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Original Research

Identifying Provinces With RMNCH-IC Disparities Between Urban - Rural Residences In Indonesia

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ABSTRACT

Background: *Intervention coverage in reproductive, maternal, newborn, and child health (RMNCH-IC) is still unequal between urban and rural residences. This inequality is considered to also occur in Indonesia. The Composite Coverage Index (CCI) measures RMNCH-IC. However, CCI measurements at provincial levels according to residences are not yet available in Indonesia due to the limited sample size at some CCI indicators. Therefore, provinces with a large RMNCH-IC inequality, or disparity, between residences have not been identified. Thus, this study aims to measure CCI as a whole at provincial levels according to residences in Indonesia through the estimation of CCI indicators using MRP, to be used to identify provinces with CCI disparities between residences.*

Methods: *Small Area Estimation (SAE), especially Multilevel Regression and Poststratification (MRP) models, can be used to estimate parameters for each province according to residences with limited samples. The secondary data used in this study come from the latest survey, the 2017 Indonesian Health Demographic Survey (IDHS).*

Results: *Based on the value of the CCI dimension, urban residences have better dimensions of maternal and newborn health, while rural residences have better dimensions of reproductive and child health. There are 5 provinces with RMNCH-IC disparities between residences in Indonesia.*

Conclusion: *Efforts to reduce CCI inequalities are still needed for each residence in their respective dimension, especially for provinces with RMNCH-IC disparities. Further research is needed to explain the determinants of the large disparities between the five provinces.*

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INTRODUCTION

Health intervention coverage in reproductive, maternal, newborn, and child aspects (RMNCH-IC) is still unequal (UNDP, 2018) (UNICEF & WHO, 2017) (WHO, 2015). At the multinational level, one form of inequality is between places of residence, namely urban and rural residences. The majority of countries have higher RMNCH-IC in urban areas compared to rural residences (WHO, 2015).

Inequality in RMNCH-IC between residences is also possible on a smaller scale at the national level. Inequalities at the national level happen when a subnational unit, for example, a province, has far bigger RMNCH-IC differences between residences compared to other provinces. In this research, these occurrences will be called "disparities".

One country that's considered to have RMNCH-IC disparities between residences is Indonesia. This assessment is based on previous research, which found significant differences between residences and geographical regions in Indonesia on several aspects related to RMNCH-IC. In the aspect of maternal health, for example, there is a different tendency for health interventions for pregnant women between residences.

Pregnant women in rural residences have a lower tendency to perform antenatal care at least four times (ANC4) and deliveries in medical facilities compared to pregnant women in urban residences (R. D. Wulandari et al., 2021) (Laksono & Wulandari, 2021). In addition, pregnant women in the eastern region of Indonesia have a lower tendency to perform ANC4 compared to other regions, especially compared to the Java-Bali region (Laksono et al., 2020). Another example of inequality is in the aspect of newborn health. Rural residences have a higher percentage of infants with incomplete immunizations than urban residences (Hardhantyo & Chuang, 2021).

Meanwhile, if studied by geographical region, the Papua and Maluku regions have the highest percentage of infants with incomplete immunizations compared to other regions in Indonesia (Hardantyo & Chuang, 2021). Thus, it is possible for RMNCH-IC inequalities as a whole that vary between residences in each province to exist in Indonesia. It is also possible for a province to have disparities in RMNCH-IC between residences.

One indicator that can measure the overall RMNCH-IC is the Composite Coverage Index (CCI), which was made by UNICEF and WHO (UNICEF & WHO, 2017). The increase in CCI, with all its constituent indicators, has been proven academically to improve the health and survival of mothers, infants, and children (WHO, 2015) (UNICEF & WHO, 2017). For example, infant immunization, which is part of the newborn health indicators in the CCI, has been proven to significantly reduce the risk of infant mortality.

Therefore, higher infant immunization coverage can certainly reduce infant mortality (Breiman et al., 2004) (Kabir et al., 2003) (McGovern & Canning, 2015) (Tiwari et al., 2015). The impact of all these indicators makes CCI measurement very important and feasible in Indonesia, considering Indonesia's high maternal mortality rate (MMR) and under-five mortality rate (AKBa), which are also above the 2030 SDGS target, and also the unequal RMNCH-IC (Badan Pusat Statistik, 2015) (Kementerian Kesehatan RI, 2018) (United Nations, 2016).

