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Segmentation of stunting, wasting, and underweight in Southeast Sulawesi using geographically weighted multivariate Poisson regression ☆

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ABSTRACT

The health profile of Southeast Sulawesi Province in 2021 shows that the prevalence of stunting is 11.69 %, wasting 5.89 % and underweight 7.67 %. This relatively high figure should be immediately reduced to zero because it greatly affects the quality of human resources. Cases of stunting, wasting and underweight are an iceberg phenomenon, especially in Southeast Sulawesi. Therefore, it is necessary to research the number of cases of stunting, wasting and underweight in Southeast Sulawesi using GWMPR. The research results show that there is a trivariate correlation between the number of cases of stunting, wasting and underweight. The GWMPR model provides better results in modeling the number of stunting, wasting and underweight cases than the MPR model. The models produced for each sub-district are different from each other based on the predictor variables that have a significant effect and the estimated parameter values for each sub-district. The segmentation of the number of stunting cases consists of 21 regional groups with 10 significant predictor variables, while the number of wasting cases consists of 10 regional groups with 9 significant predictor variables, while the number of underweight cases consists of 37 regional groups with 11 significant predictor variables. Therefore, policies on stunting, wasting, and underweight should be based on local conditions. 3 important components of this study: 1. GWMPR is the development of GWPR model when there are 2 or more response variables that are correlated. 2. GWMPR is a spatial model that considers geography. 3. Application of GWMPR to the analysis of the number of stunting, wasting, and underweight in Southeast Sulawesi province.

☆ **Related research article** Triyanto, Purhadi, B. W. Otok, and S. W. Purnami, “Hypothesis Testing of Geographically Weighted Multivariate Poisson Regression,” Far East J. Math. Sci., vol. 100, pp. 747–762, 2016. http://dx.doi.org/10.17654/MS100050747

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Resource availability:	Stunting, Wasting and Underweight Concepts Southeast Sulawesi

Background

Wasting is condition not enough nutrition, which if left happen sustainable can cause stunting. In other words, stunting is impact period long from wasting. According to [1], conditions child stunting is not sufficient need the food and experience infection repeated can cause wasting or weight no balanced with tall his body. Furthermore [2,3], there are significant relationship between stunting and wasting with underweight. [4,5] reveal that underweight is combined from stunting and wasting.

Based on [6], during many years cases of stunting, wasting and underweight seen as separate conditions in a nutrition program good on level policy and financing, as well as in a number of studies. Problem appears when factors reason in problem nutrition analyzed in a way Partial although in fact third variable each other correlated. [7] who reveals that exists connection significant between stunting, wasting and underweight.

For an example in modeling amount cases of stunting, wasting and underweight with sample units every sub-district which of course really depends on the number possible toddler big different for each sub-district. Different characteristics like distribution geographical based on indicator nutrition between regions will cause quality Health is different for each person the region. With thereby factor decider problem nutrition child varies in a way geographical remember diversity geography and culture found in the region. This matter reinforced by [8] who stated that location geographical own great influence to determinant proper nutrition direct or no direct control availability and accessibility food especially Because patterns and results agriculture. Then notice from distributed data Poisson constructed from aggregation data, it is possible exists spatial data problems namely result data loading measurements something information location. One of the impacts arising from the emergence of spatial heterogeneity is that the regression parameters vary spatially, that is, each observation area has a different influence of independent factors on the dependent variable for each location.

[9,10] revealed lower condition heterogeneity across countries can be inform the emerging global and national health agenda reason failure anthropometry child that is stunting, wasting and nutrition bad. With thereby for overcome problems with spatial data done modeling spatial that is effort repair problem nutrition translated to in regional context or area- based programs later done analysis that takes into account regional context (spatial).

Analytical study regression Poisson good univariate or often multivariate based something assumption homogeneity in size population. As an extension of Poisson regression univariate, study for Poisson regression Multivariate analysis has been carried out by researchers. Starting from the development of the Poisson distribution model bivariate by [11], followed by [12,13] successively developed the structure of the Poisson distribution model trivariate and multivariate . In his article to build a Poisson p-variate distribution model based on $(p + 1)$ varied reduction method, which guarantees the existence of correlation between variables by including the covariance of these variables. To determine parameter estimates [14–16], respectively determined parameter estimates from the Poisson distribution bivariate, and multivariate using the MLE method.

