MEDIA PENELITIAN DAN
PENGEMBANGAN KESEHATAN
Vol 35 No 3, September 2025

e-ISSN: 2338-3445
p-ISSN: 0853-9987

APPLICATION OF THE COKRIGING METHOD TO ESTIMATE IRON DEFICIENCY PREVALENCE BASED ON FERRITIN AND C-REACTIVE PROTEIN

Penerapan Metode Cokriging untuk Menduga Prevalensi Kekurangan Zat Besi Berdasarkan Ferritin dan Protein C-Reaktif

Siti Mutiah[1], Muhammad Nur Aidi[1], Asep Saefuddin[1], Fitrah Ernawati[2]
[1]Department of Statistics and Data Science, IPB University, Bogor, Indonesia
[2]Research Center for Data and Information Sciences, BRIN, Bogor, Indonesia
*Email: smutiah842@gmail.com

ABSTRAK

Analisis data spasial memiliki peranan penting dalam bidang kesehatan, khususnya ketika distribusi masalah kesehatan tidak merata di seluruh wilayah. Salah satunya adalah metode Cokriging, yang diterapkan untuk memprediksi prevalensi di daerah yang belum teramati, sekaligus mengatasi tantangan ketidaklengkapan data spasial akibat keterbatasan biaya, sumber daya, atau akses ke lokasi tertentu. Penelitian ini bertujuan untuk mengestimasi prevalensi kekurangan zat besi di Indonesia menggunakan metode Cokriging. Sebagai analisis lanjut dari data Riset Kesehatan Dasar (Riskesdas) 2018, penelitian ini menggunakan data dari 15.045 individu yang memiliki informasi kadar ferritin dan C-Reactive Protein (CRP), yang tersebar di 154 kabupaten/kota di empat pulau: Sumatera, Jawa, Kalimantan, dan Sulawesi. Ferritin digunakan sebagai variabel utama, sementara CRP sebagai variabel sekunder. Evaluasi model dilakukan dengan Leave-One-Out-Cross-Validation (LOOCV), dan akurasi model diukur menggunakan Mean Error (ME) dan Root Mean Squared Error (RMSE). Hasil penelitian menunjukkan prevalensi kekurangan zat besi bervariasi signifikan antar wilayah. Kabupaten Batang dan Minahasa Selatan teridentifikasi dalam kategori "tidak ada masalah kesehatan". Selain itu 274 kabupaten/kota di Indonesia berada pada kategori prevalensi ringan, seperti Kabupaten Berau, Gunung Mas, dan Bangkayang, sementara 132 kabupaten/kota tercatat dengan prevalensi sedang seperti Kabupaten Sidenreng Rappang, Tapanuli Tengah, dan Sukoharjo. Kabupaten Pare-pare terdeteksi pada prevalensi tinggi (≥40%), tingginya prevalensi di wilayah ini perlu dicermati lebih lanjut karena kemungkinan disebabkan oleh jumlah sampel yang sangat sedikit. Temuan ini menunjukkan bahwa sebagian besar kabupaten/kota di Indonesia tergolong dalam kategori prevalensi ringan hingga sedang. Gambaran ini dapat menjadi dasar penting dalam merancang kebijakan kesehatan terkait penanggulangan kekurangan zat besi di Indonesia.

Kata kunci*: cokriging, CRP, ferritin, kekurangan zat besi, pendugaan.*

ABSTRACT

Spatial data analysis plays a crucial role in the health sector, particularly when the distribution of health issues is uneven across regions. One of them is the Cokriging method, which is used to predict prevalence in areas that have not been observed while also overcoming the challenges of incomplete spatial data resulting from limited costs, resources, or access to specific locations. This study aimed to estimate the prevalence of iron deficiency in Indonesia using the cokriging method. As a further analysis of the 2018 Basic Health Research (Riskesdas) data, this study used data from 15,045 individuals who had information on ferritin and C-reactive Protein (CRP) levels, spread across 154 districts/cities in four islands: Sumatra, Java, Kalimantan, and Sulawesi. Ferritin was used as the primary variable, while CRP was used as a secondary variable. Model evaluation was carried out using Leave-One-Out-Cross-Validation (LOOCV), and model accuracy was measured using Mean Error (ME) and Root Mean Squared Error

