approach methods with explicit models include Empirical Best Linear Unbiased Predictor (EBLUP), Empirical Bayesian (EB) and Hierarchical Bayesian (HB). The EBLUP method is used for continuous type response variables, while the EB and HB methods can be used for continuous, binary and count response variables.

Research discussing poverty in small areas using SAE as an estimation method continues to be developed over time, including by Novianti and Zain (2014), Ubaidillah (2014), Yuliani et al (2019) and Larasati and Permatasari (2022). Based on the description above, this research will discuss further the use of the SAE EBLUP and HB methods in estimating the percentage of poverty at the sub-district level by conducting a case study of sub-district level poverty data in Bengkulu Province. Next, a comparison will be made of the effectiveness of the estimation results of the two methods in reducing the RSE figure.

2. METHOD

This research is quantitative research, where this research uses data in the form of numbers that can be calculated from various sources to estimate the level of poverty at the sub-district level in Bengkulu Province. The response variable (Y) used in this research is the percentage of poor people at the sub-district level in Bengkulu Province, which is sourced from Susenas data. Meanwhile, the predictor variables (X) that will be tested and selected are sourced from the results of the 2021 Podes data, and are as follows:

Table 1. Research Predictor Variables

Variables	Explanation
X_1	Average villages distance in one sub-district to the district/city capital,
X_2	Proportion of villages in the sub-district that have internet access,
X_3	Proportion of villages in the sub-district that have cellphone signal,
X_4	Ratio of Elementary Schools (SD) equivalent per 10,000 population,
X_5	Ratio of Junior High School (SMP) equivalent per 10,000 population,
X_6	Ratio of Senior High School (SMA) equivalent per 10,000 population,
X_7	Ratio of health facilities per 10,000 population,
X_8	*Posyandu* ratio per 10,000 population,
X_9	Ratio of resident health workers per 10,000 population,
X_{10}	Percentage of recipient of Certificate of Incapable (SKTM),
X_{11}	Percentage of families living along river banks,
X_{12}	Percentage of families living in slum areas,
X_{13}	Percentage of population receiving Direct Cash Assistance (BLT),
X_{14}	Percentage of population with disabilities,
X_{15}	Ratio of micro and small industries per 10,000 population,
X_{16}	Ratio of malnutrition cases to family size,

In carrying out the analysis, the steps that will be taken to achieve the objectives in this research are described as follows:

1. Make a direct estimate of the percentage of poor people at sub-distrit level based on Susenas Data for March 2022
2. Estimate the percentage of poor people per sub-district using the EBLUP method
3. Estimate the proportion of poor people at the sub-district level using the HB Beta distribution method.
4. Compare the effectiveness of the estimation results of the EBLUP and HB methods by comparing the RSE of each method. A lower RSE value indicates that the estimation results produced are more accurate.
5. Create a map of the distribution of poverty rates at the sub-district level based on the best method resulting from a comparison between the EBLUP and HB methods.

The following are the practical explanations regarding the methods and the theory used in this research.

2.1 Poverty

Residents are categorized as poor if their average monthly per capita expenditure is below the Poverty Line (GK). The poverty line reflects the rupiah value of the minimum expenditure needed by a person to meet his basic living needs for a month. The poverty line is formed from two components, namely the Food Poverty Line (GKM) and the Non-Food Poverty Line (GKNM). GKM is the minimum expenditure value for food needs which is equivalent to 2,100 kilocalories per capita per day, while GKNM is the minimum expenditure value for non-food needs in the form of housing, clothing, education and health.

2.2 Small Area Estimation (SAE)

SAE is a statistical technique used to estimate parameters of parts of a population (subpopulation) from a relatively small area/domain. A domain is considered large if the sample size is large enough to produce direct estimates with sufficient precision, as measured by the Relative Standard Error or RSE. Meanwhile, a domain is considered small if the sample size is not large enough to support direct estimation with sufficient precision (Rao and Maolina, 2015).

There are two main problems in the SAE technique (Pfefferman, et al. in Ubaidillah, 2014), namely how to obtain a fairly good parameter estimate in a region/area with a relatively small sample size and how to estimate the Mean Square Error (MSE) value from the estimate. resulting parameters. The way to overcome this problem is to borrow accompanying information from within the area, from outside the area, or from outside the survey. SAE uses an indirect estimation approach, namely by borrowing the strengths of other areas through the use of additional information/variables from census data or national surveys.

SAE provides advantages, including model diagnostics that can be used to see suitability to existing data, for example residual analysis. Area-specific precision measurements can also be associated through each estimation of a small area. There are two approach models in SAE, namely the unit-based SAE model (unit level) and the area-based SAE model (area level). This research uses an area-based model because the supporting variables are available at the village level obtained from the 2021 Podes data.