In its application Lots found related problems discrete (count) data analysis with size different populations [17,18]. Use of *count* data with distribution Poisson Lots found in the field health like amount editing case, wasting and underweight. [19] developed a local model for count data called Geographically Weighted Poisson Regression (GWPR). This is based on ideas derived from the GWR model. Geographically Weighted Regression (GWR) is a statistical technique developed by [20], for data analysis that contains heterogeneity spatial. The parameter estimates of the GWR model depend on the location where the data is collected . In this case, the location is expressed as a two-dimensional coordinate vector of geographic space . The advantage of the GWR model is that this model can provide an estimator of the regression parameters for each location and produce better estimates of the response variable. [21] added that parameter estimates for spatial data obtained from local models will have smaller errors, so that local models can provide a more real picture than global models.

GWMPR is development from the GWPR model introduced by [19] when there are two or more variable mutual response correlated. Basic idea from the same GWMPR with the GWPR model, i.e. use approach spatial point with consider factor location geography presented as vector two- dimensional coordinates (latitude and longitude). Several studies on Poisson regression for spatial data as described above are still limited to univariate cases, even though in its application there are many problems in spatial data analysis there are two or more variable response in the form of *count data* each other correlated, so simultaneous analysis is needed . In this regard, by considering the GWPR model, in this study a model was developed for multivariate spatial data with response variable distributed discrete Poisson via *Geographically Weighted Multivariate Poisson Regression (*GWMPR*)* . Parameter estimation and testing hypothesis in study This using MLE and MLRT [22,23]. Research This study and analyze amount cases of stunting *wasting and underweight* in Southeast Sulawesi Province in 2021 using GWMPR.

Method details

Trivariate Poisson distribution test

Testing hypothesis for determine is random variable (Y_1, Y_2, Y_3) has a trivariate Poisson distribution is used with the Crockett's Test [22], with the following test stages:

- Formulation Hypothesis

H_0 : random variable (Y_1, Y_2, Y_3) has a trivariate Poisson distribution
H_1 : random variables (Y_1, Y_2, Y_3) no trivariate Poisson distribution

- Significant Level (α)=0.05
- Test Statistics

$$T = Z' V^{-1} Z \sim \chi^2_{(3)} \tag{1}$$

where,

$$Z' = \begin{bmatrix} Z_{Y_1} & Z_{Y_2} & Z_{Y_3} \end{bmatrix}$$

$$Z_{Y_h} = S^2_{Y_h} - \bar{Y}_h ; h = 1, 2, 3$$

$$V = \frac{2}{n} \begin{bmatrix} \lambda_1^2 & \lambda_0^2 & \lambda_0^2 \\ \lambda_0^2 & \lambda_2^2 & \lambda_0^2 \\ \lambda_0^2 & \lambda_0^2 & \lambda_3^2 \end{bmatrix}$$

- Critical Area

Ho is rejected if $T > \chi^2_{(3;0.05)} = 7.815$

Multicollinearity

The term multicollinearity is an occurrence exists high correlation between variables free in the regression model. According to [24], multicolinierity is ill condition inside analysis regression, which resulted in several impacts, as follows:

1. When it happens multicollinearity perfect, then the estimator coefficient regression No can specified and variant as well as standard the error No infinite.
2. For less multicollinearity perfect, estimator coefficient regression can still be calculated, but mark variance and standard the error big.
3. Probability of error type II become the more large, due to the standard error value of large regression coefficient estimator.
4. Mark the coefficient of multiple determination (R^2) is high, but no there is or a little very coefficient significant regression.
5. Estimator the regression coefficient does not reflect the true value, either under estimate or over estimate.

Multicollinearity in analysis regression can allegedly from its height mark correlation between variable free. Coefficient correlation simple enough high ($0.8 \le r \le 1.0$) can made indicator exists collinearity. Besides that exists multicollinearity is also possible detected through stated Variance Inflation Factor (VIF) value with formula:

$$(VIF)_j = \frac{1}{1 - R_j^2}, j = 1, 2..., k \tag{2}$$

Where R_j^2 is coefficient determination from variable free $\mathbf{x}_j$ which is regressed to variable free other. Multicollinearity can is known if mark $(VIF)_j$ more of 10 [25].

Multivariate Poisson regression **model**

Multivariate Poisson distribution is distribution combined of two or more random variables, each of which has a Poisson distribution and each other correlated. Function joint probabilities from Multivariate Poisson distribution for p random variables can be used $(p + 1)$ variable reduction method. For example, $Z_0, Z_1, Z_2, ..., Z_p$ is mutual random variables independent and each has a Poisson distribution with equal parameters sequentially is $\lambda_0(s), \lambda_1(s), ..., \lambda_p(s)$ where s represents exposure.