However, CCI measurements are still limited to subgroups at the national level, such as rural and urban residences, or between provinces, but not both at the same time (WHO, 2015) (WHO, 2021) (Ren, 2021). This limitation is considered to occur due to the limited sample size of several CCI indicators, which come from the Indonesian Demographic and Health Survey (IDHS), which can be too small if disaggregated based on the combination of multiple characteristics (WHO, 2015) (Ren, 2021) (WHO & UNICEF, n.d.) (Asian Development Bank, 2021). In fact, the disaggregation of CCI in Indonesia based only on provinces can also be considered not quite reliable enough due to the presence of CCI indicators that have fewer than 25 samples in each province (WHO & UNICEF, n.d.) (WHO, 2017).

This means that CCI measurements based on a combination of characteristics, including residences in each province, cannot be carried out well enough. This limitation is very unfortunate, considering that the CCI measurement based on a combination of two characteristics is important to identify RMNCH-IC inequality more specifically in order to carry out more focused RMNCH-IC equality efforts (WHO, 2017) (WHO, 2015). In CCI measurement with the combination of residences and provinces, this measurement is considered useful to identify provinces with RMNCH-IC disparities between residences. This information can then be used to provide specific RMNCH-IC equalization advice to the province in question.

One solution for the problem of limited sample size is indirect estimation with Small Area Estimation (SAE). SAE is done by estimating parameters in areas or groups that are lacking, even without samples at all, through other variable approaches and certain models (Rao & Molina, 2015). One method that can perform SAE is Multilevel Regression and Poststratification (MRP). MRP estimates are based on a combination of geographic and demographic characteristics, such as by province and place of residence, to make better estimates at higher levels of aggregation (Zhang et al., 2014). As a result, the MRP can be used to estimate each place of residence in each province.

Overall, there are still problems with the unavailability of CCI measurements that are considered reliable based on the combination of rural and urban residences in each province in Indonesia because of the limited sample size. In fact, this measurement is considered important to equalize RMNCH-IC between residences with a more specific provincial focus. Therefore, this study will provide an overview of the indicators that construct CCI based on the place of residence in each province through direct estimates, as well as the consequences of the limited sample on the estimation.

Then, SAE will be carried out using MRP to produce an estimate of each indicator that is considered to be better. Finally, the indicators estimated through the MRP will be used to calculate CCI in each residence and province to identify provinces with RMNCH-IC disparities between residences.

MATERIALS AND METHOD

This research is conducted using the 2017 IDHS data, which is the latest data in CCI measurements. IDHS has 49627 samples of women aged 15–49 years and 17484 samples of children under five (Kementerian Kesehatan RI, 2018). In this study, the sample size for the estimation of each of the indicators that construct the CCI can be different due to differences in the definition and target population of the indicators themselves.

The main estimates in this study were carried out on several CCI indicators that have a shortage of samples when disaggregated at the combination of provincial level and/or place of residence. The sample shortage criteria are based on units with a sample of less than 25 in each place of residence in each province (WHO, 2015). However, the estimation will also be applied to all CCI indicators to provide a better picture of the estimation of each indicator through the MRP estimation method and also to give an equivalent comparison.

CCI is a composite index that specifically measures the RMNCH intervention coverage for a specific group (UNICEF & WHO, 2017). Through this, the CCI can be used to conclude the condition of the RMNCH-IC with a stable value in order to identify differences or disparities between groups in general. The indicators that construct CCI consist of four health dimensions for a total of eight indicators.