https://doi.org/10.34011/jmp2k.v35i3.3167

e-ISSN: 2338-3445
p-ISSN: 0853-9987

(RMSE). The results showed that the prevalence of iron deficiency varied significantly between regions. Batang and South Minahasa Districts were identified in the "no health problem" category. In addition, 274 districts/cities in Indonesia are categorized as having mild prevalence, such as Berau, Gunung Mas, and Bangkayang Districts. Meanwhile, 132 districts/cities were recorded as having moderate prevalence, including Sidenreng Rappang, Central Tapanuli, and Sukoharjo Districts. Pare-pare Regency was detected to have a high prevalence (≥40%). The high prevalence in this region needs to be further investigated as it may be due to the very small sample size. This finding indicates that most districts and cities in Indonesia are included in the mild to moderate prevalence category. This picture can serve as a crucial basis for designing health policies aimed at addressing iron deficiency in Indonesia.

Keywords: cokriging, CRP, estimation, ferritin, iron deficiency

INTRODUCTION

Iron deficiency is a significant factor causing anemia, especially among adolescent girls. Anemia caused by iron deficiency has a significant impact on health, can interfere with the body's ability to transport oxygen, and impacts the overall quality of life [2]. Some areas have higher prevalence rates due to environmental factors, limited access to health services, and poor nutritional status within the population [3][4]. Health data in Indonesia is often uneven, including prevalence data on iron deficiency. In addition, available data are usually limited to the specific areas, which makes it difficult to formulate policies based on the overall data. The use of spatial analysis methods is needed to estimate prevalence in undetected areas.

One of the spatial methods that can be used is the kriging method. The Kriging interpolation method is commonly used to predict values in unsampled areas by optimizing weights to minimize mean square errors and residuals. This method can also be applied to identify the spatial distribution of the high-risk regions [5][6][7][8]. This method is based on the rate of change between points in space, which can be represented through a variogram [9]. However, in cases where multiple interrelated variables such as ferritin and CRP are involved, incorporating both variables can improve prediction accuracy. Cokriging is a kriging method combining several variables to estimate values in unsampled areas [10].

In this study, the variables used were ferritin as the main variable and CRP as the secondary variable. Ferritin is the body's main iron storage protein and is a reliable marker for diagnosing iron deficiency [1]. More than just a store of iron, ferritin is also known to protect cells from the harmful effects of free iron, in addition to being involved in a variety of functions, including immune regulation [11]. Iron deficiency is indicated when ferritin levels are below 12 µg/L for less than 5 years of age and below 15 µg/L for more than 5 years [12]. Meanwhile, CRP is an acute-phase protein marker of inflammation or infection. CRP is an acute-phase protein that is an early marker of inflammation or infection. Normal CRP levels are generally below 10 mg/L, and levels above this threshold are commonly associated with inflammatory or severe pathological conditions [13][14]. Elevated CRP levels can influence ferritin concentrations, as inflammation induces ferritin synthesis as part of the acute-phase response. This means that high ferritin levels in individuals with elevated CRP may not necessarily indicate adequate iron stores but rather an inflammatory state. Therefore, considering both ferritin and CRP levels together is essential for accurately estimating the prevalence of iron deficiency and avoiding misclassification due to inflammation-related changes in ferritin.

The application of spatial analysis in public health has yielded promising results in identifying and mapping health issues. Research [15] indicates that the ordinary kriging method is the most effective approach for predicting pneumonia cases. Another study [10] demonstrates that the ordinary kriging method is effective in mapping the spatial

https://doi.org/10.34011/jmp2k.v35i3.3167

e-ISSN: 2338-3445
p-ISSN: 0853-9987

distribution of diarrheal diseases and identifying priority areas for intervention based on case estimates in areas lacking direct data. Meanwhile, the cokriging method performed well in estimating the number of positive COVID-19 cases in East Java Province [16]. These studies demonstrate how the kriging method can be utilized to overcome the limitations of health data, such as incomplete or irregular measurements, and to estimate the prevalence of a health problem more accurately.