Given new random variable $Y_1, Y_2, ..., Y_p$ as following:

$$Y_h = Z_h + Z_0 ; h = 1, 2, ..., p. \tag{3}$$

Function generator moment, mean and variance of random Y_h variable ($h = 1,2,\ldots, p$), respectively are:

$$M_{Y_h}(t) = e^{(\lambda_h(s) + \lambda_0(s))(e^t - 1)}, \tag{4}$$

$$E[Y_h] = Var[Y_h] = \lambda_h(s) + \lambda_0(s). \tag{5}$$

Pay attention to Eq. (3) which shows the dependence of each Y_h on Z_0, so it is a random variable $Y_1, Y_2, ..., Y_p$ jointly distributed Poisson Multivariate with a joint probability function can be determined using the joint probability generating function as follows:

$$G(t_1, t_2, ..., t_p) = E\left[t_1^{Y_1} t_2^{Y_2} ... t_p^{Y_p}\right]$$

$$= E\left[t_1^{Z_1} t_2^{Z_2} ... t_p^{Z_p} (t_1 t_2 ... t_p)^{Z_0}\right].$$

Considering random variables $Z_0, Z_1, Z_2, ..., Z_p$ distribute Poisson which are mutually independent, then

$$G(t_1, t_2, ..., t_p) = \sum_{z_1=0}^{\infty} t_1^{z_1} \frac{e^{-\lambda_1(s)} \lambda_1^{z_1}(s)}{z_1!} ... \sum_{z_p=0}^{\infty} t_p^{z_p} \frac{e^{-\lambda_p(s)} \lambda_p^{z_p}(s)}{z_p!} \sum_{z_0=0}^{\infty} (t_1 t_2 ... t_p)^{z_0} \frac{e^{-\lambda_0(s)} \lambda_0^{z_0}(s)}{z_0!}$$

$$= e^{-(\lambda_0(s)+\lambda_1(s)+...+\lambda_p(s))} \sum_{z_1}^{\infty} ... \sum_{z_p}^{\infty} \sum_{z_0}^{\infty} \frac{\lambda_1^{z_1}(s) ... \lambda_p^{z_p}(s) \lambda_0^{z_0}(s)}{z_1! z_2! ... z_p! z_0!} t_1^{z_1+z_0} t_2^{z_2+z_0} ... t_p^{z_p+z_0}. \tag{6}$$

For example, given transformation $v = z_0$ And $y_h = z_h + v (h = 1, 2, ..., p)$ so equality (4) can be written down as:

$$G(t_1, t_2, ..., t_p) = e^{-(\lambda_0(s)+\lambda_1(s)+...+\lambda_p(s))} \sum_{y_1=v}^{\infty} ... \sum_{y_p=v}^{\infty} \sum_{v=0}^{q} \frac{\lambda_1^{y_1-v}(s) ... \lambda_p^{y_p-v}(s) \lambda_0^{v}(s)}{(y_1-v)!(y_2-v)!...(y_p-v)!v!} t_1^{y_1} t_2^{y_2} ... t_p^{y_p}$$

$$= e^{-\sum_{h=0}^{p} \lambda_h(s)} \sum_{y_1=v}^{\infty} ... \sum_{y_p=v}^{\infty} \sum_{v=0}^{q} \frac{\lambda_0^{v}(s)}{v!} \prod_{h=1}^{p} \frac{\lambda_h^{y_h-v}(s)}{(y_h-v)!} t_h^{y_h}. \tag{7}$$

Based on function generator probability in the Eq. (7), then we get function probability together from Multivariate $Y_1 = y_1, Y_2 = y_2, ..., Y_p = y_p$ Poisson distribution as follows :

$$f(y_1, y_2, ..., y_p | \lambda_0(s), \lambda_1(s), ..., \lambda_p(s)) = \begin{cases} e^{-\sum_{h=0}^{p} \lambda_h(s)} \sum_{v=0}^{q} \frac{\lambda_0^{v}(s)}{v!} \prod_{h=1}^{p} \frac{\lambda_h^{y_h-v}(s)}{(y_h-v)!} ; y_h = 0, 1, 2, ... \\ 0; \text{others}, \end{cases} \tag{8}$$

Where, $q = \min(y_1, y_2, ..., y_p)$ and $\lambda_h(s) \geq 0$.

For example Y_h, and Y_g $(h, g = 1, 2, ..., p; h \neq g)$ are random variable has a Poisson distribution with r means respectively $(\lambda_h(s) + \lambda_0(s))$ and $(\lambda_g(s) + \lambda_0(s))$, then the covariance of Y_h And Y_g is :

$$\begin{aligned} \text{cov}[Y_h, Y_g] &= \text{cov}[Z_h + Z_0, Z_g + Z_0] \\ &= E[(Z_h + Z_0)(Z_g + Z_0)] - E[Z_h + Z_0] E[Z_g + Z_0] \\ &= E[Z_0^2] - (E[Z_0])^2 \\ &= \lambda_0(s). \end{aligned} \tag{9}$$

Multivariate Poisson regression is development from Univariate Poisson regression when there are two or more variable response in the form of count data each other correlated. Furthermore For build an MPR model, if given random $Y_{hi} \sim P(\lambda_h(s_i) + \lambda_0(s_i))$ sample; $i = 1, 2, ..., n$ and $h = 1, 2, ..., p$ with $E[Y_{hi}] = \lambda_h(s_i) + \lambda_0(s_i)$ Where s_i is defined exposure as size population in the ith unit, then *the* MPR model can written down as mark expectation from Y_{hi} which is proportional to size population s_i depends on variables independen $\mathbf{x}_i$.