The area-based SAE model is based on the availability of supporting data at the area level. The area-based SAE model contains two models, namely the sampling model and the linking model. The sampling model is calculated based on the estimated sampling error from the direct survey. Meanwhile, the linking model connects a population value (parameter) with additional variables (covariates) from a certain region or area.

Area-based models are based on the availability of specific additional data within a small area (area-specific auxiliary data). Let $z_i = (z_{i1}, \ldots, z_{ik})^T$ with the parameters of interest, θ_i, assumed to be related via a model:

$$\theta_i = z_i^T \beta + b_i v_i, \qquad i = 1, \ldots, m \tag{1}$$

where $\beta = (\beta_1, \ldots, \beta_k)^T$ is vector of regression coefficients ($k \times I$), k is the number of independent variables, I is the small area, from 1 to m, m is the number of areas, b_i is the known positive constant, and v_i is area specific random effects that are assumed to have a distribution of $v_i \overset{iid}{\sim} N(0, \sigma_v^2)$. To make inferences about the small area mean for the model in Equation (1), it is assumed that direct estimators, $\hat{\theta}_i = g\left(\hat{\bar{Y}}_i\right)$ are available, namely

$$\hat{\theta}_i = g\left(\hat{\bar{Y}}_i\right) = \theta_i + e_i, \qquad i = 1, \dots, m \tag{2}$$

where $e_i \overset{iid}{\sim} N(0, \sigma_e^2)$ and σ_e^2 are known.

The combination of Equations (1) and (2), will obtain a combined model:

$$\hat{\theta}_i = z_i^T \beta + b_i v_i + e_i, \quad i = 1, \dots, m \tag{3}$$

2.3 Empirical Best Linear Unbiased Prediction (EBLUP) method in SAE

The EBLUP method is a development of the BLUP method which still assumes that the random effect area variance components are known. In reality, random effect variance is difficult to know so it must be estimated from the existing sample. Rao and Molina (2015) stated that the variance of the random effect can be estimated from the sample using the moment method, such as the constant fitting method, the Maximum Likelihood (ML) method, or the Restricted Maximum Likelihood (REML) method. By replacing the random effect variance estimation results into the BLUP model, we will obtain the Empirical BLUP (EBLUP) estimator.

Larasati and Permatasari (2022) explain that the EBLUP method has the assumption that accompanying variables must not have errors. If accompanying variables are obtained from survey data, then the EBLUP model cannot be used because the survey data contains errors. Therefore, the accompanying variables in the research use sources from the Village Potential data collection (Podes) which is a census.

The EBLUP model is stated as follows:

$$\begin{aligned} \hat{\theta}_i^{EBLUP} &= \boldsymbol{x}_i^T \hat{\boldsymbol{\beta}} + \gamma_i (\hat{\theta}_i - \boldsymbol{x}_i^T \hat{\boldsymbol{\beta}}), \qquad i = 1, \dots, m \\ &= \boldsymbol{x}_i^T \hat{\boldsymbol{\beta}} + \gamma_i \hat{\theta}_i - \gamma_i \boldsymbol{x}_i^T \hat{\boldsymbol{\beta}} \\ &= \hat{\gamma}_i \hat{\theta}_i + (1 - \hat{\gamma}_i) \boldsymbol{x}_i^T \hat{\boldsymbol{\beta}} \end{aligned} \tag{4}$$

where

$$\hat{\gamma}_i = \frac{\hat{\sigma}_v^2}{\hat{\sigma}_v^2 + \varphi_i}$$

2.4 Hierarchical Bayesian (HB) method in SAE

The HB approach is a direct method, and the inference from the HB model is relatively clear and exact, but requires the specification of a subjective prior $f(\lambda)$ on the model parameters λ.

In SAE with the HB approach, the first step is to determine the subjective prior distribution $f(\lambda)$ on the model parameters λ, and then the posterior distribution $f(\boldsymbol{\mu}|\boldsymbol{y})$ can be obtained from the small area (random) parameter $\boldsymbol{\mu}$ with data $\boldsymbol{y}$ (Rao and Molina, 2015). The two-stage model $f(\boldsymbol{\mu}|\boldsymbol{y}, \boldsymbol{\lambda_1})$ and $f(\boldsymbol{\mu}|\boldsymbol{y}, \boldsymbol{\lambda_2})$ is combined with a prior on $\lambda = (\lambda_1^T, \lambda_2^T)^T$ using Bayes' theorem to obtain the posterior $f(\boldsymbol{\mu}|\boldsymbol{y})$. Inference based on $f(\boldsymbol{\mu}|\boldsymbol{y})$, specifically on an observed parameter, say $\emptyset = h(\mu)$, is estimated using its posterior average as shown in the equation:

$$E_{\lambda|y}(\lambda) = \mu(y) = \mu \tag{5}$$

as well as the posterior variance expressed in the equation:

$$V_{\lambda|y}(\lambda) = E_{\lambda|y}[\lambda - E_{\lambda|y}(\lambda)]^2 \tag{6}$$

Estimating the proportion of poor people in each sub-district (area-i) in this study uses the HB approach with the Beta-Normal model and area-based independent variables.

