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APPLICATION OF EMPIRICAL BEST LINEAR UNBIASED PREDICTION (EBLUP) IN ESTIMATING LABOR FORCE PARTICIPATION RATE AT THE REGENCY/CITY LEVEL IN KALIMANTAN ISLAND, 2016

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Abstract: The Labor Force Participation Rate (LFPR) is a key indicator for labor market planning, especially in Kalimantan, a region experiencing sustained economic growth. In 2016, LFPR data at the regency and city levels were unavailable due to reduced sample sizes in the National Labor Force Survey. This study applies a Small Area Estimation (SAE) approach using the Fay–Herriot area-level model and the Empirical Best Linear Unbiased Prediction (EBLUP) method to estimate LFPR at the sub-provincial level. Sampling variances are obtained from direct survey estimates, and prediction (EBLUP) uncertainty is assessed using the Prasad–Rao Mean Squared Error (MSE) estimator under restricted maximum likelihood (REML). Auxiliary variables include the number of vocational high schools (SMK), the share of villages receiving foreign aid, the proportion of trade-related enterprises, and the number of villages with migrant workers. The results show that the SAE–EBLUP approach substantially reduces Relative Standard Errors (RSE) compared with direct estimates, with an average RSE reduction of 17.47%, indicating a meaningful improvement in the accuracy of small-area LFPR estimates.

1. INTRODUCTION

The Labor Force Participation Rate (LFPR) is a key indicator that reflects the proportion of the working-age population actively engaged in economic activities, either employed or actively seeking employment [1]. This indicator is often used as a basis for formulating labor market policies, economic development strategies, and evaluating labor market absorption in a given region. LFPR also plays a crucial role in achieving the Sustainable Development Goals (SDGs), particularly Goal 8, which promotes decent work and economic growth [2]. In the context of decentralization, regional decision-making requires LFPR estimates at the regency/city level, not just at the provincial level [3]. Estimating LFPR at the regency/city level is essential for designing more targeted, effective, and efficient policies to support regional development success [4].

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Kalimantan is a region with a growing economy. Each regency/city within the provinces of Kalimantan has distinct economic characteristics. Some areas are dominated by the mining and plantation sectors, while others have developed in the service and trade sectors. For instance, in 2016, 90.86 percent of businesses in North Kalimantan were small-scale enterprises employing fewer than five workers[5]. Meanwhile, in East Kalimantan, business activities were largely concentrated in the wholesale and retail trade sector, accounting for 48.02 percent of all enterprises, highlighting the sector's significant role in absorbing labor [6]. On the other hand, Central Kalimantan had the highest number of businesses in the mining sector compared to other provinces in Kalimantan [7]. Although this sector dominates the regional economic structure, its capital-intensive nature tends to result in a lower contribution to the increase in the LFPR compared to labor-intensive sectors. The varying economic development and regional characteristics underscore the need to understand local market conditions, particularly regarding labor, which is a key component of business capital. An indicator that reflects the potential labor force of a region is the LFPR. Availability of LFPR data at smaller administrative levels, such as the regency/city level, can assist governments in designing more targeted labor market policies and optimizing the utilization of local labor potential. Therefore, estimating LFPR at the regency/city level in Kalimantan is crucial for mapping employment conditions and supporting sustainable economic development.

The Labor Force Participation Rate (LFPR) is produced by BPS through the National Labor Force Survey (Sakernas), which is conducted twice a year, in February and August. LFPR estimates at the regency/city level are only available from the August Sakernas, as this survey is specifically designed to produce estimates at the regency/city level, whereas the February Sakernas is designed to generate estimates at the provincial level. However, in the August 2016 Sakernas, the sample size was smaller than in the previous year, resulting in the availability of estimates only at the provincial level [1]. With the reduced sample size, the data may not be sufficient to generate precise direct estimates of LFPR at the regency/city level. Consequently, LFPR data at the regency/city level could not be presented for the year 2016.

