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# SMALL AREA ESTIMATION OF CHILD UNDERNOURISHMENT PREVALENCE IN BALI AND NUSA TENGGARA

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## ABSTRACT

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*Children under the age of 17 are particularly prone to undernutrition. Undernutrition can impair children's growth and development. In the process of policy formulation, it is necessary to calculate a reliable estimate of the prevalence of child undernourishment at the smallest level possible. Using the data of SUSENAS 2023 from BPS, direct estimates at the regency/city level in Bali, West Nusa Tenggara (NTB), and East Nusa Tenggara (NTT) have relative standard error values of over 25% (RSE > 25%), making them less reliable for usage. To solve this, an indirect estimating method known as small area estimation (SAE) can be applied. This study employs SAE HB Lognormal to estimate the prevalence of undernutrition in children. The results of this study show that small area estimation using the HB Lognormal approach improved the reliability of estimates (RSE) of the prevalence of undernutrition in children at the regency/city level in Bali, NTB, and NTT.*



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# 1. INTRODUCTION

The second goal of the sustainable development goals (SDGs) is to eliminate hunger by 2030 [1]. One of the indicators used is the prevalence of undernourishment (PoU) or the prevalence of inadequate energy consumption [2]. Children aged 0-17 years are vulnerable to the problem of insufficient energy consumption. Lack of energy consumption can hamper children's growth and development, both physically and mentally [3][4]. On the other hand, children are the next generation who will play an important role in nation building. Lack of energy consumption in children can reduce the quality of human resources produced in the future.

To support the policy making related to children's energy consumption, it is necessary to estimate the prevalence of children's energy consumption deficiency to the smallest level. This estimation was conducted using data from the National Socio-Economic Survey (SUSENAS). However, direct estimates at the regency/city level resulted in a relative standard error value of more than 25 percent (RSE > 25%), making the estimation less reliable [5]. This could be caused by the lack of sample size. Increasing the number of samples is often constrained because it requires additional costs. To overcome this, an indirect estimation method with small area estimation (SAE) can be used. SAE is a statistical method that utilizes information from samples in other areas linked to auxiliary information (auxiliary variables) derived from other data sources, such as censuses, other surveys, and population registrations, through statistical model equations [6]. The quality of estimation results with SAE is determined by the quality of survey data, the availability of auxiliary variables, and the selection of the proper model.

The estimation methods frequently used in SAE are Empirical Best Linear Unbiased Prediction (EBLUP), Empirical Bayes (EB), and Hierarchical Bayes (HB) [7]. The EBLUP method is used for normally distributed data, the EB method is used for count data, and the HB method can be used for data from any distributions as well as on complex modelling [8]. The HB method has the advantage that it can be used on data from various distributions, one of which is the lognormal distribution. Based on Shapiro Wilks test, the regency/city level direct estimation of child undernourishment prevalence in Bali, West Nusa Tenggara (NTB), and East Nusa Tenggara (NTT) provinces each follow the lognormal distribution. Therefore, the estimation of the prevalence of child undernourishment in these provinces are conducted with SAE HB Lognormal.

By utilizing auxiliary information from other data sources, this study would like to produce better estimation results than direct estimation in order to provide more reliable estimates, so that give the knowledge needed in the process of policy making, planning, management, and evaluation of programs related to the development of children's energy intake in the provinces of Bali, West Nusa Tenggara, and East Nusa Tenggara. The auxiliary information could be in the form of child characteristics, family characteristics, and environmental characteristics. Information on child characteristics can include the age and gender of the child [9][10]. Meanwhile, family characteristics include parents' education, income, social assistance status, number of family members, home sanitation, mother's condition, and disability status [9]–[18]. Environmental information could be in the form of access to education services, health, environmental hygiene, climate, urban status, and surrounding culture [10]–[13].

Research on estimating the prevalence of children with low energy consumption using small area estimation has been conducted in various countries, such as Cambodia [11], Bangladesh [12], Mexico [13], India [15], Rwanda [16], and Ethiopia [9], [14]. However, there is no similar study that used children aged 0-17 years old and located in Indonesia. Therefore, this study has two objectives. The first objective is to estimate the prevalence of child undernourishment at the regency/city level in Bali, West Nusa Tenggara, and East Nusa Tenggara provinces using SAE. Then, the second objective is to compare the SAE estimation results with the direct estimation.

# 2. RESEARCH METHODS

## 2.1 Data Sources

This study used data collected by Statistics Indonesia (BPS). The data used to estimate the direct estimation of child undernourishment prevalence is collected from the 2023 National Socio-Economic Survey (SUSENAS 2023). The auxiliary information used in SAE HB method is collected from the 2021 Village Potential Statistics (PODES 2021). There are 41 regencies/cities included in this study, where 9 regencies/cities are in Bali, 10 regencies/cities are in West Nusa Tenggara (NTB), and 22 regencies/cities are in East Nusa Tenggara (NTT). This study used 'saeHB' package in R to estimate the child undernourishment prevalence with SAE HB Lognormal [19].