However, to date, no studies have used the cokriging method to map the prevalence of iron deficiency in Indonesia based on a combination of ferritin and CRP variables at the district or city level. Data on the prevalence of iron deficiency in Indonesia is generally only available at the national or provincial level, while information at the smaller regional level is still minimal. Detailed data at the district or city level is essential for designing more targeted nutritional intervention policies. Therefore, a spatial estimation approach is needed to fill this information gap and support a more detailed mapping of iron deficiency conditions. Additionally, most previous studies have employed only one primary variable in the ordinary kriging method. In contrast, this study combines secondary variables (CRP) through the cokriging method to improve estimation accuracy. This is the main strength and original contribution of this study.

This study aims to estimate the prevalence of iron deficiency in Indonesia using the Cokriging method based on ferritin levels as the primary variable and CRP levels as a secondary variable. The analysis is based on the 2018 Riskesdas dataset, which includes a sample of 15,045 individuals from 154 districts/cities across four major islands in Indonesia (Sumatra, Java, Kalimantan, and Sulawesi). To test its accuracy, cross validation was carried out using LOOCV and model evaluation such as ME and RMSE. This technique is expected to overcome the problem of incomplete data and provide more accurate estimates in areas that have not been observed. The results of this study offer district and city level estimates of iron deficiency prevalence filling the current data gap, as available information in Indonesia is typically limited to national or provincial levels. By generating finer-grained spatial estimates and classifying the severity of iron deficiency across regions, the findings can support more targeted and effective nutrition intervention policies.

METHODS

Research Design

The study was a quantitative approach with descriptive and analytical designs to estimate the prevalence of iron deficiency in Indonesia using the Cokriging method. It was conducted from January to April 2025 using secondary data from the 2018 Riskesdas. The dataset was accessed with permission through the fourth author, who is affiliated with the National Research and Innovation Agency (BRIN) and had authorized access to the Riskesdas 2018 data.

The main variables analyzed were ferritin levels and CRP levels which were secondary variables to support spatial modeling. The dataset consisted of 15,045 individuals from 154 districts/cities in four large islands in Indonesia: Sumatra, Java, Kalimantan, and Sulawesi.

Data analysis was performed using Python and Google Colab. Several Python libraries were used, including pandas, numpy, matplotlib, scikit-learn, pandas, and pyrite, to implement cokriging and validate the model. Model performance was evaluated using LOOCV, with accuracy metrics including ME and RMSE.

Cokriging Method

Cokriging is a geostatistical method used to estimate values at unobserved locations by considering the spatial correlation between the primary (ferritin) and the secondary (CRP) variable. The cokriging process is carried out in several steps, from collecting and processing empirical data. The data used in this study are obtained from the Basic Health

https://doi.org/10.34011/jmp2k.v35i3.3167

e-ISSN: 2338-3445
p-ISSN: 0853-9987

Research (Riskesdas) 2018, which includes information on iron deficiency (Ferritin levels is <12 μg/L for children under 5 years of age or <15 μg/L for those over 5 years of age) and normal CRP (CRP levels < 10 mg/L) from 15,045 individuals taken from 154 districts/cities in Indonesia, distributed across the islands of Sumatra, Java, Kalimantan, and Sulawesi.

In the data processing stage, the proportion of individuals with iron deficiency is calculated based on ferritin levels for each district/city using the sort function to arrange the data and count function to calculate the number of cases. The proportion of individuals with iron deficiency and inflammation is calculated using the following formula:

$$Z(X_i) = \frac{x_i}{n_i} \quad (1)$$

Where $Z(X_i)$ represents the proportion of ferritin or CRP in district/city $-i$, and n is the sample size.

Data analysis using the cokriging method begins with the assumption of stationarity, which means the data does not change at various locations. Then, the correlation between ferritin and CRP will be calculated. Calculate the empirical variogram to describe the spatial relationship between observation points. According to [17], the kriging method is for known sample data pairs and estimated sample data pairs. In the cokriging method, the cross-variogram is also used to model the relationship between ferritin and CRP. After that, cross-validation was carried out with LOOCV with various theoretical variogram models (Spherical, Gaussian, Linear, and Exponential). The best semivariogram model was selected based on ME and RMSE.

Next, the prevalence of iron deficiency was estimated using the kriging method for each island. After obtaining the estimated prevalence of iron deficiency, the results were mapped spatially. This distribution map provides a clearer picture of the distribution of iron deficiency on each island, which can help understand the variation in prevalence between regions and identify areas that need further treatment. Finally, the results of the estimated prevalence of iron deficiency are classified based on WHO categories [1].