The availability of LFPR data over time is essential for local governments to identify labor market trends, evaluate the effectiveness of local economic development policies, and design more targeted interventions to sustainably increase labor force participation. The use of direct estimation in areas with small sample sizes can lead to high variance and low precision in the estimation results. This condition arises from the limited sample size in direct estimates, which may cause bias and insufficient representation of the overall population. As a result, the information produced may be unreliable for policy-making at the local level. Therefore, to supplement missing LFPR data series, it is necessary to apply Small Area Estimation (SAE) methods to obtain precise estimates despite limited sample data. SAE is an indirect estimation technique that leverages auxiliary information, such as census data or administrative records, and borrows strength from neighboring areas to improve the precision of estimates. It serves as an alternative when the sample size is too small to produce reliable direct estimates [8].

2. LITERATUR REVIEW

2.1. Labor Force Participation Rate (LFPR)

According to BPS (Statistics Indonesia), the Labor Force Participation Rate (LFPR) is the percentage of the working-age population (aged 15 and over) who are part of the labor

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force, either employed or actively seeking employment, out of the total working-age population. LFPR is an indicator that reflects the proportion of the working-age population actively involved in economic activities, whether as workers or job seekers. In other words, LFPR measures the extent to which the working-age population is engaged in the labor market.

$$LFPR = \left(\frac{number\ of\ labor\ force}{working - age\ population}\right) \times 100\% \quad (1)$$

Career choice theory and the LFPR are closely related, as a person's decision in choosing a career can be influenced by several factors, including the economic and educational conditions in a given area [9]. This aligns with several related studies which state that education and the economy of a region significantly affect the LFPR [10],[11]. According to the theory proposed by Keynes [12], the economic condition of a region can influence its LFPR. This is because the better the economy in a region, the higher the demand for labor. It can encourage individuals who were previously inactive to enter the labor force, thereby increasing the LFPR. One example is when a region receives external assistance or investment whether from the government or non-government entities which can be used to finance regional development. This development is closely related to the expansion of employment opportunities [13]. Furthermore, this is also linked to local production capacity and investment levels, where the flow of funds becomes a source of capital that can stimulate trade activities and small enterprises, such as the weaving industry and revolving fund programs, which in turn can create new opportunities to improve LFPR [14].

Furthermore, education can be observed through indicators such as the availability of educational facilities, which can be proxied by the number of schools in a given area. According to Becker [15], investment in human capital through education can influence an individual’s employment opportunities and income. An increase in the level of education can encourage individuals to enter the labor market, thereby increasing their participation rate. In this study, the education variable is proxied by the number of senior high schools (SMA), vocational high schools (SMK), and higher education institutions, where formal education pursued by individuals also enhances their skills and employment opportunities [15]. Harris and Todaro [16] argue that differences in expected income can drive individuals to migrate to other regions, including working abroad. In Indonesia, many individuals of productive age become migrant workers (TKI) in search of better income. This phenomenon may influence the LFPR, as the more workers employed overseas, the more the composition of the domestic labor force changes.

There has been a study in Maluku Province that estimated the LFPR using small area estimation (SAE) [17]. SAE was applied because direct estimation methods often produce unstable estimates when the sample size is small. This research shows that the Small Area Estimation approach with Kernel–Bootstrap is able to provide fairly precise estimates of the LFPR at the district/city level in Maluku Province. However, although this method is considered flexible when the relationship between the small area mean and the accompanying variables is not linear, nonparametric approaches such as Kernel–Bootstrap have theoretical limitations [18]. This method does not produce an explicit model structure, making interpretation of relationships between variables less intuitive than parametric models such as EBLUP. Furthermore, the results are sensitive to bandwidth selection and require more intensive computation due to the repeated resampling process. Therefore, the

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use of Kernel–Bootstrap still requires consideration of the complexity of interpretation and data characteristics so that the estimation results are not only precise but also easily understood by policy users. However, there has been no studies have implemented this approach in Kalimantan Island. Therefore, an indirect estimation method using SAE is needed to obtain more precise and reliable LFPR estimates at small-area levels.

SAE has evolved from basic models such as the area-level Fay-Herriot (FH) model to a variety of advanced approaches, including unit-level models, GLMMs for non-normal data, Bayesian methods, spatial and spatio-temporal models, M-quantile methods, and combinations with machine learning. Although many variants exist, this study adopted the basic SAE approach, the FH model, because it is simpler, more stable, easier to estimate, and better suited to the available data structure. Furthermore, the basic FH model performs well on area-level data if its basic assumptions are met and is more computationally efficient than more complex model variants [19]. Therefore, the use of the basic FH model is considered the most appropriate and proportional in the context of this study. Because the LFPR is a proportion indicator, the basic FH model can be applied initially, and if the assumptions of normality or stability of variance are not met, further analysis can be conducted using appropriate transformations.