### 2.2 Direct Estimation

Direct estimation is a traditional estimation method for small areas using a specific designed survey. However, this method sometimes provides unreliable estimation regarding the insufficient data collected [6]. In this study, direct estimation is conducted to obtain the SAE interest variable by using Weighted Probability Sampling (WPS) following the SUSENAS Maret 2023 sampling procedure, which is two stages one phase sampling [20]. The direct estimation formula used in this research can be written as:

$$\widehat{\bar{Y}}_{dk}^{dir} = \frac{\hat{Y}_{dk}^{dir}}{\hat{N}_d^{dir}}, \hat{Y}_{dk}^{dir} = \sum_{j \epsilon s_d} w_{dj} y_{dkj}, \hat{N}_d^{dir} = \sum_{j \epsilon s_d} w_{dj}$$

and the variance formula of the direct also can be written as :

$$v(\widehat{\bar{Y}}) = \frac{1}{N_d} \sum_{j \in s_d} \left(y_{dkj} - \bar{Y}_{dk}\right)^2$$

Where $\widehat{\bar{Y}}_{dk}^{dir}$ is the direct estimation of SAE interest variable (expressed in percentage form) with $\hat{Y}_{dk}^{dir}$ is the direct estimation of total population in area-$d$ which satisfies the category-$k$. While $\hat{N}_d^{dir}$ is the total population. This study used the children aged 0-17 years old as the analysis unit. In order to obtain the indicator, this study used this formula :

$$\textbf{Children Undernourishment } (\%) = \frac{\textbf{Total children } (0-17) \textbf{ with energy consumption less than 1400kcal}}{\textbf{Total children } (0-17)} \times 100\%$$

### 2.3 Small Area Estimation Hierarchical Bayes (SAE HB) Lognormal

In order to avoid the skewed distribution problem which likely appeared when estimating the prevalence of child undernourishment, this research used SAE HB Lognormal model. The SAE HB Lognormal model could be written as [6]:

$$\begin{array}{ll} \text{Level 1. Sampling function} & \hat{Y}_i | Y_i, \beta, \hat{\sigma}_v \sim^{ind} Lognormal(Y_i, \tau_i) \\ \text{Level 2. Linking function} & \log(Y_i) \,|\beta, \hat{\sigma}_v \sim^{ind} N(\chi^T, \beta, b_i^2, \hat{\sigma}_v) \\ \text{Level 3.} & f(\beta, \sigma_v^2) = f(\beta) f(\sigma_v^2) \propto f(\sigma_v^2) \end{array} \quad (1)$$

The prior distribution in this model consists of $\sigma_v^2 \sim IG(\varphi_{ua}, \varphi_{ub})$ and $\beta \sim N(\mu_\beta, \varphi_\beta)$. $\hat{Y}_i$ is the interest SAE variable, prevalence of child undernourishment. To acquire the model parameters used to estimate the SAE interest variable, SAE HB Lognormal used the MCMC procedure with Gibbs Sampling algorithm. This study used relative standard error (RSE) as the main reliability metrics. However, standard error (SE) is also used in this study [5].

### 2.4 Analysis Procedure

The analysis procedure in this study was carried out with the following steps:

1. Conduct a literature review to obtain candidate auxiliary variables to be used
2. Perform data aggregation and data integration
3. Perform direct estimation at regency/city level and check for the unreliable estimates
4. Select auxiliary variable in PODES based on its correlation and VIF value
5. Perform SAE HB Lognormal estimation at regency/city level for each province
6. Compare the results obtained from direct estimation and SAE HB Lognormal

## 3. RESULTS AND DISCUSSION

### 3.1 Direct Estimation of Child Undernourishment Prevalence

**Figure 1** shows the direct estimation of child undernourishment prevalence at regency/city level in Bali, West Nusa Tenggara, and East Nusa Tenggara. Based on the direct estimation, the highest prevalence of child under the age of 17 whose energy consumption is less than 1400 kcal is located in Rote Ndao Regency, East Nusa Tenggara. In contrast, the lowest prevalence is located in Jembrana Regency, Bali. In addition, the direct estimation could not estimate the prevalence in Lombok Timur Regency, West Nusa Tenggara because of non-sample problem.