Table 1. Population Prevalence Ranges to Define the Magnitude of Iron Deficiency as a Public Health Problem Using Ferritin Concentrations.

Magnitude of the Public Health Problem	Prevalence Range (%)
High	≥40.0
Moderate	20.0–39.9
Mild	5.0–19.9
No Public Health Problem	≤4.9

RESULTS

Data analysis was performed using Excel and Python. Data processing began with individual data from 15,045 respondents, including variables such as area code, age, ferritin levels, and CRP levels. The first stage involves converting numeric data into categorical data. Ferritin levels are categorized as one if the value is <12 μg/L for children under 5 years of age or <15 μg/L for those over 5 years of age. Additionally, it is assigned a value of 0. Likewise, the recommended CRP level is one if <10 mg/L (normal) and zero if ≥10 mg/L (indicating inflammation). After the individual data is broken down, the next step is to aggregate the data to the district or city level based on the area code. Prevalence was calculated as the proportion of individuals with low ferritin and normal CRP levels relative to the total number of respondents in each area.

Descriptive statistics for the prevalence of iron deficiency indicate that the average prevalence of iron deficiency in Indonesia is 18.34%, with a minimum value of 1.33% and a maximum value of 40.00%. Most regions have a prevalence of iron deficiency ranging from 13.3% to 22.44%, with a standard deviation of 0.06, indicating significant variation across regions. By region, Sulawesi had the highest average prevalence (22%),

https://doi.org/10.34011/jmp2k.v35i3.3167

e-ISSN: 2338-3445
p-ISSN: 0853-9987

followed by Kalimantan (20%), Sumatra (19%), and Java (17%). These variations indicate an uneven geographic pattern of iron deficiency.

The correlation between ferritin and CRP variables shows a strong positive relationship throughout Indonesia, with a correlation coefficient of 0.901. Sumatra has the highest correlation of 0.929, followed by Kalimantan 0.924, Sulawesi 0.887, and Java 0.829, indicating a moderate to strong correlation. The results of the Bivariate Moran's I analysis show a value of 0.212 with a p-value of 0.0010, which means that there is a positive and significant spatial relationship between the ferritin and CRP variables. This result aligns with previous studies, which reported that elevated CRP can influence ferritin levels, potentially masking iron deficiency in inflammatory conditions [18] [11]. Stationarity tests showed that all regions were stationary ($p > 0.05$), indicating that there was no significant trend in prevalence changes across geographic locations. The highest p-value was found in Jawa (1.000), and the lowest in Sumatera (0.886), but all values indicated stability in data distribution.

After confirming the stability of the iron deficiency prevalence data through a stationarity test, an empirical variogram calculation was performed to model the spatial relationship between ferritin and CRP using four theoretical models: Spherical, Exponential, Gaussian, and Linear. Based on the evaluation of ME and RMSE through Cross Validation and LOOCV, the results of the study show that on the island of Sumatra, the Spherical model has the best performance with ME and RMSE values of (0.074, 0.093). The Linear model showed the best performance on the islands of Java and Sulawesi with ME and RMSE values of (0.074, 0.0905) and (0.104, 0.074), respectively, while on the island of Sulawesi, the Gaussian model showed the best results with ME of 0.059 and RMSE of 0.079.

The estimation results indicate an imbalance in the prevalence of iron deficiency across different regions. The three districts/cities with the highest prevalence of iron deficiency in Sumatra are Central Tapanuli Regency (33.33%), Batam City (32.4%), and Rokan Hulu (31%). In contrast, the lowest prevalence rates are observed in Aceh Besar (5.89%), Banyuasin (6.25%), and Aceh Jaya (6.51%). In Java Island, sampled data from 88 out of 119 districts/cities showed significant variation in the prevalence of iron deficiency across districts/cities. The three districts/cities with the highest prevalence of iron deficiency were Sukoharjo District (32.73%), Gunung Kidul District (32.14%), and Kuningan District (27.78%). In contrast, the three provinces with the lowest prevalence of iron deficiency were Central Java, with Batang district (1.33%), Wonogiri district (6%), and East Java, with Lumajang district (8.21%). In Kalimantan, 11 out of 56 districts and cities have observation values. Based on the estimation results, there are three districts/cities with the highest prevalence of iron deficiency, namely Banjar Regency (28.00%), Tarakan City (27.73%), and Singkawang City (27.45%). In contrast, the lowest prevalence rates are observed in Sambas (8.82%), Kapuas Hulu (9.52%), and Banjarmasin City (13.73%). In Sulawesi, sampled data were from 16 out of 80 districts/cities, and the estimation results showed significant variation in the prevalence of iron deficiency across provinces. The three provinces with the highest prevalence of iron deficiency were Pare-Pare City (40.00%), Sidenreng Rappang Regency (35.37%), and Tojo Una Una Regency (33.78%). In contrast, the three provinces with the lowest prevalence of iron deficiency were South Minahasa Regency (2.50%), Talaud Islands Regency (5.88%), and Tana Toraja Regency (12.66%).