If covariance is constant, namely: $\lambda_0(s_i) = \lambda_0$, then the MPR model is:

$$E[Y_{hi}] = s_i e^{\mathbf{x}_i^T \beta_h}; i = 1, 2, ..., n; h = 1, 2, ..., p, \tag{10}$$

or can be written down

$$\lambda_h(s_i) = s_i e^{\mathbf{x}_i^T \beta_h} - \lambda_0. \tag{11}$$

Temporary that, if covariance is function variable independen, namely: $\lambda_0(s_i) = s_i e^{\mathbf{x}_i^T \beta_0}$, then the MPR model is:

$$E[Y_{hi}] = s_i \left(e^{\mathbf{x}_i^T \beta_h} + e^{\mathbf{x}_i^T \beta_0}\right); i = 1, 2, ..., n; h = 1, 2, ..., p. \tag{12}$$

Therefore $E[Y_{hi}] = \lambda_h(s_i) + \lambda_0(s_i)$, then the MPR model in Eq. (12) can written:

$$\lambda_0(s_i) = s_i e^{\mathbf{x}_i^T \beta_0}; i = 1, 2, ..., n, \tag{13}$$

$$\lambda_h(s_i) = s_i e^{\mathbf{x}_i^T \beta_h}; i = 1, 2, ..., n; h = 1, 2, ..., p, \tag{14}$$

Where

$$\mathbf{x}_i = \left[1 x_{1i} x_{2i} \dots x_{ki}\right]^T,$$

$$\boldsymbol{\beta}_0 = \left[\beta_{00}\beta_{01}\beta_{02} \dots \beta_{0k}\right]^T,$$

$$\boldsymbol{\beta}_h = \left[\beta_{h0}\beta_{h1}\beta_{h2} \dots \beta_{hk}\right]^T.$$

Testing MPR model hypothesis is carried out Good for parameter testing simultaneously as well as parameter testing Partial. Parameter testing simultaneously used for determine in a way simultaneous significance from coefficient regression in the model, while testing in a way Partial used for knowing which parameters give influence significant to the model. For determine test statistics are performed with use method Likelihood Ratio Test (LRT).

Basic idea LRT method for determine mark the test statistic is compare mark maximum from likelihood function on parameter space on H_0 (for parameter values in simple models without involve variable free) against parameter space on the population (for parameter values in the models involved all variable free).

Testing simultaneously MPR model with covariance is constants are formulated as following:

$$\begin{aligned} &H_0 : \beta_{h1} = \beta_{h2} = \dots = \beta_{hk} = 0; h = 1, 2, \dots p, \\ &H_1 : \text{there is at least one} \beta_{hl} \neq 0; h = 1, 2, \dots p;\ l = 1, 2, \dots k. \end{aligned} \tag{15}$$

Critical area of LRT test with level significance $\alpha \in (0, 1)$ for MPR models with covariance is constants formulated in Eq. (15), defined as following:

$$\Lambda_1 = \frac{\text{maks} L(\omega_1)}{\text{maks} L(\Omega_1)} < k_\alpha, \tag{16}$$

Where k_α is something constant value depending on α with $0 \le k_\alpha \le 1$.

Based on equality (16), the test statistic G_1 which is function from random variable, can written:

$$G_1 = -2 \ln \Lambda_1. \tag{17}$$

Simultaneous test critical area obtained with notice equality (17), as following:

$$\begin{aligned} \alpha &= P(\Lambda_1 < k_\alpha; \omega_1) \\ &= P(-2 \ln \Lambda_1 > -2 \ln k_\alpha; \omega_1) \\ &= P(G_1 > c_1; \omega_1), \text{with} c_1 = -2 \ln k_\alpha \\ &= P(G_1 > \chi^2_{pk,\alpha}; \omega_1). \end{aligned} \tag{18}$$