2.2. Small Area Estimation

Small Area Estimation (SAE) is an indirect estimation method that employs an explicit linking model. According to Rao and Molina [8], this model utilizes auxiliary information, either from other data sources (census or administrative records) or from variations between areas that cannot be explained by those data sources. The unexplained variation is accounted for as a random effect, while the additional information is referred to as an auxiliary variable.

One of the commonly used approaches in SAE is the area-level Fay–Herriot (FH) model. The parameter θ_i is assumed to be related to the auxiliary variables, $\mathbf{x}_i = \left(x_{1i}, \dots., x_{pi}\right)^T$. In Equation (2), a linear model is specified as the linking model in this approach [8].

$$\theta_i = \mathbf{x}_i^T \boldsymbol{\beta} + b_i v_i,\;\; i = 1,2,3, \dots., m \tag{2}$$

where $\mathbf{x_i}$ is a $p \times 1$ vector of auxiliary variables, $\boldsymbol{\beta}$ is a $p \times 1$ vector of fixed coefficients, b_i is a known positive constant, and v_i is the area-specific random effect, assumed to be independently and identically distributed as $v_i \sim \; iidN(0, \sigma_v^2)$. The index i denotes the area, and m is the total number of small areas.

Let $\hat{\theta}_i$ be a direct estimator of θ_i. Since this estimate contains sampling error, it can be modeled using the sampling model shown in Equation (3).

$$\hat{\theta}_i = \theta_i + e_i,\; i = 1, 2, 3, \dots, m \tag{3}$$

where e_i is the sampling error, assumed to be independent with zero mean $E(e_i) = 0$, and variance $V(e_i) = D_i$ The quantity D_i represents the sampling variance, which is assumed to be known or estimated from the survey as the variance of the direct estimator. By combining Equations (2) and (3), the complete area-level model is obtained and expressed in Equation (4).

$$\hat{\theta}_i = \mathbf{x}_i^T \boldsymbol{\beta} + b_i v_i + e_i, i = 1, 2, 3, \dots., m \tag{4}$$

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Various SAE Fay-Herriot (FH) model have been widely applied, including Best Linear Unbiased Prediction (BLUP), Empirical Best Linear Unbiased Prediction (EBLUP), Empirical Bayes (EB), and Hierarchical Bayes (HB). BLUP provides optimal and unbiased predictions when all model parameters are known, but it is rarely used in practice because variance components are almost never known with certainty. EBLUP is more practical since these components are estimated from the data, making it stable for small-sample areas, although it still carries slight bias and does not fully capture parameter uncertainty. Empirical Bayes (EB) also produces stable, shrinkage-based estimates, but it depends strongly on model assumptions and similarly ignores uncertainty in the variance components. In contrast, the hierarchical Bayesian (HB) approach is more flexible and accounts for all sources of uncertainty, yet it requires heavier computation, appropriate prior specification, and is more complex to implement.

Labor Force Participation Rate (LFPR) data often exhibit distributions approaching normality, making the EBLUP method highly appropriate, as it is based on a linear mixed model that assumes normally distributed random effects [20]. In addition, several studies have shown that EBLUP provides higher precision than direct estimators and is more stable in the context of small area estimation [21], [22].

2.2.1. Empirical Best Linear Unbiased Estimator (EBLUP) Approach

According to Rao and Molina [8] and if we set $b_i = 1$, the small area estimator under the EBLUP method can be obtained using equation (5).

$$\hat{\theta}_i^H = \hat{\gamma}_i \hat{\theta}_i + (1 - \hat{\gamma}_i)\mathbf{x}_i^T \hat{\boldsymbol{\beta}} \tag{5}$$

where $\hat{\gamma}_i = \hat{\sigma}_v^2 / (\hat{\sigma}_v^2 + D_i)$. The level of uncertainty of EBLUP can be measured through the Prasad-Rao Mean Square Error (MSE), which is formulated in equation (6) [8].