The reproductive dimension consists of 1 indicator, namely the use of modern methods to fulfill demands for family planning in married women (FPSM); The maternal dimension consists of 2 indicators, namely at least 4 antenatal care visits (ANC4) and assisted births by trained personnel (SBA), both in a woman that gave birth in the last 5 years before the survey; The newborn Dimension consists of 3 indicators, namely BCG, DTP3, and Measles (MSL) immunizations in the infant; and finally, the child dimension consists of 2 indicators, namely children who suffer from diarrhea and are given ORS (ORS) and children who have symptoms of pneumonia and are taken to a healthcare provider (CNM). Each of these indicators has the form of a percentage, which describes the health intervention coverage of each indicator in the group concerned. The CCI calculation formula is written in Formula 1.

Formula 1

$$CCI_{pj} = \frac{1}{4} \times \left(FPSM_{pj} + \frac{ANC4_{pj} + SBA_{pj}}{2} + \frac{BCG_{pj} + 2DTP3_{pj} + MSL_{pj}}{4} + \frac{ORS_{pj} + CNM_{pj}}{2} \right)$$

With index p as place of residence ($p=1$ for Urban, dan $p=0$ for rural) and j as province ($j=1,..,34$, for Aceh, ..., Papua). The variables used in this study include the place of residence and province. Places of residence are classified as urban and rural. There are 34 provinces in Indonesia, with a total of 34 urban residences and 33 rural residences. Only one province does not have rural residences, namely DKI Jakarta Province (Badan Pusat Statistik, 2020).

The estimation of CCI indicators based on residence in each province will be carried out using Multilevel Regression and Poststratification (MRP) with a logistic approach. MRP was chosen because the poststratification method was considered suitable for categorizing sample data into certain categories, such as province and place of residence, to then be used for estimating the parameters at the population level (Wang et al., 2015). Meanwhile, multilevel modeling is based on a hierarchical data structure, such as the relationship between residents in the same province compared to other provinces (Gelman & Little, 1997) (Saragih et al., 2020).

Lastly, the logistical approach is caused by the type of dependent variable in the form of a binary, which is classified as "included" or "not included" in the proportion of each indicator (Saragih et al., 2020). The computer program used for processing MRP is SAS Academy Edition. MRP stages include (1) model specification, (2) prediction of the model, (3) poststratification with better quality data such as a census, and finally (4) comparing the SAE-MRP model results with direct estimates (Zhang et al., 2014).

The first step, namely the model specification, is carried out by forming a Multilevel Binary Logistic Regression (MBLR) model using weights to generate parameter estimates. The weights are first rescaled according to the response variables using the probability from the level 1 logistic regression model. This is done to correct the unequal probabilities of the IDHS raw data and to avoid errors when modeling in the SAS program.

Errors in SAS can arise because SAS reads the weights as frequency weights, which should be based on probability (Zhang et al., 2014). The level 1 logistic regression model used is in formula (2), without using the division of provinces. The probability results are then used for rescaling the weights using formula (3).

Formula 2

$$Pr_{ip}^{b}\left(y_{ip}^{b}=1\right)=logit^{-1}(\alpha_{p}^{b}+e_{p}^{b})$$

Formula 3

$$RW_{ip}^{b}=\frac{W_{ip}^{b}}{\sum_{i} W_{ip}^{b}Pr_{ip}^{b}}$$

In formulas (2) and (3), index *i* refers to *i*-th individual units, *p* refers to the place of residence (rural or urban), and *b* refers to CCI indicator (FPSM, ..., CNM). α_{p}^{b} is the regression coefficient for the variable place of residence. The second step, namely the model prediction stage; predictions are made from each place of residence in each province using the estimated parameters of the MBLR model results. The assumption of random effect significance was also checked using the likelihood ratio test. The MBLR model that will be used for prediction is in formula (4):

Formula 4

$$Pr_{pj}^{b}\left(y_{pj}=1\right)=logit^{-1}(\alpha_{p}^{b}+\gamma_{j}^{b}+e_{pj}^{b})=\frac{exp(\alpha_{p}+\gamma_{j}+e_{pj})}{1+exp(\alpha_{p}+\gamma_{j}+e_{pj})}$$

In formula (4), γ_j and e_{pj} are random effects from province category and residual, respectively. To get proportion prediction in each province, the prediction results from the model for each characteristic in a province are summed up. In this study, there are only characteristics of residence within 2 categories, namely urban and rural residences, in each province.