https://doi.org/10.34011/jmp2k.v35i3.3167

e-ISSN: 2338-3445
p-ISSN: 0853-9987

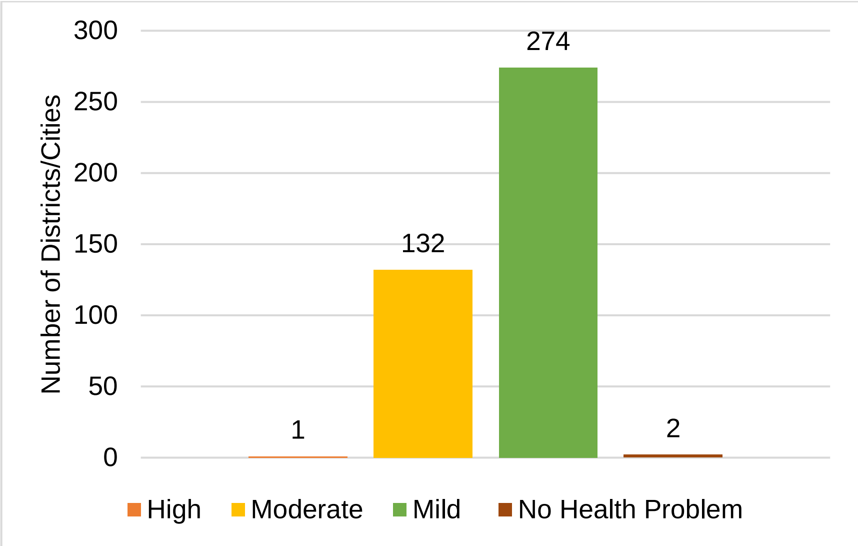

Figure 1. Number of Districts/Cities Based on Iron Deficiency Prevalence Categories

Iron deficiency can cause anemia, as iron is an essential component in the formation of hemoglobin, which transports oxygen in the blood. However, not all cases of anemia are caused by iron deficiency; anemia can also result from chronic diseases, infections, genetic disorders, or other nutritional deficiencies. Based on the prevalence of iron-deficiency anemia determined by ferritin levels <12 μg/L for children under 5 years of age or <15 μg/L for those over 5 years of age, with CRP levels <10 mg/L, it is evident that most regions in Indonesia fall into the mild to moderate category. Figure 1 shows that only the city of Pare-Pare is recorded as falling into the high severity category (40%). However, the high prevalence in this region requires further scrutiny as it may be due to the very small sample size (only 5), resulting in an unusually high prevalence proportion. A total of 132 districts/cities fall into the moderate category, such as Tapanuli Tengah District (33.33%), and 274 districts/cities fall into the mild category (5–19.9%), such as Muara Enim District (19.89%). Only two regions, Batang District (1.33%) and Minahasa Selatan District (2.5%), fall into the non-problematic category (<4.9%).

These results are consistent with previous studies that have shown kriging and cokriging methods to be effective for spatial estimation of health conditions using limited data [16]. While other studies have also applied similar methods to disease mapping [15][10]. This study expands their application to micronutrient-related nutritional problems by combining two key indicator variables. In conclusion, the findings confirm that cokriging-based spatial analysis provides detailed and geographically adaptive estimates of iron deficiency prevalence. These findings lay a strong foundation for further interpretation and discussion, particularly in relation to spatially targeted nutrition policy interventions.