$$MSE\ (\hat{\theta}_i^H) = g_{1i}(\hat{\sigma}_v^2) + g_{2i}(\hat{\sigma}_v^2) + 2g_{3i}(\hat{\sigma}_v^2) \tag{6}$$

with

$$g_{1i}(\hat{\sigma}_v^2) = \hat{\gamma}_i D_i \tag{7}$$

$$g_{2i}(\hat{\sigma}_v^2) = (1 - \hat{\gamma}_i)^2 \mathbf{x}_i^T \left[\sum_{i=1}^m \mathbf{x}_\mathbf{i} \mathbf{x}_\mathbf{i}^\mathbf{T} / (\hat{\sigma}_v^2 + D_i)\right]^{-1} \mathbf{x}_\mathbf{i} \tag{8}$$

when $\hat{\sigma}_v^2$ is obtained using the restricted maximum likelihood (REML) method, $g_{3i}(\hat{\sigma}_v^2)$ is given as in equation (9):

$$g_{3i}(\hat{\sigma}_v^2) = 2\left[\sum_{i=1}^m 1/(\hat{\sigma}_v^2 + D_i)^2\right]^{-1} \tag{9}$$

To evaluate the quality of an estimator, both direct and indirect estimators such as EBLUP, the Relative Standard Error (RSE) measure is used, which is calculated using the formula in equation (10).

$$RSE(\ \hat{\theta}_i) = \frac{\sqrt{MSE(\hat{\theta}_i)}}{\hat{\theta}_i} \times 100\% \tag{10}$$

3. METHODOLOGY

3.1. Data Collection Methods

This study uses secondary data obtained from various sources. The unit of analysis in this study is 56 regencies/cities in Kalimantan Island. The variable of interest in this study

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is the Labor Force Participation Rate at the regency/city level in Kalimantan Island in 2016 obtained from the raw data of Sakernas in August 2016. Then, the auxiliary variables used in this study were obtained from the 2014 Village Potential Statistics (Podes) Publication and the 2014 Village Potential (Podes) Census raw data. The variables that have a significant correlation with the Labor Force Participation Rate can be seen in Table 1.

Table 1. List of Auxiliary Variables

Variables	Explanation	Sources
Number of senior high school (SMA)	Number of senior high school (SMA) in a regency/city	Raw data village potential census (Podes) 2014
Number of vocational high school (SMK)	Number of vocational high school (SMK) in a regency/city	Raw data village potential census (Podes) 2014
Number of Universities	The number of universities in a regency/city	Raw data village potential (Podes) 2014
Percentage of trading business	Percentage of the number of trading businesses	Publication of the Economic Census 2016
Percentage of villages with foreign assistance	Percentage of villages receiving assistance/grants from abroad	Publication of village potential (Podes) statistics 2014
Percentage of villages with foreign assistance	Percentage of villages receiving assistance/grants from abroad	Publication of village potential (Podes) statistics 2014
Percentage of villages with private assistance	Percentage of villages receiving assistance/grants from the private sector	Publication of village potential (Podes) statistics 2014
Percentage of villages with Central government assistance	Percentage of villages receiving assistance/grants from the central government	Publication of village potential (Podes) statistics 2014
Number of villages with migrant workers	The number of villages that have residents working as Indonesian Migrant Workers (TKI)	Publication of village potential (Podes) statistics 2014
Number of weaving industries	Many villages have weaving industries	Publication of village potential (Podes) statistics 2014
Revolving fund for non-agricultural businesses	Percentage of villages that have a revolving fund for non-agricultural businesses	Publication of village potential (Podes) statistics 2014

3.2. Estimation Method

The estimation methods used in this study consist of direct and indirect methods. The indirect method uses Empirical Best Linear Unbiased Prediction (EBLUP). Estimation using the indirect method requires auxiliary variables that are linked through an explicit model. The selection of auxiliary variables begins by examining the significance of the correlation between the auxiliary variables and the direct estimate of the LFPR. From these correlated variables, it is necessary to ensure that there is no multicollinearity between them. Next, variable selection is performed using stepwise regression to obtain auxiliary variables that can be used in the estimation process using EBLUP.