3. RESULTS AND DISCUSSION

To find out the characteristics of the data, it is necessary to explore the data so that the analysis carried out can be correct. There are 129 sub-districts in Bengkulu Province spread across ten districts/cities. In the March 2022 Susenas activities, there was one sub-district that was not sampled, namely Enggano sub-district in North Bengkulu Regency, so direct estimation could only be carried out in 128 sub-districts.

Direct estimation is carried out by calculating the proportion of the population whose expenditure is below the Poverty Line in each sub-district. A summary of the direct estimation results can be seen in Table 2 below.

Table 2. Statistics of Direct Estimates of the Percentage of Poor Population at District Level in Bengkulu Province, 2022

Statistics	Poverty Rates
Minimum	0
Median	12,340 %
Mean	15,886 %
Maximum	76,090 %
Total Observation	128

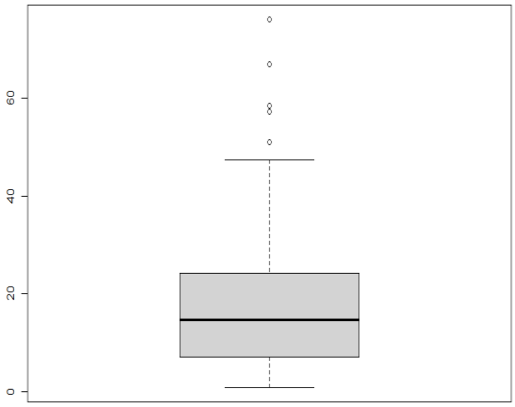
In Table 2 it is known that the poverty rates at sub-district level in Bengkulu Province is quite diverse. The poverty rates at sub-district level in Bengkulu Province has an average value of 15.886% and a median of 12.340%, this shows that the percentage of sub-district level population using direct estimation is close to the poverty rates in Bengkulu Province, namely 14.62% (BPS, March 2022). The highest poverty is in Sindang Dataran District, Rejang Lebong Regency with 76.090%. There are several sub-districts with a direct sub-district level poverty estimation value of 0%.

The direct estimation value of 0% is due to the absence of samples with expenditure below the Poverty Line in the sub-district. This can happen if there are so few samples at the small area level that they cannot represent that area. For example, if there is only one sample in a certain sub-district, then the direct estimation value for the percentage of poor people in that sub-district has only two values, namely 0% or 100%. Because the data from direct estimation will be used in the indirect estimation of SAE EBLUP and SAE HB, the data must have a variance for each observation. The minimum and maximum values in Table 2 are invalid because there are 16 sub-districts that have zero variance. Due to this consideration, 17 sub-districts were not included in the model. Below is a summary of statistics after 17 sub-districts were eliminated.

Table 3. Direct Estimation Results in All Valid Sub-district

Statistics	Poverty Rates
Minimum	0,87 %
Median	14,64 %
Mean	18,16 %
Maximum	76,09 %
Total Observation	112

Based on Table 3, it can be seen that the 112 valid sub-districts have an average value of 18.16% and a median of 14.64%, which is greater than the figures released for Bengkulu and National Provinces. Henceforth, the data used will only be in valid areas, namely 112 sub-districts in Bengkulu Province so that estimation results between methods can be compared.



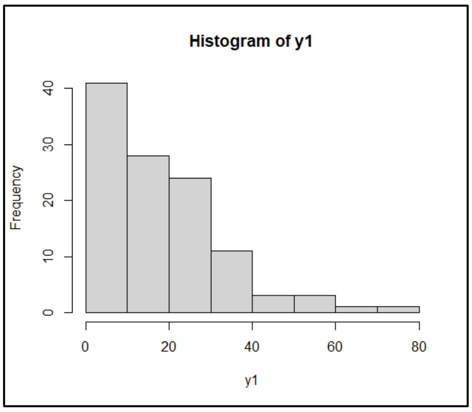


Figure 1. Distribution of Direct Estimated Values of the Percentage of Poor Population at District Level in Bengkulu Province, 2022

From the boxplot and histogram in Figure 1, it shown that among of all sub-districts, the data has outliers in 5 sub-districts. Then a normality test was carried out to see whether the data from the direct estimation of the percentage of poverty at the sub-district level was normally distributed. One way to see the normality of data is the Shapiro Wilk Normality Test. From the test results, the $p - value = 3.018e - 08$, less than $\alpha = 0.05$, so it can be concluded that the data does not follow a normal distribution.