DISCUSSION

Iron deficiency is a primary cause of anemia in adolescents, exacerbated by insufficient intake of nutrients such as vitamin A, vitamin C, folate, riboflavin, and vitamin B12, as well as poor dietary habits like consuming iron with substances that inhibit its absorption. This analysis provides a deeper understanding of iron deficiency distribution in Indonesia based on the 2018 Riskesdas data. These findings are crucial for designing more targeted, region-specific health policies. Indonesia, categorized as a low- to middle-income country, had 10.6% of its population living in poverty in 2017, contributing to malnutrition, including iron deficiency. Children and adolescents from lower socioeconomic backgrounds are at higher risk due to limited access to iron-rich foods.

https://doi.org/10.34011/jmp2k.v35i3.3167

e-ISSN: 2338-3445
p-ISSN: 0853-9987

This situation is further aggravated by chronic blood loss from parasitic infections or malaria, as well as menstrual factors and impaired iron absorption due to gastrointestinal issues [19]. Similar to findings in previous studies, variations in the prevalence of iron deficiency between regions are primarily due to a combination of socioeconomic factors, dietary habits, health and inflammatory status, and limitations in data and healthcare systems [20].

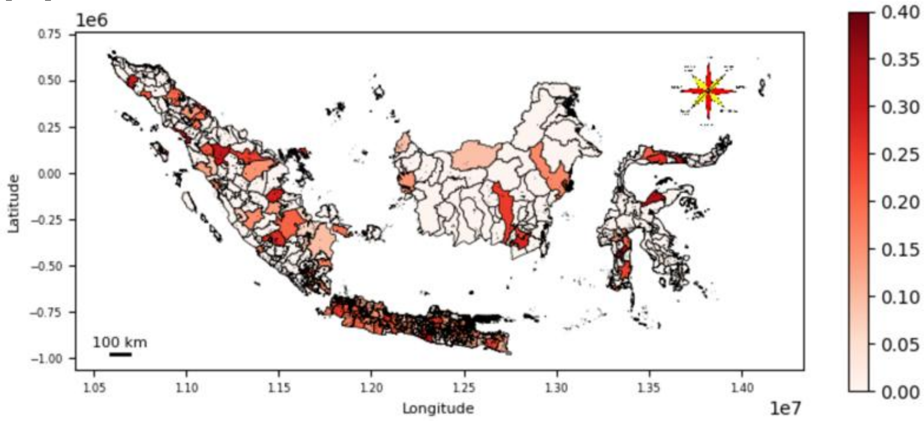

Figure 2. Map of Iron Deficiency Proportion Distribution in Indonesia

Figure 2 shows several areas such as Sulawesi and Sumatra have a higher prevalence of iron deficiency with a darker red color. In contrast, Java and Kalimantan tend to be lower. Previous research shows that Sulawesi is the island with the highest coverage of iron supplementation programs in schools (83.7%) [21]. This is in contrast to the results of the existing mapping. The prevalence of iron deficiency in Sulawesi is not due to the iron supplementation program but rather due to factors of compliance with supplementation hampered by discomfort or lack of awareness of its importance. In addition, the tendency of adolescents to choose fast food also contributes to low iron intake and increases the risk of iron deficiency anemia [22].

The correlation between the proportion of ferritin and CRP showed a strong relationship in each island. In the case of inflammation, ferritin showed an increase that did not reflect the actual iron reserves but from the inflammatory condition that caused iron to be less accessible to the body even though the ferritin levels were high. Therefore, CRP must be considered an iron indicator [13]. The results of the stationary test in this study showed stationary with a consistently high p-value, meaning there was no significant trend change in the prevalence of iron deficiency throughout the region.

The results of the estimation in Sumatra Island showed that there was an imbalance in the prevalence of iron deficiency in various regions. Areas with high prevalence, such as Central Tapanuli and Batam City, are likely to experience greater nutrition and health services challenges. Previous studies have shown a significant prevalence of iron deficiency in Central Tapanuli, especially among pregnant women and toddlers, which is caused by the majority of pregnant women who experience anemia not consuming iron supplements [23]. This can cause the risk of complications such as miscarriage and premature birth. Therefore, pregnant women should consume foods rich in iron and follow the recommendations of health workers to consume iron supplements [24].