4. RESULTS AND DISCUSSION

4.1. Direct Estimates of LFPR for Regencies/Cities in Kalimantan Island

The direct estimate of the LFPR is generated from a calculation process that takes into account sampling weights from the National Labor Force Survey (Sakernas). A

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summary of the direct estimate of the LFPR for 56 regencies/cities in Kalimantan is shown in the Table (2).

Tabel 2. Summary of direct estimates of regency/city LFPR

Average	Variance	Minimum	Median	Maximum
70,26	40,50	57,71	70,04	88,23

Based on Table 2, the direct estimate of the Labor Force Participation Rate (LFPR) for regencies/cities in Kalimantan Island in 2016 shows an average LFPR of 70.26 percent. This direct estimate did not find any cases of non-sampled areas. Variance value of 40.50 was obtained, indicating a fairly widespread distribution of the data. This reinforces the assumption that labor market conditions at the regency/city level in Kalimantan Island exist heterogeneously. This variation also emphasizes the importance of a statistical approach that can handle inter-regional differences, particularly to formulate employment policies.

Next, it is necessary to check the RSE values from the direct estimates to determine their precision. Table 3 presents a summary of the RSE values from the direct estimates of the LFPR for regency/city in Kalimantan in 2016.

Table 3. Summary of RSE direct estimates of LFPR regency/city

Mininum	Median	Maximum	Mean
0.68	4.18	7.86	4.35

In Table 3, it is known that the maximum RSE value of the regency/city LFPR in Kalimantan Island is 7.86 percent. However, considering the importance of the estimation of the regency/city LFPR as the basis for making various policies, it is necessary to estimate the LFPR with a high level of precision or the minimum RSE value possible. Therefore, an indirect estimation of LFPR is needed to increase the precision of the estimation results.

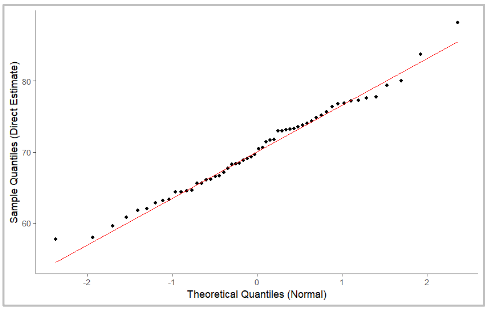

Fig 1. QQ plot of direct estimation of regency/city LFPR in Kalimantan 2016

Based on the exploration of the direct estimates using the QQ plot in Figure 1, the data points lie along the reference line with minimal deviation, indicating that the data are normally distributed or approximately normal. To validate the normality suggested by the QQ plot, a Shapiro–Wilk test was performed. The test produced a statistic of 0.9866 with a p-value of 0.7877, indicating that the direct LFPR estimates follow a normal distribution. This normality satisfies one of the key assumptions for applying the SAE method, specifically the EBLUP approach [23].

4.2. Indirect Estimation With EBLUP

EBLUP is an indirect estimation method used for normally distributed and continuous data [18]. In this study, the regency/city LFPR data are normally distributed and

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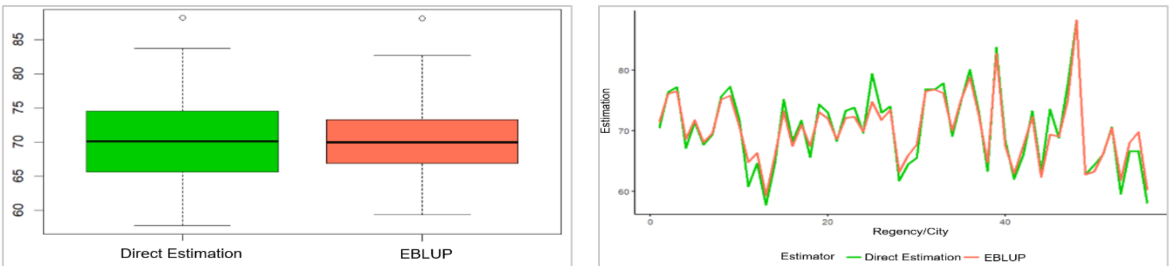
continuous. Therefore, EBLUP is an appropriate method to estimate the regency/city LFPR in Kalimantan.