The third step is post-stratification with better-quality data for estimation at the population level. Better data in this study were taken from the results of the 2010 Population Census by BPS and the Directorate General of Disease Prevention and Control in the 2019 Indonesian Health Profile by the Indonesian Ministry of Health (Kemenkes RI). It should be noted that the two data sets approximate the actual population. The population of FPSM, ANC4, and SBA was approximated by the number of married women aged 15–49 years in 2010.

The population of BCG, DTP3, and MSL was approximated by the number of children aged 1 year in 2010. Finally, the population of ORS and CNM was approached based on the estimated percentage of diarrhea and pneumonia in children under five in 2019 in each province, adjusted for the number of children under five from the 2010 Population Census in each place of residence and province. All these approaches were taken due to the unavailability of exact population data in the same year for the population in each indicator. The postratification process is carried out by formula (5).

Formula 5

$$Pr_{pj}^{b}=\frac{\sum_{p} (Pr_{pj}^{b}\times Pop_{pj}^{b})}{\sum_{p} Pop_{pj}^{b}}=\frac{\sum_{p} (Pr_{pj}^{b}\times Pop_{pj}^{b})}{Pop_{j}^{b}}$$

To improve the estimation of the Pr_{pj}^{b} proportion, 1,000 samples were drawn using *Monte Carlo* simulation in each province based on the place of residence. Sampling with the *Monte Carlo* simulation is done by selecting a random sample from the population that is assumed to follow a certain distribution (Raychaudhuri, 2008). The last step is to compare the results of the SAE-MRP estimation that has been resampled using a *Monte Carlo* simulation with a direct estimate. Comparisons were made using Mean Squared Error (MSE), Mean Absolute Difference (MAD), and Relative Standard Error (RSE).

MSE and MAD are calculated by aggregating the provincial values to the national level, as well as urban and rural residences in each province to the provincial level. The results of SAE aggregation that have a large difference with direct estimates for units that have a large sample and are assessed as reliable may indicate a model discrepancy (Bell et al., 2013). Reference to the national level is made because the estimation at the national level from the IDHS is believed to be the most reliable estimate and is above the provincial level (Kementerian Kesehatan RI, 2018).

Meanwhile, RSE will only be calculated for national estimates. The reason for this is the fact that MSE from MRP in this research is only calculated as an aggregation, including national aggregation.

Formula 6

$$MSE = \frac{1}{N} \times \sum_{k=1}^{N} \quad (c_k - d_k)^2$$

Formula 7

$$MAD = \frac{1}{N} \times \sum_{j=1}^{N} \quad |c_k - d_k|$$

Formula 8

$$RSE = \frac{\sqrt{MSE(c_k)}}{c_k}$$

In formulas (6), (7), and (8); c_k is the result of MRP estimation with *Monte Carlo*, while d_k is the result of direct estimation with weight. Formula (6) and (7) aggregate c_k and d_k both to provincial or national level. Meanwhile, c_k and $d_k$in formula (8) are only aggregated to national level. Index k in the formula only consists of 1 unit when aggregated at the national level, because this research is only carried out in 1 country, which is Indonesia.

Estimation results from each indicator according to residences and provinces will then be used to measure CCI in their respective units. To identify provinces with RMNCH-IC disparities, a boxplot of absolute CCI differences between residences will be used. Provinces with outlier CCI differences will be considered provinces with RMNCH-IC disparities. Through that identification, this research will then try to give recommendations for each of those provinces to reduce the RMNCH-IC disparities through the analysis of CCI in their respective provinces.

In this study, the selection of the variables needed for each indicator from the raw data of the IDHS was based on the Guide to the DHS Statistics Program. In addition, data cleaning was carried out by removing observations that had missing data on the variables needed in the study. This approach was taken due to the unavailability of an explanation that was considered detailed enough for processing indicators directly from the IDHS raw data for each CCI indicator.

Therefore, it is considered that the direct estimation results for each indicator from this research could differ from direct estimation results in other publications. Even then, the concept and definition of each indicator and the CCI itself are still considered to align with the CCI results from other publications.