To measure the level of accuracy of population parameter estimates, RSE is used which is expressed as a percentage. Table 4 shows that the RSE value for direct estimation of the percentage of poverty at the sub-district level in Bengkulu Province is in the range 0 to 0. 104.88%. This provides information that the direct estimation results are still not accurate enough. There is an RSE value of 0 due to the rounding process in the calculation.

Table 4. The Statistics of RSE of the Direct Estimate Method

Statistics	RSE
Minimum	0
Median	45.36 %
Mean	46.87 %
Total Observation	104.84 %

The relative standard error (RSE) value that is considered accurate is $RSE \leq 25\%$. In direct estimation there are 21 sub-districts with RSE that are considered quite accurate. This number is relatively small compared to the number of sub-districts sampled in the March 2022 Susenas, which was 128 sub-districts.

Table 5. Number of Sampled Sub-districts according to Direct Estimation RSE of Poverty Rates at Sub-district Level in Bengkulu Province, 2022

RSE	Number of Sub-district
RSE = 0	1
0 < RSE ≤ 25%	20
25% < RSE ≤ 50%	43
RSE > 50%	48

After exploring the data based on the results of direct estimates of the percentage of poverty at the sub-district level, indirect estimates were then carried out using the SAE EBLUP and SAE HB methods. Of the 16 accompanying variables that will be used based on the results of the literature study, it is necessary to select accompanying variables. The selection was carried out using stepwise regression and 5 variables were obtained that had a significant influence in the model, namely:

Table 6. Research Predictor Variables After Stepwise Regression

Variables	Explanation
X_4	Ratio of Elementary Schools (SD) equivalent per 10,000 population,
X_8	*Posyandu* ratio per 10,000 population,
X_{10}	Percentage of recipient of Certificate of Incapable (SKTM),
X_{15}	Ratio of micro and small industries per 10,000 population,
X_{16}	Ratio of malnutrition cases to family size.

Next, the five accompanying variables are used to carry out indirect estimates using the SAE EBLUP and SAE HB methods. These accompanying variables will be used consistently to obtain good comparability between the estimation methods used.

3.1 SAE EBLUP Method

In estimating parameters, 5 accompanying variables were used which had a significant effect on the percentage of poor people. From the five variables used, a Random Effect Variance estimate of 143.8425 was obtained. The results of the estimated beta value and standard error are shown in Table 7.

Table 7. Estimation Results of Beta Values and Standard Errors of the SAE EBLUP Method

Variables	Beta	Standard Error
$Intercept$	3.437388e+00	4.503009e+00
X_4	2.250285e+00	5.482939e-01
X_8	-3.951526e-01	2.456158e-01
X_{10}	5.726939e-01	4.413767e-01
X_{15}	-2.138974e-02	1.272037e-02
X_{16}	-3.404550e+03	1.352387e+03

Table 8. The Statistics of SAE EBLUP Poverty Rates Estimation

Statistics	RSE
Minimum	0.9328 %
Median	15.4668 %
Mean	17.1112 %
Maximum	66.6654 %

From Table 7 it can be seen that there is a decrease in the average result of estimating the poverty rates using EBLUP compared to the direct estimation in Table 3. On average there is a decrease of around one percent between the direct estimate and the EBLUP method, but if we look at the median statistics between of these two methods, the reduction that occurred was not very significant.

Visually, a comparison between the direct estimation results and the EBLUP method for 112 sub-districts in Bengkulu Province can be seen in Figure 3. It can be seen in the figure that the direct estimation results and EBLUP have a relatively similar pattern, although it can be seen that the EBLUP estimation graph is relatively slightly lower compared to the graph of direct estimation.