The estimation results in Java Island also showed variations in the prevalence of iron deficiency caused by differences in access to health services and socio-economic conditions in each region. The areas with a higher prevalence than other areas in Java Island are Sukoharjo, Gunung Kidul, and Kuningan. Previous studies have revealed that iron deficiency in several areas of Java Island is caused by an unbalanced diet, skipping breakfast, and a history of infectious diseases that disrupt metabolism. In addition, nutritional status and family anemia history also affect iron deficiency [19]. In 2012, the

https://doi.org/10.34011/jmp2k.v35i3.3167

e-ISSN: 2338-3445
p-ISSN: 0853-9987

prevalence of iron deficiency in DI Yogyakarta was recorded at 36% due to a lack of knowledge about iron sources, diet, and intake. This iron deficiency causes decreased productivity and immunity, physical and mental disorders, and increased morbidity and mortality [25].

The estimation results in Kalimantan also show variations between regions which may be influenced by access to health services and other socio-economic factors. Prevalence in most regions is relatively stable due to the nutritional education efforts in Kalimantan, especially in Pontianak, which have encouraged adolescent girls to adopt healthier lifestyles. Nutrition education was provided to inform the importance of iron tablet consumption, while the nutrition diary book aimed to encourage teenage girls to track and monitor their consumption more systematically, which has been shown to improve knowledge and adherence to iron tablet consumption [26].

The prevalence of iron deficiency in Sulawesi requires special attention in regional health policies. South Sulawesi and Gorontalo, which have higher prevalence, require further intervention to improve access to nutrition and healthcare services. In contrast, areas such as North Sulawesi, with lower prevalence, show better stability in the distribution of iron deficiency. South Sulawesi and Central Sulawesi have a wider distribution, indicating higher variability, while North Sulawesi shows a narrower and more stable distribution.