In the estimation process with EBLUP, auxiliary variables are required. The selection of auxiliary variables begins by looking at the significance of the correlation between the candidate auxiliary variables and the direct estimate of LFPR. Furthermore, a multicollinearity check is conducted. The results show that all auxiliary variables have a Variance Inflation Factor (VIF) less than 10, so there is no multicollinearity. Then the variable selection was carried out using stepwise regression. From the selection process, the best model was obtained with the selected auxiliary variables, including the number of vocational high schools, the percentage of villages with foreign assistance, the percentage of trading businesses, and the number of villages with migrant workers. The EBLUP estimation process was conducted using the interest variables from the direct estimation and the four auxiliary variables. The parameters and standard errors from the EBLUP estimation process are listed in Table 4.

Table 4. Parameter estimation with EBLUP

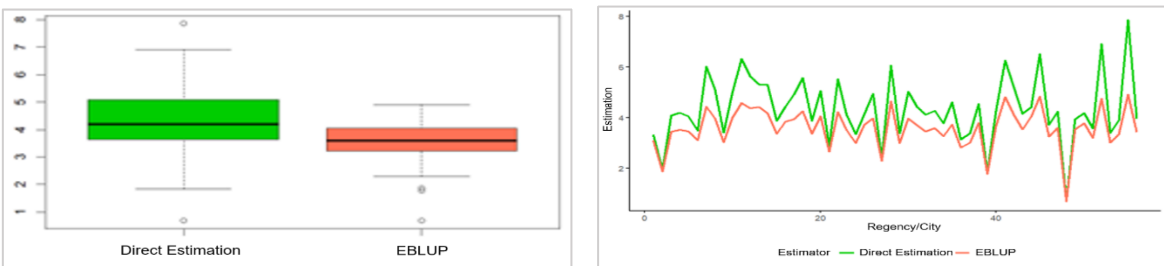
Variable	β	Standard Error
Intercept	55,141	8,993
Number of vocational high school (SMK)	-0,284	0,084
Percentage of villages with foreign assistance	0,413	0,167
Percentage of trading businesses	0,335	0,183
Number of villages with migrant workers	0,063	0,019

In the EBLUP estimation method, there is an assumption of normality in the random effect [23]. Based on the Shapiro-Wilk test, the p-value is 0.17. Since the p-value is greater than the significance level, it can be concluded that the random effect is normally distributed or the normality assumption in EBLUP estimation has been met. Based on the calculation process of the EBLUP estimation, the estimated value of LFPR can be seen in Figure 2. Figure 2 shows a boxplot and line graph comparison to see the EBLUP results compared to the direct estimation results.



(a) (b)

Fig 2. Comparison of direct estimate and EBLUP with: (a) boxplots; (b) line graphs



(a) (b)

Fig 3. Comparison of RSE of direct estimate and EBLUP with: (a) boxplot; (b) line graph

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Table 5. Summary statistics of direct and EBLUP estimation along with RSE

Statistic	Estimation		RSE		Percentage Reduction in RSE (%)	EBLUP Shrinkage ($\hat{\gamma}$)
	Direct	EBLUP	Direct	EBLUP		
Minimum	57.71	59.33	0.68	0.68	0	0.40
Median	70.04	69.91	4.18	3.59	14.11	0.67
Mean	70.26	70.25	4.35	3.59	17.47	0.67
Maximum	88.23	88.21	7.86	4.91	37.53	0.98

Based on Figure 2, it is known that the EBLUP estimation results have a smaller data range than the direct estimation. In addition, the direct and EBLUP estimation values produce similar patterns. This shows that EBLUP produces consistent estimation values and does not deviate far from the direct estimation results.

Based on Figure 3, it can be seen that EBLUP has a lower RSE than direct estimation. This shows that EBLUP can produce more precise estimates. Summary statistics of estimation and RSE values between direct estimation and EBLUP can be seen in Table 5.

The EBLUP method achieved a moderate reduction in RSE, with a mean decrease of 17.47% and a median of 14.11%. Most areas showed $\hat{\gamma}$ values above 0.5, reflecting limited shrinkage due to relatively precise direct estimates with RSE below 10%. The three areas with the highest shrinkage were Nunukan ($\hat{\gamma}_{55} = 0.40$), Malinau ($\hat{\gamma}_{52} = 0.44$), Kutai Timur ($\hat{\gamma}_{45} = 0.45$), all with $\hat{\gamma}$ values below 0.5, where the model contributed more heavily than the direct estimates in forming the EBLUP values.