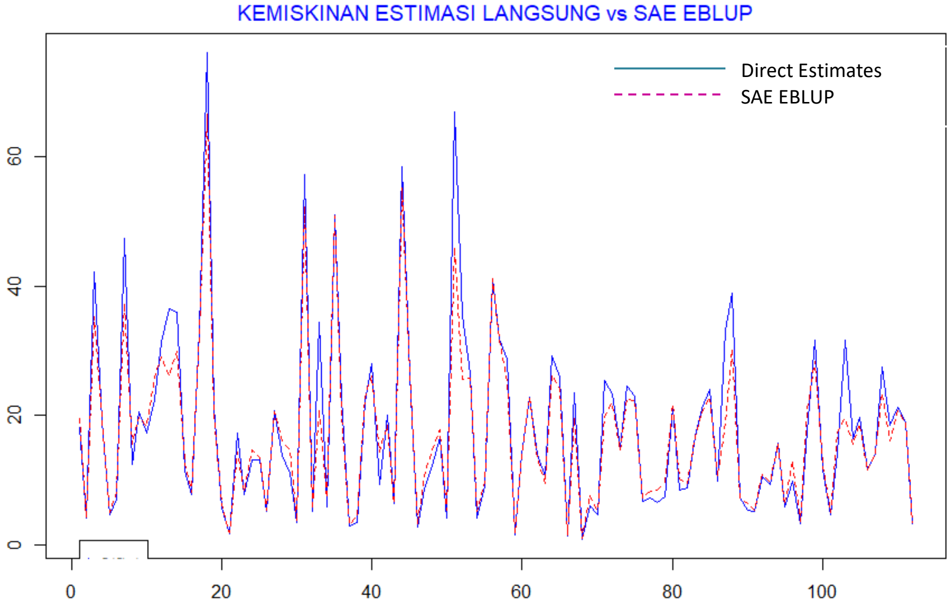


Figure 2. Comparison of Direct Estimation Results and EBLUP Method Estimation Results

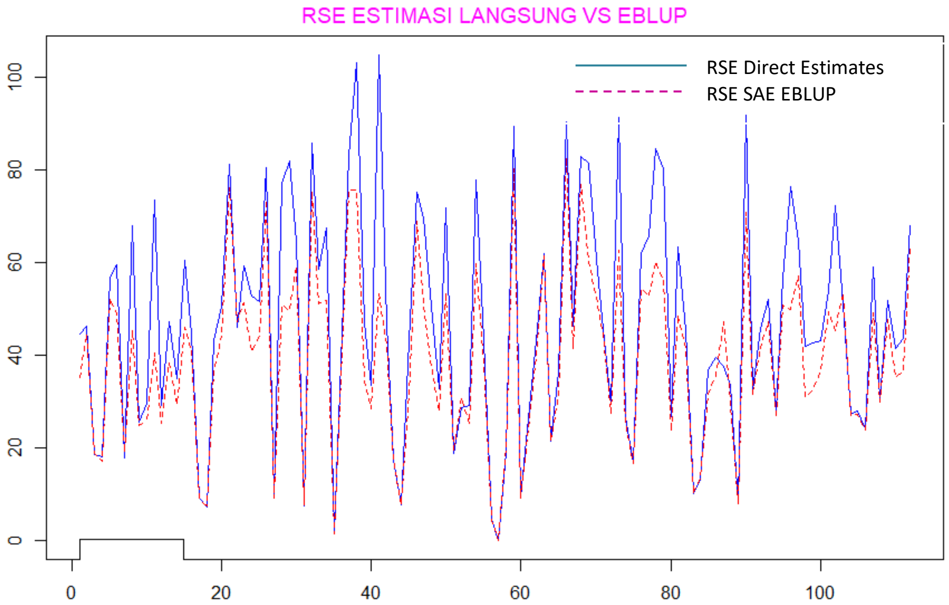


Figure 3. Comparison of Direct Estimated RSE and EBLUP Method RSE

In addition, based on Figure 5 and Figure 6, it can be concluded that the EBLUP method is able to produce RSE values that tend to be lower than the direct estimation results in 112 valid sub-districts.

3.2 SAE HB Method

Parameter estimation using the SAE HB method was carried out using the same five predictor variables as the EBLUP method. However, the response variable used is the proportion of poor people. From the results of the iterations in the MCMC process, an estimated random effect area of 0.9210998 and an estimated beta parameter can be seen in Table 9 below:

Table 9. Estimation Results of Beta Values and Standard Errors of the SAE HB Method

Variables	Beta	Standard Error
Intercept	-2.738598867	0.0567967378
X_4	0.128304635	0.0050168626
X_8	-0.023527168	0.0027605790
X_{10}	0.057249837	0.0074710375
X_{15}	-0.001409743	0.0002599775
X_{16}	-0.208286633	1.0207227947

Table 10. The Statistics of SAE HB Poverty Rates Estimation

Statistics	RSE
Minimum	1.612 %
Median	14.584 %
Mean	18.154 %
Maximum	74.943 %

From Table 10 it is known that there is no significant decrease in the average results of estimation using HB compared to direct estimation in Table 3. A comparison between the results of direct estimation and the HB method for 112 sub-districts in Bengkulu Province can be seen in Figure 4. It can be seen in the picture that the results direct and HB estimates have relatively similar patterns.