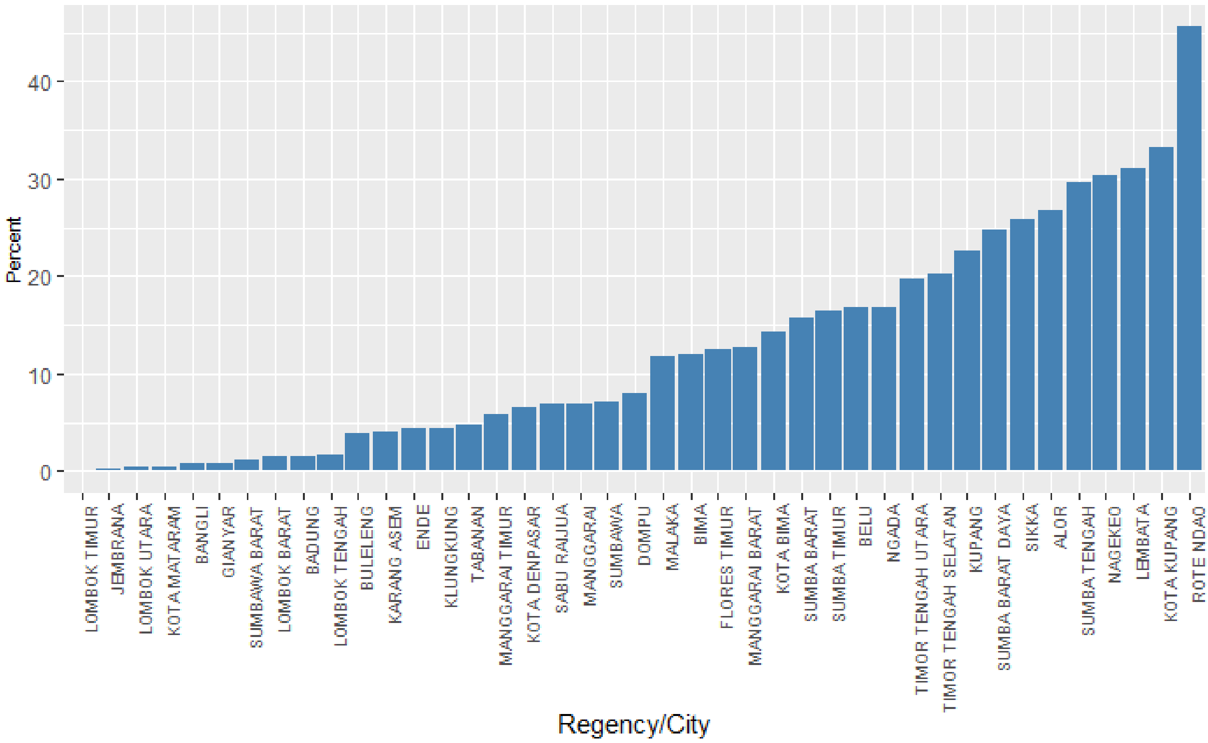



**Figure 1.** **Direct Estimation of Child Undernourishment Prevalence in Bali and Nusa Tenggara**

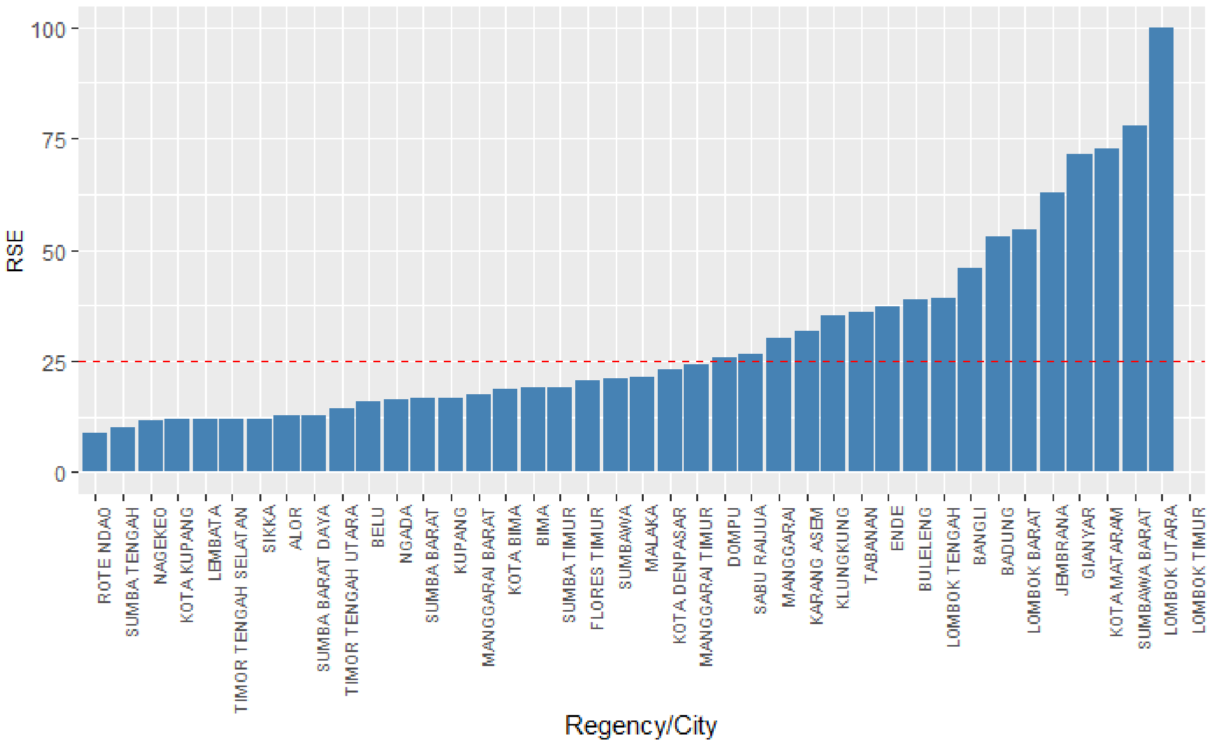



**Figure 2.** **RSE of Direct Estimation of Child Undernourishment Prevalence in Bali and Nusa Tenggara**

**Figure 2** shows the relative standard error (RSE) of the direct estimation of child undernourishment prevalence in Bali and Nusa Tenggara. The direct estimation produces a reliable estimation (RSE < 25%) [5] in 23 regencies/cities in Bali and Nusa Tenggara. However, the direct estimation could not produce reliable estimations in 18 regencies/cities. The unreliable estimation mainly located in Bali (8 regencies/cities) followed by West Nusa Tenggara (7 regencies/cities) and East Nusa Tenggara (3 regencies/cities). Because of that, indirect estimation using small area estimation is needed to improve the reliability of child undernourishment prevalence estimation in Bali and Nusa Tenggara.

### 3.2 SAE HB Lognormal Estimation of Child Undernourishment Prevalence

Before SAE HB Lognormal is applied to estimate the prevalence of child undernourishment, it is vital to select the proper auxiliary information to improve estimation accuracy and reliability. Auxiliary variables are chosen based on the correlation between the direct estimation and the auxiliary variables, the compatibility of the direction of correlation with theory or past study, and the presence of multicollinearity among the auxiliary variables. Then, estimations are generated for each province. **Table 1** shows the selected auxiliary variable with their correlation and variance inflation factor (VIF) value.