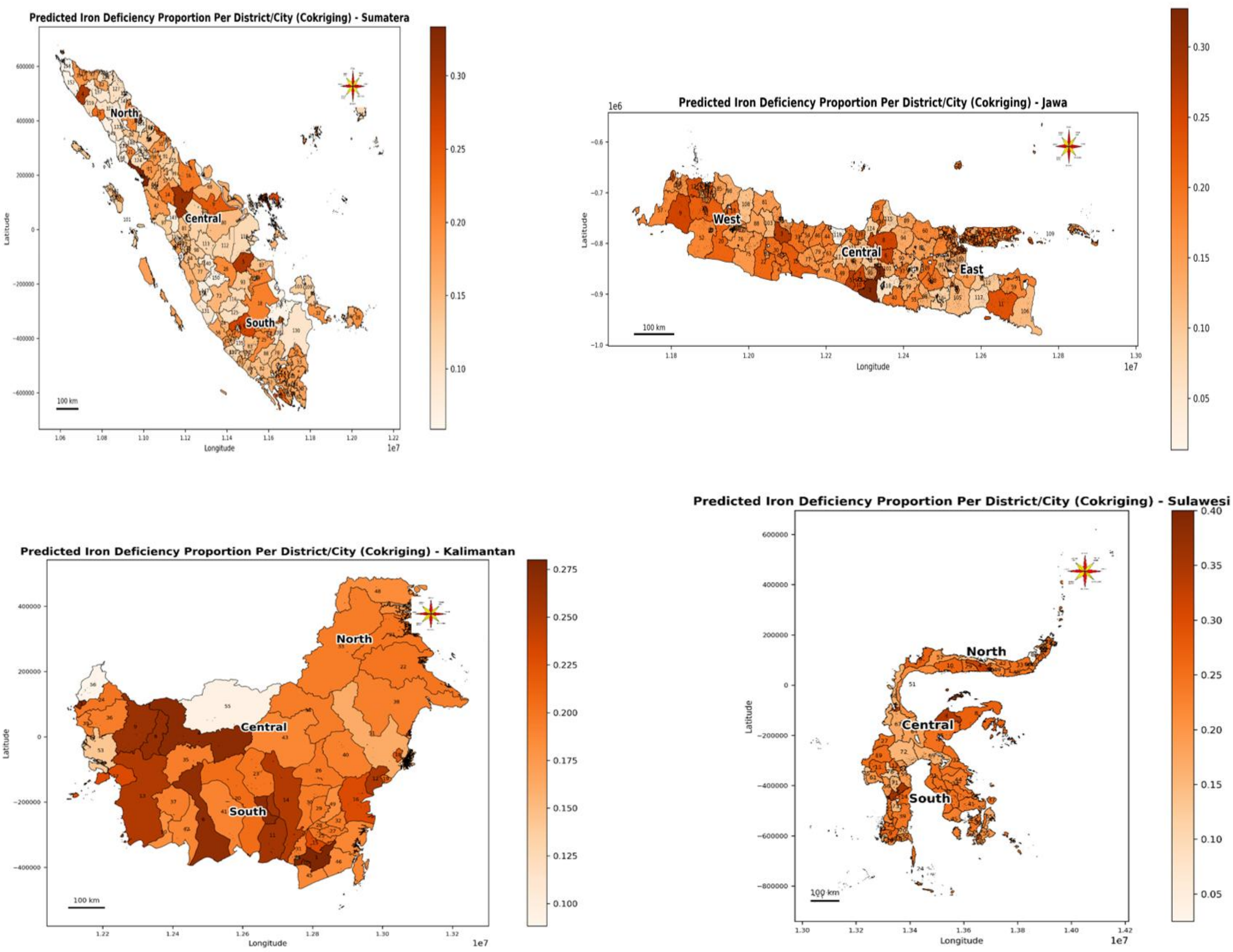

Figure 3. The Map of the proportion of iron deficiency based on Cokriging

These maps in figure 3 illustrate the differences in the prevalence of iron deficiency across Sumatra, Java, Kalimantan, and Sulawesi. Darker colors indicate higher

https://doi.org/10.34011/jmp2k.v35i3.3167

e-ISSN: 2338-3445
p-ISSN: 0853-9987

proportions of iron deficiency, while lighter colors represent lower prevalence. This map helps identify areas with high prevalence that require more attention regarding nutrition and health interventions.

The Indonesian government has actually implemented an iron supplementation program for adolescent girls aged 12-18 years in schools, but the program has not been comprehensive in all schools. Limited knowledge can affect nutritional status and health in everyday life. Although most districts/cities fall into mild and moderate categories, interventions are still needed. Moderate and mild prevalence still indicate problems and require attention in health policies to prevent further health impacts. The cokriging method can estimate the prevalence of iron deficiency, allowing for more targeted and focused health programs for optimal results. Efforts to increase this knowledge can be done through early nutrition education [19].

Strengths of this study include the use of a large, country-representative dataset, and the application of cokriging with a two-variable approach. This improves the accuracy of predicting iron deficiency prevalence based on ferritin and CRP. The use of spatial analysis also allows mapping in unsampled areas, a technique increasingly used in nutritional epidemiology [27].

However, there are several limitations. The study used secondary data, which lacks individual-level information on diet, income, and adherence to supplementation. Mapping is limited to the district/city level and does not capture sub-district nuances. As cross-sectoral data, mapping cannot establish causality. Nonetheless, these findings are valuable for policy. Practically, these results can guide regional prioritization for interventions, particularly in settings where iron deficiency is moderate but neglected. Nutrition education, especially among adolescent girls, should be strengthened through schools and community programs. The model also has potential for early warning systems for micronutrient deficiencies, enhancing public health surveillance.

CONCLUSION

This study reveals a strong correlation between ferritin and CRP levels as indicators of iron deficiency. It demonstrates that the cokriging method can produce detailed estimates of iron deficiency prevalence at the district or city level in Indonesia. By combining these two variables, this approach fills the data gap at the subnational level and provides a new contribution to spatial-based nutrition monitoring. Only the city of Pare-Pare is recorded as falling into the high severity category (40%). However, the high prevalence in this region requires further scrutiny, as it may be due to the very small sample size, resulting in an unusually high prevalence proportion. A total of 132 districts/cities fall into the moderate category, such as Tapanuli Tengah District (33.33%), and 274 districts/cities fall into the mild category (5–19.9%), such as Muara Enim District (19.89%). Only two regions, Batang District (1.33%) and Minahasa Selatan District (2.5%), fall into the non-problematic category (<4.9%).

These findings emphasize the importance of more targeted nutritional interventions in areas with moderate prevalence rates because even though they are not categorized as severe, their impact on public health remains significant. These areas are often overlooked, even though they are at risk of worsening if not addressed early. Nutrition education through schools and increasing compliance with iron supplementation tablets need to be strengthened. Further research is recommended to consider additional factors, such as diet and socioeconomic conditions, to obtain a more comprehensive understanding.

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p-ISSN: 0853-9987

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