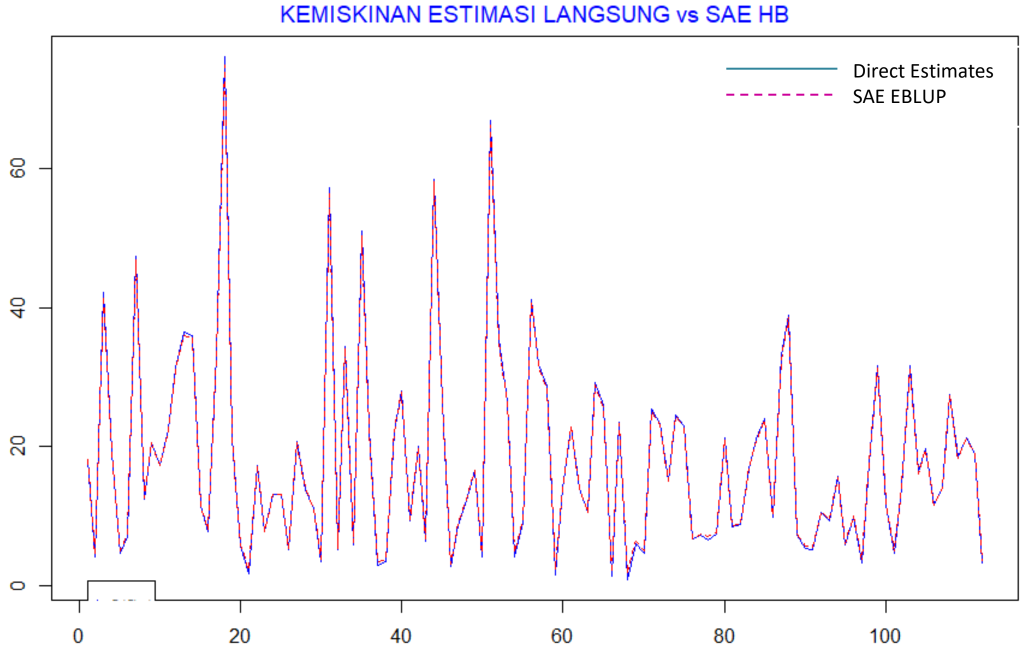


Figure 4. Comparison of Direct Estimation Results and HB Method Estimation Results

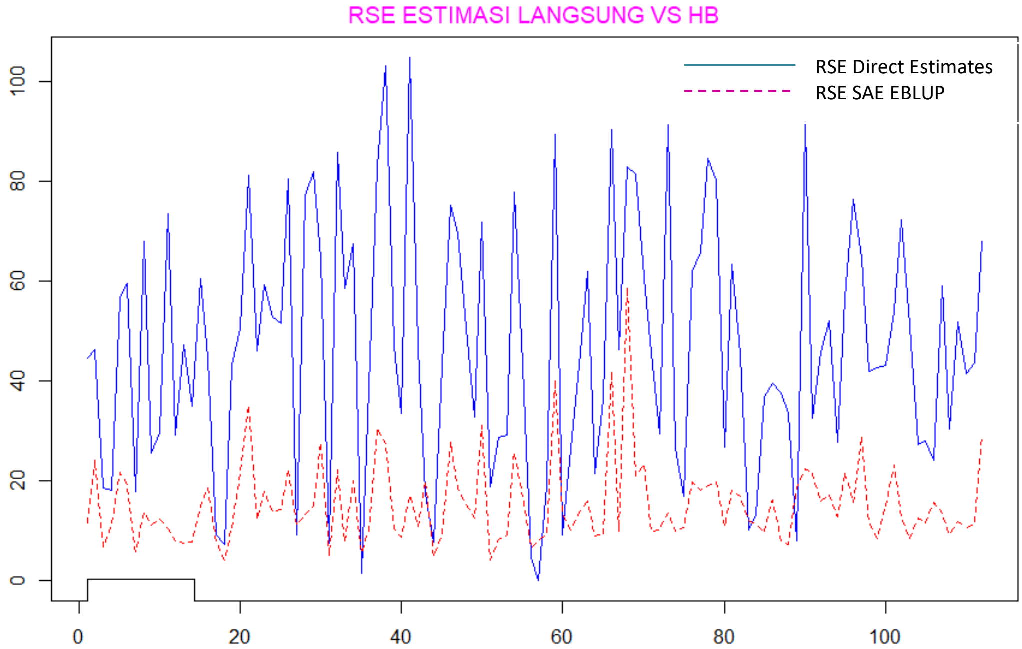


Figure 5. Comparison of Direct Estimated RSE and HB Method RSE

Based on Figure 4 and Figure 5, it can be concluded that the HB method is able to produce RSE values that are lower than the direct estimation results in 112 valid sub-districts.

3.3 Comparison of Direct Estimation Results with EBLUP and HB

The SAE EBLUP and HB methods are relatively capable of estimating the percentage of poor people. Based on the estimation results, the SAE HB method is relatively capable of producing mean and average values that are close to the direct estimated values. The highest value resulting from the HB method is similar to the direct estimation results, in contrast to the EBLUP estimation which has a lower maximum value than the direct estimation results.