Based on equality (18), area critical simultaneous test of the MPR model with covariance is constant is:

$$H_0 \text{isrejectedif} G_1 > \chi^2_{pk,\alpha}. \tag{19}$$

Testing partial MPR model with covariance is constant used for test whether each parameter $\beta_{hl}(h = 1, 2, \dots, p; l = 1, 2, \dots, k)$ has an effect on the model. Formulation testing partial, for example for value $h = m$ can be written:

$$\begin{aligned} &H_0 : \beta_{ml} = 0, \\ &H_1 : \beta_{ml} \neq 0. \end{aligned} \tag{20}$$

test statistics for hypothesis on the Eq. (20) can written down as:

$$G_{11} = \frac{\hat{\beta}^2_{ml}}{\widehat{\text{var}}[\hat{\beta}_{ml}]} \sim \chi^2_1 \tag{21}$$

or can also use root square from equality (21), so obtained test statistics:

$$Z_1 = \frac{\hat{\beta}_{ml}}{\sqrt{\widehat{\text{var}}[\hat{\beta}_{ml}]}} \sim N(0, 1) \tag{22}$$

Where $\widehat{\text{var}}[\hat{\beta}_{ml}]$ obtained from diagonal elements to $[(k + 1)(m - 1) + (l + 2)]$ from the matrix $[\mathbf{I}(\theta_1)]^{-1}$.

Geographically weighted multivariate Poisson regression model

In the GWMPR model, variables response $Y_{1i}, Y_{2i}, \dots, Y_{pi}$ predicted by variable independent $\mathbf{x}_i$ of each coefficient the regression depending on location where is the data observed. To build the GWMPR model, if a random sample is given $Y_{hi} \sim P(\lambda_h(s_i, \mathbf{u}_i) + \lambda_0(s_i, \mathbf{u}_i))$; $i = 1, 2, \dots, n$ and $h = 1, 2, \dots, p$, with $E[Y_{hi}] = \lambda_h(s_i, \mathbf{u}_i) + \lambda_0(s_i, \mathbf{u}_i)$, s_i is the *exposure* which is defined as the population size of the *i*th location, *and* is $\mathbf{u}_i = (\ u_{1i} \quad u_{2i})$ a two-dimensional coordinate vector (latitude and longitude) at the i -location, then the

GWMPR model can written right as mark expectation from Y_{hi} which is proportional to size population s_i depends on variables free $\mathbf{x}_i$ and location $\mathbf{u}_i$.

If covariance is constant, ie $\lambda_0(s_i,\mathbf{u}_i) = \lambda_0(\mathbf{u}_i)$, then the GWMPR model is:

$$E[Y_{hi}] = s_i e^{\mathbf{x}_i^T \beta_h(\mathbf{u}_i)};i = 1,2,....,n;h = 1,2,....,p, \tag{23}$$

or can written:

$$\lambda_h(s_i,\mathbf{u}_i) = s_i e^{\mathbf{x}_i^T \beta_h(\mathbf{u}_i)} - \lambda_0(\mathbf{u}_i). \tag{24}$$

Temporary that, if covariance is function variable free, that is $\lambda_0(s_i,\mathbf{u}_i) = s_i e^{\mathbf{x}_i^T \beta_0(\mathbf{u}_i)}$, then the GWMPR model:

$$E[Y_{hi}] = s_i(e^{\mathbf{x}_i^T \beta_h(\mathbf{u}_i)}+e^{\mathbf{x}_i^T \beta_0(\mathbf{u}_i)});i = 1,2,....,n;h = 1,2,....,p. \tag{25}$$

Therefore $E[Y_{hi}] = \lambda_h(s_i,\mathbf{u}_i) + \lambda_0(s_i,\mathbf{u}_i)$, then the GWMPR model in Eq. (25) can written:

$$\lambda_0(s_i,\mathbf{u}_i) = s_i e^{\mathbf{x}_i^T \beta_0(\mathbf{u}_i)};i = 1,2,...,n, \tag{26}$$

$$\lambda_h(s_i,\mathbf{u}_i) = s_i e^{\mathbf{x}_i^T \beta_h(\mathbf{u}_i)};i = 1,2,...,n;h = 1,2,...,p, \tag{27}$$

Where

$$\mathbf{x}_i = \begin{bmatrix}1 & x_{1i} & x_{2i} & ...x_{ki}\end{bmatrix}^T,$$

$$\beta_0(\mathbf{u}_i) = \begin{bmatrix}\beta_{00}(\mathbf{u}_i) & \beta_{01}(\mathbf{u}_i) & \beta_{02}(\mathbf{u}_i) & ... & \beta_{0k}(\mathbf{u}_i)\end{bmatrix}^T,$$

$$\beta_h(\mathbf{u}_i) = \begin{bmatrix}\beta_{h0}(\mathbf{u}_i) & \beta_{h1}(\mathbf{u}_i) & \beta_{h2}(\mathbf{u}_i) & ...\beta_{hk}(\mathbf{u}_i)\end{bmatrix}^T.$$

In section This will discussed about determination test statistics along with its distribution to test the similarity of the GWMPR and MPR models, test the parameters individually simultaneously, and test parameters simultaneously Partial from the GWMPR model with covariance is constant.