**Table 1. Correlation and VIF Value for Selected Auxiliary Variables**

| Model | Auxiliary Variable | Correlation | VIF |
|---|---|---|---|
| Bali | Percentage of villages with primary drinking water sources of refillable water (refill_water) | -0.307 | 1.270 |
| | Percentage of villages that have services for mother with child under 5 years old (services_u5) | -0.501 | 1.337 |
| | Percentage of families living on river banks (fam_river) | 0.696 | 1.453 |
| West Nusa Tenggara | Percentage of families who received a poverty letter (SKTM) in 2020 (sktm) | 0.852 | 1.354 |
| | Percentage of villages that have proper drinking water services (proper_drink) | -0.726 | 1.354 |
| East Nusa Tenggara | The ratio of midwives per 100,000 population (midwives_ratio) | -0.383 | 1,115 |
| | Percentage of families who received a poverty letter (SKTM) in 2020 (sktm) | 0.168 | 1.081 |
| | Number of micro/small/medium enterprises (UMKM) per 10 $km^2$ (enterprise) | -0.224 | 1.076 |

After selecting the auxiliary variables, the SAE HB Lognormal was constructed. HB Lognormal is used in all provinces because the result of Shapiro-Wilks in **Table 2** shows that the direct estimation of child undernourishment prevalence in Bali, West Nusa Tenggara, and East Nusa Tenggara follow the lognormal distribution. **Table 3** Shows that all selected auxiliary variables are significant in each model. This is shown by none of the parameter coefficients which are in the range of 2.5 percent to 97.5 percent in each model include zero.