RESULTS

The boxplot from direct estimation results in Figure 1 shows a pattern of differences in CCI indicators between provinces and places of residence. The pattern of difference is indicated by the difference in the median, the length of the boxplot, and the presence of outliers in the boxplot. A pattern based on the median shows higher ANC4, SBA, BCG, DTP3, ORS, and CNM indicators in urban residences; while FPSM and MSL indicators are higher in rural residences. However, it should be noted that based on the indicator average at the national level, the CNM indicator is higher in rural residences and the MSL indicator is higher in urban residences. Thus, this indicates better dimensions of reproductive health in rural residences and better dimensions of maternal and newborn health in urban residences, while dimensions of children's health still cannot be determined with certainty.

A pattern based on the length of the boxplot and outliers shows the distribution of indicators in each province. The boxplot length on the DTP3, MSL, ORS, and CNM indicators looks longer than other indicators. Meanwhile, based on outliers, it can be seen that several provinces have an absolute value of 0 on the ORS and CNM indicators. This is considered very extreme, especially in CNM, where there are also provinces with an absolute value of 100. These two patterns are considered to occur due to a lack of sample cases in urban and rural residences in some provinces for these indicators.

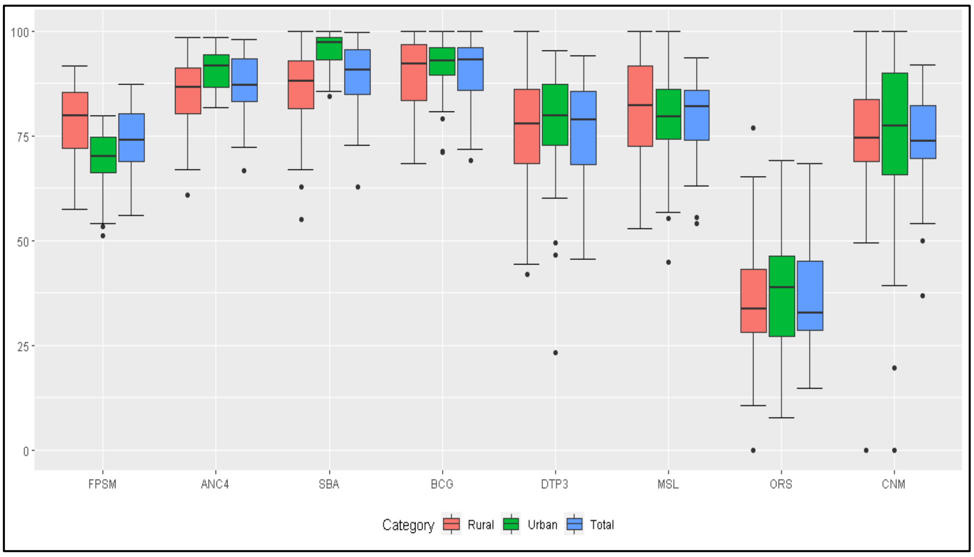

Figure 1. Boxplot of CCI Indicators from Direct Estimation

Besides ORS and CNM indicators, BCG, DTP3, and MSL indicators are also indicated to have several places of residence in each province with a case sample of less than 25, although the estimation results are not as extreme as ORS and CNM. Thus, the application of indirect estimates, such as through the MRP, is considered feasible to estimate the value of indicators in each residence and province. The application of MRP is also considered feasible for the FPSM, ANC4, and SBA indicators, in order to produce estimates that are not constrained by the number of samples and through the same method as other indicators.

Estimation through MRP should begin by forming a regression model for each indicator. The results are shown in Table 1.