Testing This is used to find out whether there are differences between the GWMPR and MPR models, which formulated as follows:

$$\begin{aligned}&H_0 : \beta_{hl}\left(\mathbf{u}_i\right) = \beta_{hl};h = 1,2,...,p;l = 1,2,...,k;i = 1,2,...,n\\&H_1 : \text{there is at least one}\beta_{hl}\left(\mathbf{u}_i\right) \neq \beta_{hl}\end{aligned} \tag{28}$$

Test formula hypothesis on the Eq. (28) is a *non-nested* model, so in study This used test statistics from *Voung's test* as following:

$$G_{13} = \frac{\sqrt{n}\left(\frac{1}{n}\sum_{i=1}^{n} m_i\right)}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(m_i - \bar{m})^2}} \tag{29}$$

Where

$$m_i = (p-1)(\hat{\lambda}_0 - \hat{\lambda}_0(\mathbf{u}_i)) - \sum_{h=1}^{p} s_i(e^{\mathbf{x}_i^T\hat{\boldsymbol{\beta}}_h} - e^{\mathbf{x}_i^T\hat{\boldsymbol{\beta}}_h(\mathbf{u}_i)}) + (\ln \hat{A}_i - \ln \hat{C}_i).$$

$$\hat{A}_i = \sum_{v=0}^{q}\left(\frac{\hat{\lambda}_0^v}{v!}\prod_{h=1}^{p}\frac{(s_i e^{\mathbf{x}_i^T\hat{\boldsymbol{\beta}}_h} - \hat{\lambda}_0)^{y_{hi}-v}}{(y_{hi}-v)!}\right)$$

$$\hat{C}_i = \sum_{v=0}^{q}\left(\frac{\hat{\lambda}_0^v(\mathbf{u}_i)}{v!}\prod_{h=1}^{p}\frac{(s_j e^{\mathbf{x}_j^T\hat{\boldsymbol{\beta}}_h(\mathbf{u}_i)} - \hat{\lambda}_0(\mathbf{u}_i))^{y_{hj}-v}}{(y_{hj}-v)!}\right)$$

$\hat{\lambda}_0$ and $\hat{\beta}_h$ is an estimator for λ_0 and β_h, $\hat{\lambda}_0(\mathbf{u}_i)$ and $\hat{\beta}_h(\mathbf{u}_i)$ is an estimator for the parameters $\lambda_0(\mathbf{u}_i)$ and $\boldsymbol{\beta}_h(\mathbf{u}_i)$ obtained from algorithm *Newton-Raphson*.

Based on central limit theorem, statistics test the similarity of the GWMPR and MPR models in the Eq. (29) distribute asymptotically N(0,1), so area critical with level significant α from testing This is H_0 will rejected If mark $|G_{13}| > Z_{\alpha/2}$.

Testing simultaneously used for determine in a way simultaneous significance from coefficient regression in the GWMPR model, which is formulated as following:

$$\begin{aligned}&H_0 : \beta_{h1}(\mathbf{u}_i) = \beta_{h2}(\mathbf{u}_i) = ... = \beta_{hk}(\mathbf{u}_i) = 0;h = 1,2,....p;i = 1,2,...,n\\&H_1 : \text{there is at least one}\beta_{hl}(\mathbf{u}_i) \neq 0;l = 1,2,....k\end{aligned} \tag{30}$$

- The LR test statistics are obtained as follows:

$$G_3 = -2\ln\frac{L(\hat{\boldsymbol{\theta}}_{302})}{L(\hat{\boldsymbol{\theta}}_3)} = 2[\ln L(\hat{\boldsymbol{\theta}}_3) - \ln L(\hat{\boldsymbol{\theta}}_{302})] \tag{31}$$

The test statistics in Eq. (30) can be written [24]:

$$\begin{aligned} G_3 &= 2\left(\left[(p-1)\sum_{i=1}^{n}\hat{\lambda}_0(\mathbf{u}_i) - \sum_{i=1}^{n}\sum_{h=1}^{p} s_i e^{\mathbf{x}_i^T\hat{\boldsymbol{\beta}}_h(\mathbf{u}_i)} + \sum_{i=1}^{n}\ln\hat{C}_i\right] - \right.\\ &\left.\left[(p-1)\sum_{i=1}^{n}\hat{\lambda}_{00}(\mathbf{u}_i) - \sum_{i=1}^{n}\sum_{h=1}^{p} s_i e^{\hat{\beta}_{h00}}(\mathbf{u}_i) + \sum_{i=1}^{n}\ln\hat{C}_{i0}\right]\right)\\ &= 2\left((p-1)\sum_{i=1}^{n}(\hat{\lambda}_0(\mathbf{u}_i) - \hat{\lambda}_{00}(\mathbf{u}_i)) - \sum_{i=1}^{n}\sum_{h=1}^{p} s_i(e^{\mathbf{x}_i^T\hat{\boldsymbol{\beta}}_h(\mathbf{u}_i)} - e^{\hat{\beta}_{h00}(\mathbf{u}_i)}) + \sum_{i=1}^{n}(\ln\hat{C}_i - \ln\hat{C}_{i0})\right) \end{aligned} \tag{32}$$