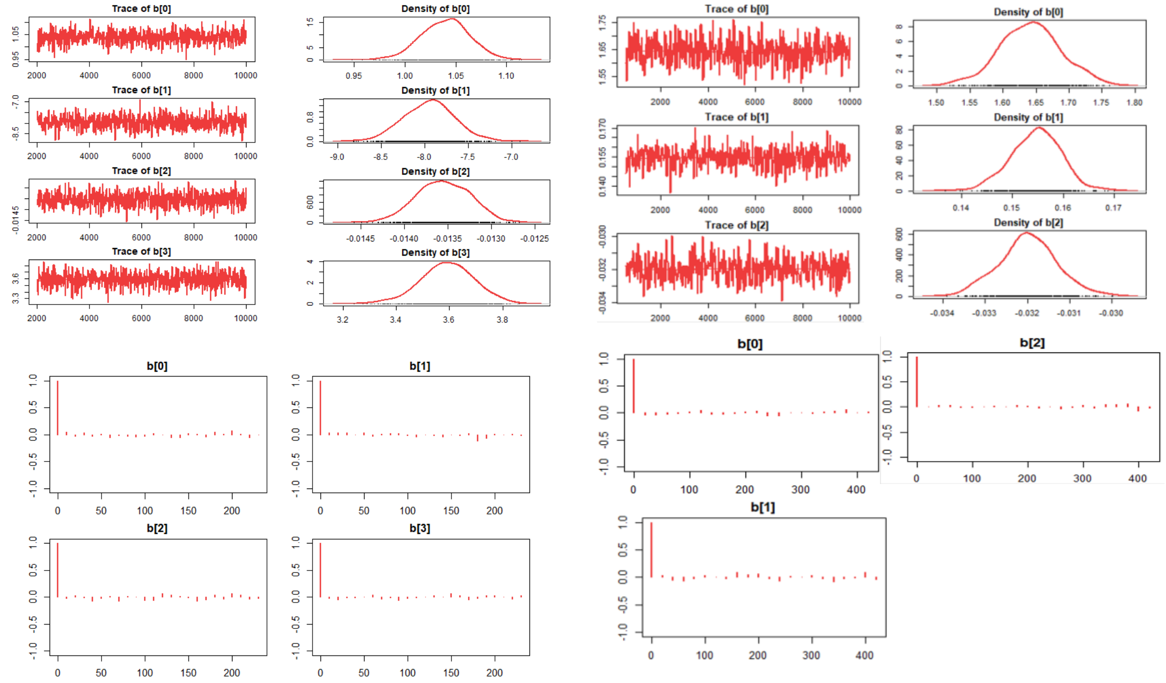
**Table 2. Shapiro-Wilks Test for Lognormal Distribution**

| Province | $W$-stat | $p$-value | Conclusion |
|---|---|---|---|
| Bali | 0.879 | 0.152 | Lognormal distributed |
| NTB | 0.890 | 0.197 | Lognormal distributed |
| NTT | 0.942 | 0.216 | Lognormal distributed |

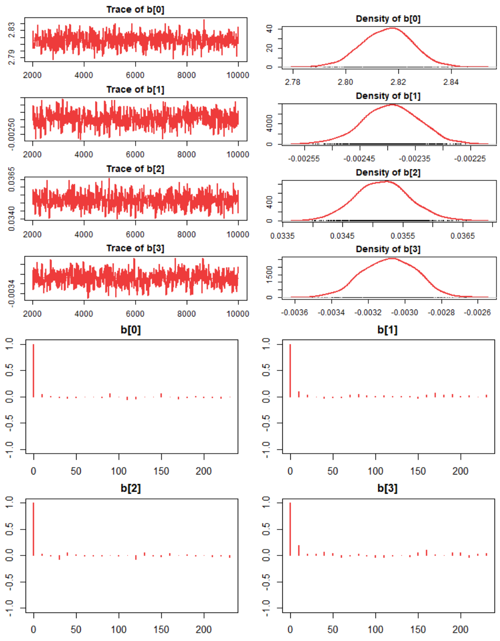
**Table 3. SAE HB Lognormal Coefficient of Parameter**

| Model | Parameter | Mean | SD | 2.5% | 97.5% |
|---|---|---|---|---|---|
| Bali | C | 1.040 | 0.024 | 0.991 | 1.086 |
| | refill_water | -7.951 | 0.291 | -8.524 | -7.377 |
| | services_u5 | -0.014 | 0.000 | -0.014 | -0.013 |
| | fam_river | 3.591 | 0.101 | 3.370 | 3.782 |
| NTB | C | 1.642 | 0.045 | 1.548 | 1.730 |
| | sktm | 0.155 | 0.005 | 0.145 | 0.163 |
| | proper_drink | -0.032 | 0.001 | -0.033 | -0.031 |
| NTT | C | 2.816 | 0.009 | 2.796 | 2.833 |
| | midwives_ratio | -0.002 | 0.000 | -0.002 | -0.002 |
| | sktm | 0.035 | 0.000 | 0.034 | 0.036 |
| | enterprise | -0.003 | 0.000 | -0.003 | -0.003 |

Estimation using SAE HB Lognormal is based on Bayesian inference using the prior distribution and likelihood function to obtain the posterior distribution. The posterior distribution was obtained using the Markov Chain Monte Carlo (MCMC) technique. A good posterior distribution is when the algorithm conditions have converged. **Figure 3** shows the trace plot, density plot, and autocorrelation plot. Based on the diagnostic plot, the MCMC algorithm has converged, namely stationary trace plot, smooth density plot, and a 'cut off' autocorrelation plot **[21]**. Stationary trace plot indicates that the burn-in process has been completed so that the posterior distribution has converged and provides quite stable values because it does not form a particular pattern. Smooth density plot shows that estimated probability distribution of the parameter follows a normal distribution, which tends to be symmetrical. A 'cut-off' or rapid decay autocorrelation plot indicates good mixing of the Markov chain.