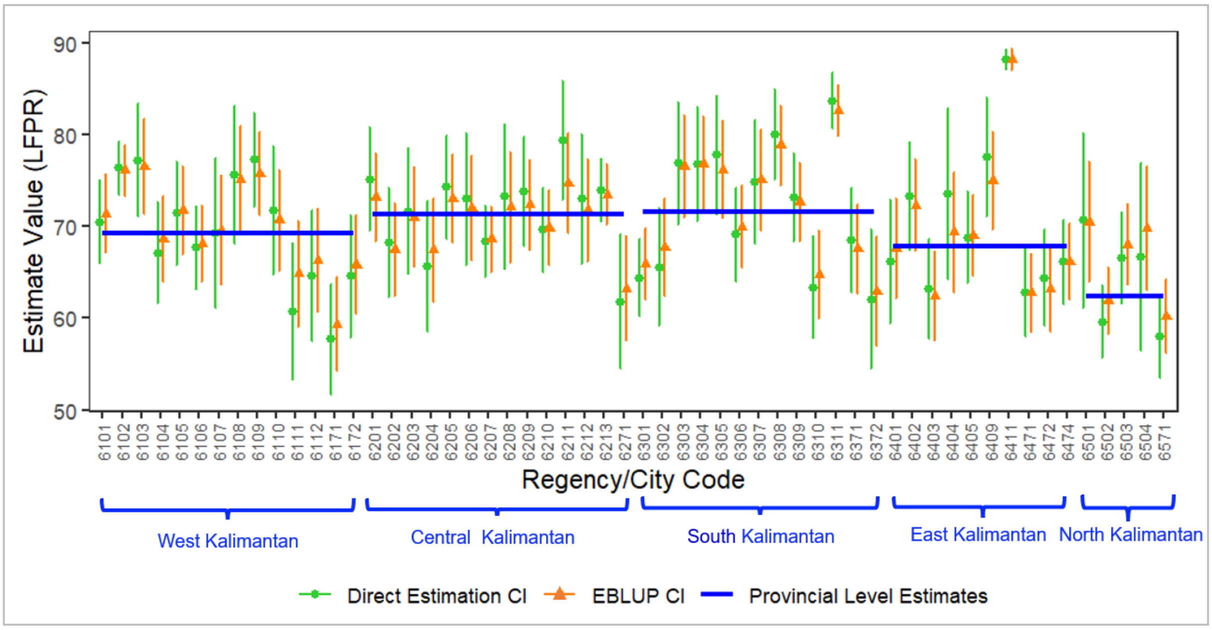

Fig 4. Comparison of confidence intervals between direct estimation and EBLUP

Figure 4 shows that in most areas, Confidence Interval (CI) for direct estimation tends to be wide, reflecting a high level of uncertainty. In contrast, the CI for EBLUP shows narrowing as a result of utilizing model information and borrowing strength between areas. It means EBLUP consistently provides more precise estimates in almost all areas. This narrowing of the CI occurs without shifting the estimator value extremely, as indicated by the fairly strong overlap between the two CI in the majority of areas.

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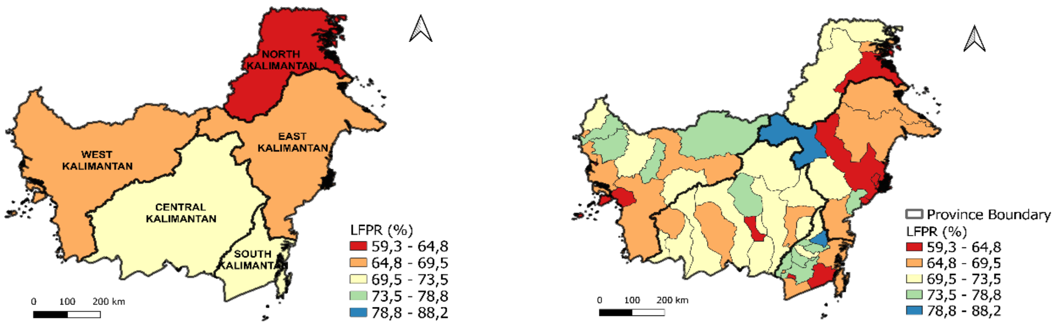
Based on Figure 4, it can be observed that the range of LFPR estimates at the regency/city level in Kalimantan Island, obtained using direct and EBLUP methods, includes their respective provincial estimates. This indicates that the estimation results are valid. Therefore, both direct and EBLUP methods are capable of producing valid estimates. However, EBLUP offers the highest level of precision. This suggests that EBLUP is more reliable for use in planning and policy-making at the regency/city level.