Table 1. Significance Test for Multilevel Effect and Their Respective Model According to Indicators and Dimensions

Dimension	Indicators	LR Stat	Model
Reproductive	FPSM	534.562*	$Pr_{pj}^{FPSM}(y_{pj}=1)=(1.2754^{*}-0.397^{*}x+\gamma_j)$
Maternal	ANC4	581.618*	$Pr_{pj}^{ANC4}(y_{pj}=1)=(1.9140^{*}+0.558^{*}x+\gamma_j)$
	SBA	1143.127*	$Pr_{pj}^{SBA}(y_{pj}=1)=(2.0772^{*}+1.378^{*}x+\gamma_j)$
Newborn	BCG	116.478 *	$Pr_{pj}^{BCG}(y_{pj}=1)=(2.2832^{*}+0.392^{*}x+\gamma_j)$
	DTP3	167.138*	$Pr_{pj}^{DTP3}(y_{pj}=1)=(1.2754^{*}+0.405^{*}x+\gamma_j)$
	MSL	96.591*	$Pr_{pj}^{MSL}(y_{pj}=1)=(1.3188^{*}+0.195^{*}x+\gamma_j)$
Child	ORS	54.193*	$Pr_{pj}^{ORS}(y_{pj}=1)=(-0.5779^{*}-0.013x+\gamma_j)$
	CNM	0.792	$Pr_{pj}^{CNM}(y_{pj}=1)=(1.1824^{*}-0.1833x)$

Note : $Koef^{*}$ = Significant at (α:0.05), $x = 1\ for\ Urban; 0\ for\ Rural$

Table 1 shows that FPSM, ANC4, SBA, BCG, DTP3, MSL, and ORS indicators have a significant multilevel effect at α = 0.05. This is indicated by the LR Statistics which is greater than $\chi^2_{(0.05,1)} = 3{,}84$, as shown in Table 1, column "LR Stat". However, the CNM indicator is indicated to have an insignificant multilevel effect. Therefore, the modeling will be carried out using a multilevel model on all indicators except for the CNM indicator. The modeling results are shown in column "Model".

Based on the modeling in column "Model", the coefficient on the place of residence variable is significant at α = 0.05, indicating a significant difference in individual tendency between rural and urban residences. The significant difference is in the FPSM, ANC4, SBA, BCG, DTP3, and MSL indicators; but not in ORS and CNM indicators. However, the place of residence variable will still be used to estimate the ORS and CNM indicators. This is because the use of these variables in the model is used for estimation and aggregation based on urban and rural residences.

The model that has been obtained is then used to estimate the value of each indicator in each province based on the place of residence. Estimation is done by postratification and *Monte Carlo* simulation. The validation of the indirect estimation results based on MRP is shown in Table 2 below.

On aggregation to the national level, it can be seen that MSE and MAD are quite small in each indicator. The highest MSE and MAD values are in the DTP3 indicator, which is still considered quite small. Meanwhile, when aggregating from urban and rural residences to the provincial level, it is seen that the MSE and MAD values are larger.

The DTP3 indicator also still has the largest MSE and MAD. Correlation results between direct estimates and MRP results at the provincial level were also carried out, with the smallest correlation value being the BCG indicator of 0.82. These results show that the MRP estimate of each indicator is still strongly correlated and in accordance with the direct estimate (Schober & Schwarte, 2018).

Table 2. Consistency of SAE Using MRP Methods with Direct Estimate at National and Provincial Aggregation Level

Estimation Level	Validation Criteria	Indicators							
		FPSM	ANC4	SBA	BCG	DTP3	MSL	ORS	CNM
National	MSE	0.01	0.02	0.13	0.03	2.38	0.94	0.11	0.40

Estimation Level	Validation Criteria	Indicators							
		FPSM	ANC4	SBA	BCG	DTP3	MSL	ORS	CNM
	MAD	0.08	0.13	0.37	0.16	1.54	0.97	0.33	0.63
Provincial	MSE	7.06	6.65	6.61	19.43	32.28	24.19		
	MAD	1.96	1.96	1.88	3.36	4.38	4.21		
	Correlation	0.94	0.94	0.96	0.82	0.89	0.88		
	RMSE	2.658	2.579	2.571	4.408	5.682	4.919		

SAE validation was not carried out at the provincial level for ORS and CNM indicators, because both of them still had several provinces with samples fewer than 25 units. Meanwhile, RSE comparison between direct estimate and SAE using MRP is shown in Table 3.