Critical area *of likelihood ratio* test with level significance $\alpha \in (0,1)$ for the GWMPR model with covariance is constants formulated in Eq. (32), defined as following:

$$\Lambda_3 = \frac{\text{maks}\, L(\omega_3)}{\text{maks}\, L(\Omega_3)} < k_\alpha \tag{33}$$

Where k_α is something constant value depending on α with $0 \le k_\alpha \le 1$.

Based on equality (33), the test statistic G_3 which is function from random variable, can be written:

$$G_3 = -2\ln\Lambda_3. \tag{34}$$

Testing partial on the GWMPR model with covariance is constant used for test whether the parameters $\beta_{hl}(\mathbf{u}_i)(h = 1,2,\ldots,p; l = 1,2,\ldots,k; i = 1,2,\ldots,n)$ have an effect on the model.

Formulation testing partial, for example the values $h = m$ and $i = j$ can be written:

$$\begin{aligned} H_0 &: \beta_{ml}(\mathbf{u}_j) = 0\\ H_1 &: \beta_{ml}(\mathbf{u}_j) \neq 0 \end{aligned} \tag{35}$$

test statistics for hypothesis on the Eq. (35) can written down as:

$$G_{33} = \frac{\hat{\beta}_{ml}^2(\mathbf{u}_j)}{\widehat{\text{var}}[\hat{\beta}_{ml}(\mathbf{u}_j)]} \sim \chi_1^2 \tag{36}$$

or can also use root square from equality (36), so obtained test statistics:

$$Z_3 = \frac{\hat{\beta}_{ml}(\mathbf{u}_j)}{\sqrt{\widehat{\text{var}}[\hat{\beta}_{ml}(\mathbf{u}_j)]}} \sim N(0,1) \tag{37}$$

Where $\widehat{\text{var}}(\hat{\beta}_{ml}(\mathbf{u}_j))$ obtained from diagonal elements to $[(k+1)(m-1)+(l+2)]$ from the matrix $[\mathbf{I}(\hat{\boldsymbol{\theta}}_3(\mathbf{u}_j))]^{-1}$.

The critical area of the partial test with the level of significance $\alpha \in (0,1)$ for the GWMPR model with covariance is a constant formulated in Eq. (35), which can be written as follows:

$$\begin{aligned} \alpha &= P(G_{33} > c; \omega_3)\\ &= P(Z_3 < -\sqrt{c} \vee Z_3 > \sqrt{c}; \omega_3)\\ &= P(Z_3 < -Z_{\alpha/2} \vee Z_3 > Z_{\alpha/2}; \omega_3)\\ &= P(|Z_3| > Z_{\alpha/2}; \omega_3) \end{aligned} \tag{38}$$

Based on equality (38), then area critical can written down as:

$$H_0 \text{ is rejected if } |Z_3| > Z_{\alpha/2} \tag{39}$$

Method validation

Data source

Data used is secondary data from data collected by the Southeast Sulawesi Provincial Health Service in 2021 carried out by officer data manager Health Service Data obtained with submit permission to Head of the Southeast Sulawesi Provincial Health Service [26]. Data collection is based on the data presented in district / city level aggregate. Furthermore, Focus Group Discussion (FGD) confirms and validates research data together Southeast Sulawesi Provincial Health Service. The sample in this study is data on cases of stunting, wasting and underweight at the Southeast Sulawesi Provincial Health Service in 2021 with an analysis unit of 222 sub-districts.

Table 1
Statistics descriptive variable study.