(a) (b)




(c)

**Figure 2. Diagnostic Plot of MCMC Algorithm, (a) Bali, (b) West Nusa Tenggara, (c) East Nusa Tenggara**

**Figure 4** shows the SAE HB Lognormal estimates of child undernourishment prevalence which categorized using natural breaks into three categories. Based on this map, it is known that all regencies/cities in Bali Province are included in the low category. In West Nusa Tenggara Province, 7 regencies/cities are included in the low category and 3 other regencies/cities are included in the medium category. In NTT Province, 4 regencies/cities are in the low category, 10 regencies/cities are in the medium category, and 8 regencies/cities are in the high category.

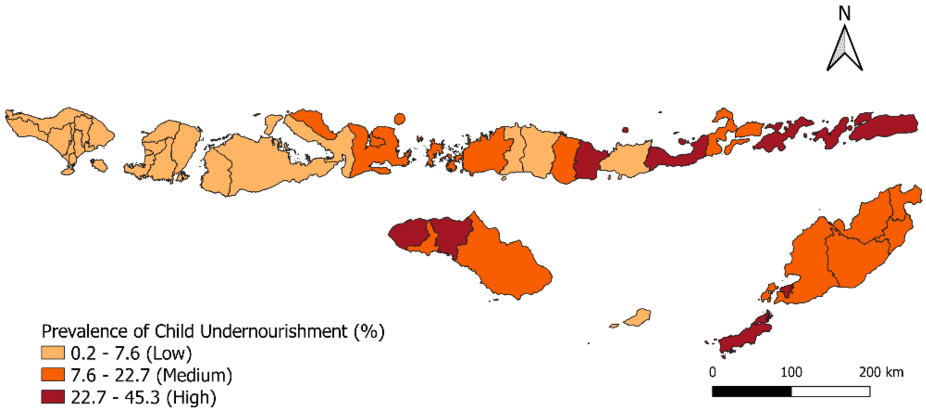



**Figure 4. SAE HB Lognormal Estimates of Child Undernourishment Prevalence**

### 3.3 Comparison between Direct Estimation and SAE HB Lognormal

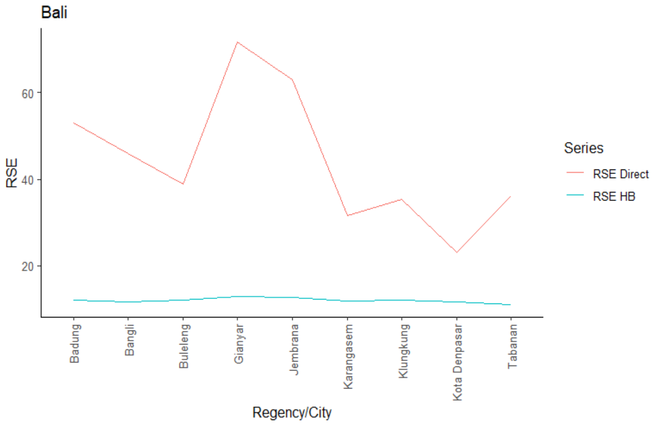
**Table 4** shows that based on the summary statistics, direct estimations and SAE HB model estimates are generally similar. In comparison to NTB and NTT, Bali has the lowest mean prevalence of child undernourishment. However, according to the median, NTB is the province with the lowest prevalence. This is consistent with the distribution in NTB province, which is positively skewed so that the mean value is greater than the median. Based on the standard deviation, NTT is the province with the most variability. This is consistent with the range, specifically the gap between the minimum and maximum values for NTT province, which is also the highest.