Table 11. Summary of Estimated Results Statistics, and RSE Poverty Rates at Sub-district Level in Bengkulu Province according to the Method Used

Statistics	Estimation			RSE		
	Direct	EBLUP	HB	Direct	EBLUP	HB
Minimum	0,87	0.9328	1.612	0	0.00	4.058
Median	14,64	15.4668	14.584	45.36	40.27	13.172
Mean	18,16	17.1112	18.154	46.87	39.40	15.318
Maximum	76,09	66.6654	74.943	104.84	82.70	58.958

Looking at the RSE values for the three estimation methods, the HB method appears to be able to reduce the average and median RSE values from direct estimation results. It can be seen from the results that the RSE of the HB method is reduced quite a lot compared to direct estimation and EBLUP. However, there are still sub-districts with RSE values above 50% even though they have used the EBLUP and HB methods, but this has been quite reduced compared to the direct estimation method.

It can be seen in Table 12 that there are significant changes in the majority of RSE values in the range 0 < RSE ≤ 25%, namely in 100 sub-districts out of a total of 112 sub-districts studied. So it can be concluded that based on calculations, the HB method can improve direct estimates and is better than the EBLUP method.

Table 12. Number of Sampled Sub-districts according to RSE of Poverty Rates at Sub-district Level Estimation in Bengkulu Province based on Method Used

RSE	Direct Estimates	EBLUP	HB
$\mathbf{RSE = 0}$	1	1	0
$\mathbf{0 < RSE \leq 25\%}$	20	23	100
$\mathbf{25\% < RSE \leq 50\%}$	43	55	11
$\mathbf{RSE > 50\%}$	48	33	1

3.4 Map of Distribution of Poverty Rates at District Level with the Best Method

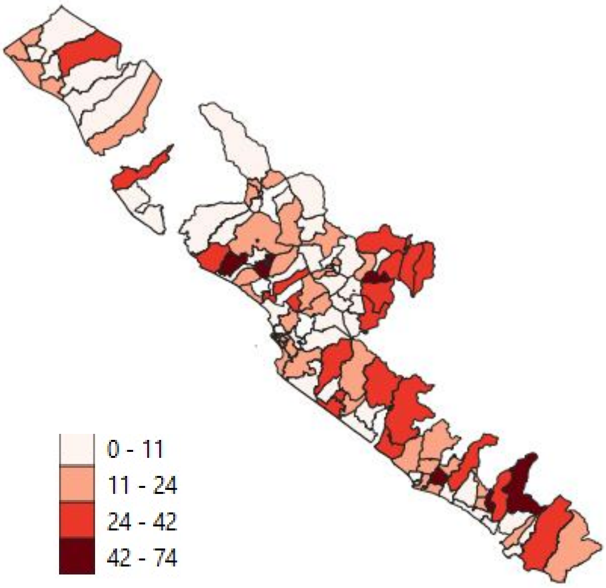


Figure 9. Map of Distribution of Poverty Rates at District Level with the Best Method

The distribution of the poor population appears to be concentrated in the eastern and southern areas of Bengkulu Province. This can be seen from Figure 6 which shows the distribution of red to dark red sub-district polygons which are mostly around the east and south of Bengkulu Province. If we look at the districts, there are four districts with a higher concentration of poor people at sub-district level than the others, namely Rejang Lebong District, Seluma District, South Bengkulu District and also Kaur District.

In 2022, BPS noted that at a macro level it also shows the same conditions where Seluma Regency is the district with the highest poverty rate in Bengkulu Province with 18.36 percent, followed by Kaur (18.10 percent), South Bengkulu (17.86 percent) and Rejang Lebong (15.65 percent). Pockets of poverty in these four districts can become priority targets in various poverty alleviation programs.

4. CONCLUSION

Based on the results of the discussion carried out in the previous chapter, several things can be concluded as follows:

1. The direct estimation results show that the average percentage of poor people in each sub-district in Bengkulu Province is 18.6%. The highest percentage of poor people is in the Sindang Dataran sub-district, Rejang Lebong Regency, at 76.09%.
2. The estimation results using SAE with the EBLUP approach obtained an average percentage of poor people at 17.1112%, with the highest percentage of poor people at 66.6654% in the same sub-district as the direct estimation, namely Sindang Dataran District, Rejang Lebong Regency.

3. The estimation results using SAE with the HB approach obtained an average percentage of poor people at 18.154%, with the highest percentage of poor people at 74.943% in the same sub-district as the direct estimation, namely Sindang Dataran District, Rejang Lebong Regency.
4. In this research, the use of the SAE method with the HB approach produces a much smaller RSE so that it can be used to estimate a smaller area.
5. Research using the HB approach can be a reference in obtaining information on poverty rates for smaller areas, so that the policies taken by the government in alleviating poverty can be more targeted to the smallest areas.