Table 3. RSE Comparison Between SAE Using MRP Methods and Direct Estimate at National Level

RSE For Proportion Estimate	Indicators							
	FPSM	ANC4	SBA	BCG	DTP3	MSL	ORS	CNM
MRP	0.1084	0.1487	0.4011	0.1785	1.9654	1.2430	0.9101	0.8454
Direct	0.4146	0.2980	0.2851	0.6368	1.1441	1.0901	3.3150	2.7064
Absolute Diff.	0.3062	0.1493	0.1160	0.4583	0.8213	0.1529	2.4048	1.8609

According to Table 3, RSE from SAE estimation using MRP method is smaller for FPSM, ANC4, BCG, ORS, and CNM indicators; while RSE from direct estimation is smaller for SBA, DTP3, and MSL indicators. Even then, it should be noted that RSE differences between both estimation methods are still quite small, with the biggest difference value at ORS indicators, which is 2.4048 (Asian Development Bank, 2020). Overall, the MRP results are considered in accordance with the direct estimation results at a higher level of aggregation; including the provincial and national levels.

This is considered to be good, especially on the indicators of BCG, DTP3, MSL, ORS, and CNM, which previously had a sample of fewer than 25 cases in urban or rural residences in each province. Based on these results, the estimated results from SAE using MRP method and MC simulation are considered feasible to use. The MRP estimation results are then used to construct the dimensions of the CCI and measure the CCI itself. To identify the province with the large CCI difference, or namely “disparate” to be precise, a boxplot that describes the absolute difference in CCI between residences can be formed.

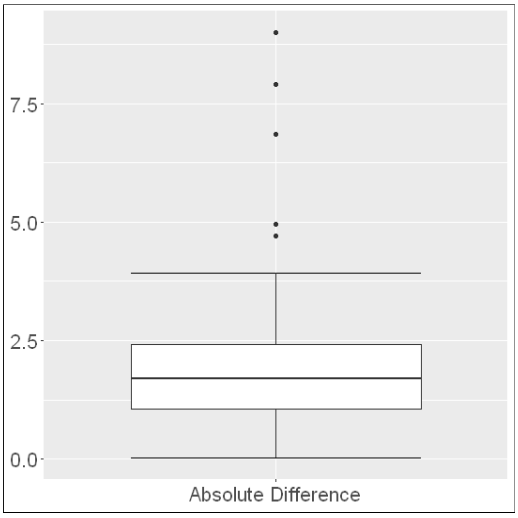

Figure 2. Boxplot of Absolute CCI Differences Between Place of Residence from MRP Estimation

The illustration from the boxplot in Figure 2 shows that there are 5 provinces where the absolute CCI difference between places of residence is classified as outliers. These provinces are North Maluku, Central Kalimantan, Papua, DI Yogyakarta, and West Java. From those five provinces, it should be noted that the Province of DI Yogyakarta is the only province that has a better CCI score in rural than urban residences. Therefore, these 5 provinces are considered as provinces with RMNCH-IC disparities between residences. The breakdown of dimensions differences between residences for those provinces is shown in Table 4.

Table 4. CCI and its dimensions difference between urban-rural residences in 5 provinces with RMNCH-IC disparities

Province	Dimension				CCI
	Reproductive	Maternal	Newborn	Child	
North Maluku	-5.636	26.374	14.420	0.850	9.002
Central Kalimantan	-3.238	3.423	22.368	9.101	7.913
Papua	-2.101	24.439	11.591	-6.546	6.846
DI Yogyakarta	-13.145	-0.398	0.458	-6.754	-4.960
West Java	-1.003	11.944	5.537	2.313	4.697

DISCUSSION

Through CCI and its constituent indicators, the difference in RMNCH-IC between residences in Indonesia can be identified. According to Table 1, based on the coefficient values of variable residence in the model, the individual "success" cases in each ANC4, SBA, BCG, DTP3, and MSL indicator are indicated to have a greater tendency in urban compared to rural residences, which is due to the positive coefficient in the model. Meanwhile, the individual "success" cases on the FPSM, ORS, and CNM indicators are indicated to have a greater tendency in rural compared to urban residences.