**Table 4. Direct Estimation and SAE HB Lognormal Estimates of Child Undernourishment Prevalence**

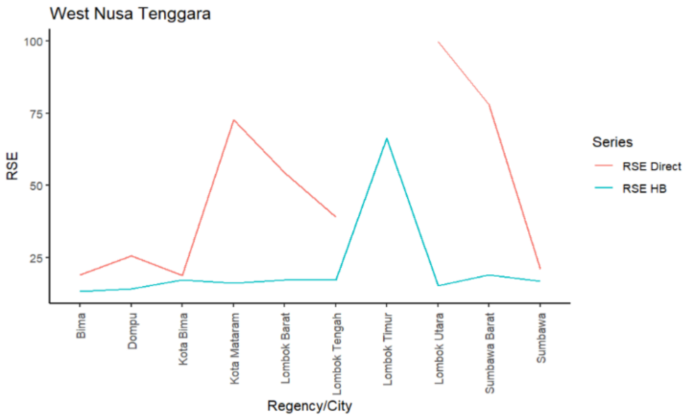
| Criteria | Direct Estimate | | | SAE HB Lognormal Estimate | | |
|---|---|---|---|---|---|---|
| | Bali | NTB | NTT | Bali | NTB | NTT |
| Mean | 3.030 | 5.167 | 19.834 | 3.031 | 4.840 | 19.827 |
| Median | 3.899 | 1.625 | 18.302 | 3.912 | 1.900 | 18.335 |

| Criteria | Direct Estimate | | | SAE HB Lognormal Estimate | | |
|---|---|---|---|---|---|---|
| | Bali | NTB | NTT | Bali | NTB | NTT |
| Std Dev | 2.239 | 5.328 | 10.409 | 2.240 | 5.127 | 10.305 |
| Minimum | 0.223 | 0.473 | 4.338 | 0.231 | 0.498 | 4.357 |
| Maximum | 6.627 | 14.317 | 45.573 | 6.712 | 14.622 | 45.429 |

It is known that based on the direct estimation, there are 24 regencies/cities that have RSE that meets Statistics Indonesia (BPS) standard, which is less than 25%. In other words, there are still 17 regencies/cities that do not meet the standards. Based on **Figure 5**, RSE of SAE HB Lognormal estimates for each province, all regencies/cities in Bali and East Nusa Tenggara (NTT) Provinces have meets BPS standards. However, there is still one regency/city in West Nusa Tenggara (NTB) that has an RSE of more than 25%, namely Lombok Timur Regency (a nonsampled regency). Even though the RSE of Lombok Timur Regency has not meet the standard yet, the standard error for Lombok Timur Regency is below 5 percent (1.42%), which is good enough for SAE estimation **[5]**.




**(a)**

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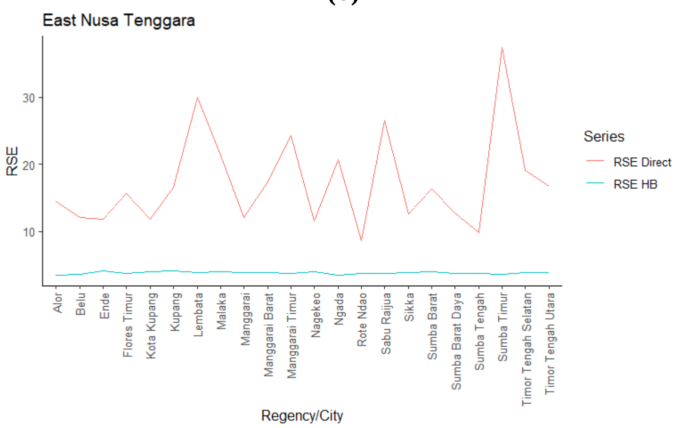


**(c)**

**Figure 5. RSE of SAE HB Lognormal Estimates on Child Undernourishment Prevalence, (a) Bali, (b) West Nusa Tenggara, (c) East Nusa Tenggara**

The SAE HB Lognormal estimation results were validated by comparing provincial-level direct estimates to SAE HB Lognormal estimations. According to Table 5, provincial-level direct estimation in all three provinces fall within the range of SAE model estimates. Thus, the SAE model can be regarded valid.

**Table 5. Validation of SAE HB Lognormal Estimation**

| Province | Provincial-Level Direct estimates | SAE HB Lognormal Estimates | | |
|---|---|---|---|---|
| | | Min | Median | Max |
| Bali | 3.562 | 0.231 | 3.912 | 6.712 |
| NTB | 3.365 | 0.470 | 1.753 | 14.308 |
| NTT | 19.470 | 4.357 | 18.335 | 45.429 |

Table 6 shows the estimates and relative standard error of direct estimation and HB Lognormal for each regency/city. SAE HB Lognormal has succeeded reducing relative standard error in Bali, West Nusa Tenggara, and East Nusa Tenggara, so that the estimates can be more reliable. Estimation using SAE HB Lognormal showed that from 41 regency/city located in those three provinces, there are 20 regency/city that has prevalence of child undernourishment lower than 7.6 percent (low), 11 regency/city with prevalence of child undernourishment between 7.6 – 20.3 percent (medium), and 10 regency/city with prevalence of child undernourishment higher than 20.3 percent (high).