REFERENCES

[1] Badan Pusat Statistik, "Statistik Komuter Jabodetabek: Hasil Survei Komuter Jabodetabek 2014," Jakarta: Badan Pusat Statistik, 2014.
[2] Badan Pusat Statistik Provinsi Bengkulu, "Provinsi Bengkulu dalam Angka," Bengkulu: Badan Pusat Statistik, 2023.
[3] W. M. Bolstad, "Introduction to Bayesian Statistics," Canada: John Wiley & Sons, Inc., 2004.
[4] Direktorat Statisik Ketahanan Sosial, "Data dan Informasi Kemiskinan Kabupaten/Kota Tahun 2022," Jakarta: Badan Pusat Statistik, 2022.
[5] M. Hidroglou, "Small Area Estimation: Theory and Practice," Survey Research Methods, pp. 3445-3456, 2007.
[6] A. Juliyanto, "Model Hierarchical Bayes Pada Small Area Estimation untuk Pendugaan Proporsi Pengangguran pada Desain Survei Kompleks," Tesis Magister, Institut Teknologi Sepuluh Nopember, 2016.
[7] W. Larasati and N. Permatasari, "Perbandingan Metode SAE EBLUP dan SAE HB Pada Pendugaan Area Kecil (Studi Kasus Pendugaan Kemiskinan di Provinsi Jawa Timur)," Jurnal Statistika dan Aplikasinya (JSA), vol. 6, no. 1, pp. 96-108, 2022.
[8] H. Li, Q. Chen, C. Fu, Z. Yu, D. Shi, and Z. Wang, "Bayesian Estimation on Load Model Coefficients of ZIP and Induction Motor Model," Energies, vol. 12, p. 547, 2019.
[9] R. Ningtyas, R. Rahmawati, and Y. Wilandari, "Penerapan Metode Empirical Best Linear Unbiased Prediction (EBLUP) pada Model Penduga Area Kecil dalam Pendugaan Pengeluaran Per Kapita di Kabupaten Brebes," Jurnal Gaussian, vol. 4, no. 4, pp. 977-986, 2015.
[10] S. Nugroho, "Pengantar Statistika Matematika," Bengkulu: UNIB Press, 2008.
[11] J. N. K. Rao and I. Molina, "Small Area Estimation," Canada: John Wiley & Sons, Inc., 2015.
[12] E. Sunandi, P. Novianti, I. Sriliana, and D. Agustina, "Estimasi Tingkat Kemiskinan Pada Level Desa di Kabupaten Mukomuko dengan Menggunakan Small Area Estimation (Estimation of Poverty Rate in Village Level at Mukomuko District Using Small Area Estimation)," in Prosiding Semirata2015 bidang MIPA BKS-PTN Barat, Pontianak, 2015, pp. 363-371.1.
[13] A. Ubaidillah, "Small Area Estimation Dengan Pendekatan Hierarchical Bayesian Neural Network Untuk Pemetaan Kemiskinan di Kota Jambi," Tesis Magister, Institut Teknologi Sepuluh Nopember, 2014. [Online]. Available: https://www.researchgate.net/profile/Azka-Ubaidillah/publication/340172483_Small_Area_Estimation_Dengan_Pendekatan_Hierarchical_Bayesian_Neural_Network_untuk_Pemetaan_Kemiskinan_di_Kota_Jambi/links/5e7c115292851caef49d92ee/Small-Area-Estimation-Dengan-Pendekatan-Hierarchical-Bayesian-Neural-Network-untuk-Pemetaan-Kemiskinan-di-Kota-Jambi.pdf.
[14] R. E. Walpole, R. H. Myers, S. L. Myers, and K. Ye, "Probability and Statistics for Engineers and Scientists 9th ed.," United States of America: Pearson Education, Inc., 2012.
[15] World Bank, "Handbook on Poverty + Inequality," Washington, DC: The World Bank, 2009.
[16] J. R. B. Yuliani, Diana Maiyastri, and Rita, "Pendugaan Angka Kemiskinan di Kabupaten Padang Pariaman Menggunakan Small Area Estimation dengan Pendekatan Hierarchical Bayesian (HB) Loglogistik," Jurnal Matematika UNAND, vol. VIII, no. 2, pp. 76-83, 2019.
[17] "Kemiskinan dan Ketimpangan," Badan Pusat Statistik, [Online]. Available: https://www.bps.go.id/subject/23/kemiskinan-dan-ketimpangan.html. [Accessed: 8-Dec-2022].