This is due to the coefficient on the model being negative. However, the variable place of residence on the ORS and CNM indicators, which has no significant effect, may indicate a not very significant difference in the tendency of "successful" cases between places of residence. These results can be considered in accordance with the direct estimation from the boxplot in Figure 1.

Aggregation to the level of dimensions through the tendency in each indicator indicates a higher value in dimensions of maternal and newborn health in urban compared to rural residences. Based on the model, both are caused by all the positive coefficients of the constituent indicators. Based on the literature, the better dimension of maternal health in urban residences is considered to occur because of limited access to health facilities and the availability of traditional workers to assist deliveries in rural areas, but not so in urban residences (R. D. Wulandari et al., 2021) (Aryastami & Mubasyiroh, 2021).

Meanwhile, the better dimensions of newborn health in urban residences are considered to occur due to a lack of trained health workers, a lack of access to proper transportation, long distances to health facilities, a lack of information related to immunization, and fewer births in health facilities in rural areas, but not so in urban residences (Hardhantyo & Chuang, 2021). On the other hand, the dimensions of reproductive and child health are indicated to have higher values in rural residences. Based on the model, both are due to all the coefficients of the constituent indicators, which are negative, although there are coefficients that have no significant effect on the dimensions of children's health.

Based on previous literature, the better dimensions of reproductive health in rural residences are considered less important in accordance with the literature related to RMNCH-IC at the multinational level (WHO, 2015) (Amouzou et al., 2020). However, these results are in line with the 2017 IDHS report, and several other studies with a research focus on Indonesia (Kementerian Kesehatan RI, 2018) (Syamsul et al., 2020) (Wijayanti, 2021) (Ibad et al., 2021) (Yainahu & Marsisno, 2021). The reason is considered to be that residents of rural areas are more likely to get socialized about family planning through Contact Person messages compared to urban residents (Syamsul et al., 2020).

Meanwhile, the better dimensions of child health in rural residences are also considered less important in accordance with previous research or publications (WHO, 2015). However, the non-significant influence of the variables on the indicators making up this dimension indicates that there are no significant differences between residences in the dimensions of child health in Indonesia. This condition is considered to also happen in Indonesia, just as it does in other countries (Noordam et al., 2015).

The CCI calculation from SAE using the MRP method identified 5 provinces with RMNCH-IC disparities between residences, as shown in Table 4. The biggest differences in the dimension of maternal health in North Maluku, Papua, and West Java are considered to occur due to culture and belief regarding pregnancies, as well as health infrastructure conditions that are worse in rural residences compared to urban residences (Astri & Alhadar, 2018) (Yufuai & Widadgo, 2018) (Alwi, 2007) (Mahwati, 2013). Unfortunately, the reason for the biggest difference between the dimension of reproductive health in DI Yogyakarta and the dimension of newborn health in Central Kalimantan is still not identified precisely.

In DI Yogyakarta, the reason for the biggest difference in modern contraceptive method usage between urban and rural residences is not related to family planning information, family planning access, household income, or even culture and belief in each residence (Chotimah & Utami, 2019) (S. Wulandari, 2016). Finally, the reason for the biggest difference in the dimension of newborn health in Central Kalimantan is still unknown due to limited research regarding the differences in immunization coverage between residences in the provinces. It should also be noted that the reasons for the big dimension differences in each province stated before still need further research because those reasons are still not directly comparing the dimensions of reproductive, maternal, or newborn health between their respective provinces and other provinces in Indonesia.

CONCLUSION

The estimation of RMNCH-IC through CCI indicators shows that there are differences between urban and rural residences and also between geographical regions in Indonesia. Rural residences are indicated to have better reproductive and child health. Meanwhile, urban residences are indicated to have better maternal and newborn health. In addition, there are still five provinces that are considered to have RMNCH-IC disparities between places of residence.

Based on this result, the researcher suggests focusing on improving aspects of reproductive and child health in urban residences as well as aspects of maternal and newborn health in rural residences. In addition, it is also recommended to equalize coverage between urban and rural residences, especially in the five provinces that still have RMNCH-IC disparities between residences. Meanwhile, further research can be carried out by covering more dimensions of inequality or more specific geographical regions, such as certain islands or provinces.

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