**Table 6. Direct Estimation and SAE HB Lognormal Estimates of Child Undernourishment Prevalence**

| Regency/City | Direct Estimation | | HB Lognormal | |
|---|---|---|---|---|
| | Estimates | RSE | Estimates | RSE |
| **BALI** | | | | |
| Jembrana | 0.223 | 62.947 | 0.231 | 12.576 |
| Tabanan | 4.825 | 36.166 | 4.825 | 11.048 |
| Badung | 1.508 | 52.946 | 1.505 | 11.969 |
| Gianyar | 0.854 | 71.700 | 0.880 | 12.903 |
| Klungkung | 4.472 | 35.245 | 4.363 | 11.942 |
| Bangli | 0.778 | 45.844 | 0.796 | 11.714 |
| Karangasem | 4.083 | 31.590 | 4.049 | 11.876 |
| Buleleng | 3.899 | 38.828 | 3.912 | 12.030 |
| Kota Denpasar | 6.627 | 23.153 | 6.714 | 11.581 |
| **WEST NUSA TENGGARA** | | | | |
| Lombok Barat | 1.501 | 54.498 | 1.526 | 17.358 |
| Lombok Tengah | 1.625 | 39.005 | 1.657 | 17.231 |
| Lombok Timur | - | - | 2.143 | 66.283 |
| Sumbawa | 7.031 | 21.052 | 6.577 | 16.881 |
| Dompu | 7.931 | 25.731 | 7.627 | 14.338 |
| Bima | 11.977 | 18.987 | 11.994 | 13.470 |
| Sumbawa Barat | 1.168 | 77.974 | 1.253 | 19.044 |
| Lombok Utara | 0,473 | 99.746 | 0.498 | 15.368 |
| Kota Mataram | 0.488 | 72.620 | 0.501 | 16.263 |
| Kota Bima | 14.317 | 18.835 | 14.622 | 17.358 |
| **EAST NUSA TENGGARA** | | | | |
| Kupang | 15.758 | 16.627 | 15.861 | 4.170 |
| Timor Tengah Selatan | 16.479 | 19.056 | 16.511 | 3.952 |
| Timor Tengah Utara | 22.594 | 16.773 | 22.606 | 3.839 |
| Belu | 20.241 | 12.096 | 20.173 | 3.650 |
| Alor | 19.695 | 14.507 | 19.711 | 3.550 |
| Flores Timur | 16.907 | 15.733 | 16.959 | 3.775 |
| Sikka | 26.783 | 12.583 | 26.740 | 3.829 |
| Ende | 30.989 | 11.842 | 30.871 | 4.136 |
| Ngada | 12.582 | 20.738 | 12.588 | 3.551 |
| Manggarai | 25.789 | 12.144 | 25.757 | 3.847 |
| Sumba Timur | 4.338 | 37.369 | 4.357 | 3.576 |
| Sumba Barat | 16.909 | 16.375 | 16.921 | 3.968 |

| Regency/City | Direct Estimation | | HB Lognormal | |
|---|---|---|---|---|
| | Estimates | RSE | Estimates | RSE |
| Lembata | 6.923 | 29.975 | 6.930 | 3.869 |
| Rote Ndao | 45.573 | 8.645 | 45.429 | 3.754 |
| Manggarai Barat | 12.588 | 17.454 | 12.608 | 3.860 |
| Sumba Tengah | 29.567 | 9.805 | 29.575 | 3.757 |
| Sumba Barat Daya | 24.798 | 12.739 | 24.775 | 3.760 |
| Nagekeo | 30.254 | 11.541 | 30.145 | 4.068 |
| Manggarai Timur | 5.806 | 24.282 | 5.836 | 3.730 |
| Sabu Raijua | 6.825 | 26.528 | 6.846 | 3.795 |
| Malaka | 11.697 | 21.334 | 11.746 | 4.040 |
| Kota Kupang | 33.246 | 11.837 | 33.248 | 4.022 |

## 4. CONCLUSIONS

Based on the results, SAE HB Lognormal has succeeded improving the reliability of child undernourishment prevalence estimation at regency/city level in Bali, West Nusa Tenggara, and East Nusa Tenggara. Estimation using SAE HB Lognormal showed that from 41 regency/city located in those three provinces, there are 20 regency/city that has prevalence of child undernourishment lower than 7.6 percent, 11 regency/city with prevalence of child undernourishment between 7.6 – 20.3 percent, and 10 regency/city with prevalence of child undernourishment higher than 20.3 percent. These estimation results can be used by the government to provide better policy regarding child undernourishment in Bali, West Nusa Tenggara, and East Nusa Tenggara.

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