4.3. Spatial Distribution of LFPR Estimates Across Regency/City

The EBLUP estimates of the Labor Force Participation Rate (LFPR) at the regency/city level in Kalimantan Island are presented in the choropleth map in Figure 5, categorized using the natural breaks method. In addition, Figure 5 also includes a map of provincial-level LFPR, with figures obtained from the 2016 Labor Force Situation publication by BPS.

In the provincial-level LFPR map, North Kalimantan shows an LFPR in the range of 59.3–64.8 percent, making it the province with the lowest LFPR in Kalimantan. However, when examining LFPR at the regency/city level, it is evident that some regencies/cities in North Kalimantan have higher LFPRs than the provincial average. A similar pattern is observed in other provinces on the island. In the provincial-level map, East Kalimantan has an LFPR ranging from 64.8–69.5 percent. However, when disaggregated to the regency/city level, LFPRs in East Kalimantan vary widely, covering all five LFPR categories rom 59.3–64.8 percent to 78.8–88.2 percent.



(a) (b)

Fig 5. Mapping of LFPR Estimates in Kalimantan: (a) by province [1]; (b) by regency/city

In the provincial-level LFPR map, no areas are shown within the 79.8–88.1 percent range. However, at the regency/city level, it becomes apparent that Mahakam Hulu Regency and Balangan Regency both fall within this highest LFPR category. Being in this range indicates that these two regencies have greater labor force potential compared to other regencies/cities. Given their high LFPR, attention should now turn to improving workforce quality. It is thus essential to expand access to job training programs that align with current labor market demands. Additionally, local governments should promote regional economic development based on local potential. Considering these areas's strengths in mining and plantations, downstream industrialization must be encouraged. This would ensure that labor absorption extends beyond extraction (upstream) sectors into processing industries. By processing local resources locally, downstream industrialization can generate new employment opportunities and increase economic value. Furthermore, governments should invest in infrastructure to support mobility and connectivity between regions, enabling the workforce to access economic growth centers more effectively.

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In the regency/city-level LFPR map, several areas fall within the lowest range of 59.3 to 64.8 percent, including Bulungan Regency, Kutai Kartanegara Regency, the cities of Samarinda, Banjarbaru, Palangkaraya, and Pontianak. These areas exhibit lower labor force participation compared to others. A low LFPR indicates that a significant portion of the working-age population is not participating in the labor force. To encourage active labor force participation, especially among vulnerable groups such as persons with disabilities and women, it is essential to expand accessible employment and entrepreneurship opportunities, as well as to develop skill training programs aligned with current labor market demands. These efforts can help individuals better utilize their potential and local resources productively. This highlights the importance of data availability at more granular levels, as it enables a clearer understanding of regional disparities and variations. Consequently, policy interventions can be more effective, efficient, and well-targeted.

5. CONCLUSION

This study demonstrates that the application of EBLUP improves the precision of LFPR estimates at the small-area level in Kalimantan. The mean RSE decreased by 17.47% and the median by 14.11% across regions. Most areas showed limited shrinkage because the direct estimates were already reasonably precise, while the largest adjustments were observed in Nunukan, Malinau, and Kutai Timur, where the model contributed substantially more information than the direct survey estimates. These results confirm that EBLUP enhances precision and provides appropriate adjustments to direct estimates. Nonetheless, the analysis is restricted to a single year of data and may not fully capture within-region heterogeneity. Future research could incorporate spatial or heteroscedasticity-aware models and utilize multi-year data to further improve small-area LFPR estimates.

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