Variable	Mean	Standard Deviation	Minimum	Maximum
Stunting (Y1)	87.252	95.760	0.00	620.00
Wasting (Y2)	24.446	27.199	0.00	146.00
Underweight (Y3)	57.969	62.619	0.00	376.00
Percentage toddler type sex male (X1).	52.512	10.604	12.40	98.60
Percentage toddler aged 12–59 months (X2).	69.463	16.481	19.60	98.60
Percentage LBW baby (X3).	3.527	3.345	0.00	23.10
Percentage of anemic pregnant women (X4)	43.678	37.396	0.00	101.40
Percentage baby 6 months old receive exclusive breast milk (X5).	51.996	11.262	0.00	98.60
Percentage toddler with Immunization base complete (X6)	85.823	30.482	0.00	201.70
Percentage toddler get vitamin A (X7).	74.129	25.191	0.00	168.10
Percentage Mother postpartum get vitamin A (X8).	86.511	18.893	17.90	157.10
Percentage Integrated Healthcare Center active (X9).	58.556	40.045	0.00	100.00
Percentage visit Mother pregnant K4 (X10)	75.375	20.098	23.70	145.00
Percentage toddler suffering from Pneumonia (X11).	6.262	14.529	0.00	107.00
Percentage toddler suffer diarrhea (X12).	17.785	18.160	0.00	161.30

Variable study

The research variables used in this study consist of three discrete type response variables, namely Stunting (Y1), Wasting (Y2) and Underweight (Y3) for each sub-district in Southeast Sulawesi Province in 2021. The continuous type predictor variable consists of 12 variables, namely the percentage of toddlers who are male- male (X1), Percentage of toddlers aged 12–59 months (X2), Percentage of LBW babies (X3), Percentage of anemic pregnant women (X4), Percentage of babies aged 6 months receiving exclusive breast milk (X5), Percentage of toddlers with complete basic immunization (X6), the percentage of toddlers received vitamin A (X7), the percentage of puerperal mothers received vitamin A (X8), the percentage of active "*posyandu*" (X9), the percentage of visits of pregnant women K4 (X10), the percentage of toddlers suffering from pneumonia (X11), the percentage of toddlers suffering from diarrhea (X12) [26,27].

Data analysis method

Analyze the data to create the "best" regression model from potential factors influence amount cases of stunting, wasting and underweight in Southeast Sulawesi Province using MPR and GWMPR is carried out in the following stages:

a. Calculate the minimum, maximum, average and standard deviation values of the research variables.
b. Calculate the correlation value between response variables and between independent variables.
c. Testing the significance of correlation between response variables .
d. Testing multicollinearity of the independent variables.
e. Determine the MPR model with the following stages:
    1. Calculating MPR model parameter estimates using the maximum likelihood method .
    2. Carry out simultaneous testing of regression parameters.
    3. Carry out partial testing of each regression parameter.
    4. Determining the "best" MPR model based on the smallest AIC value.
    5. Presents interpretation of analysis results.
f. Testing spatial heterogeneity.
g. Determine the GWMPR model with the following stages:
    1. Calculating GWMPR model parameter *estimates* with kernel function weighting *Gaussian* and *bandwidth* optimum is obtained using the *golden section search method based on generalized* values *cross smallest validation*.
    2. Do testing for similarity of the "best" MPR model and GWMPR model.
    3. Carry out simultaneous testing of regression parameters.
    4. Carry out partial testing of each regression parameter for each location.
    5. Presents interpretation of analysis results.
h. Comparing the goodness of the MPR and GWMPR models, where both covariance is a constant and a function of the independent variable, taking into account the AIC and MSE values.

Application model

Descriptive analysis of the number of stunting, wasting and underweight cases as well as predictor variables are presented in the following table.

Table 1 shows that the average number of stunting cases (Y1) is 87.25, with the lowest number of sufferers being 0 and the highest being 620 sufferers. Furthermore, the average number of wasting cases (Y2) was 24.44, with the lowest number of sufferers being 0

Table 2
Statistical values of the trivariate poisson distribution test variable response.

Regency/City	T	Regency/City	T	Regency/City	T
Bau	1.132	Kendari	0.293	North Konawe	6.572
Bombana	1.411	East Kolaka	2.924	Konawe	1.379
South Buton	0.377	North Kolaka	1.281	West Muna	0.462
Central Buton	3.222	Kolaka	4.007	Muna	1.055
North Buton	6.470	Konawe Islands	2.616	Wakatobi	3.825
Buton	2.468	South Konawe	0.232		

Table 3
Correlation values between variables response.

Variable Response	Y1	Y2	Y3
Y1	1	0.640 (0.000)	0.751 (0.000)
Y2	0.640 (0.000)	1	0.662 (0.000)
Y3	0.751 (0.000)	0.662 (0.000)	1

and the maximum number being 146 sufferers. Meanwhile, for underweight (Y3) the average number of cases was 57.96, with the lowest number of sufferers being 0 and the maximum number being 376 sufferers. Thus, it can be said that the number of toddlers experiencing stunting is greater than the number of wasting and underweight children. The percentage of male toddlers (X1) in each sub-district is at least 12.24 % and at most 98.6 %. The percentage of toddlers aged 12–59 months (X2) in each sub-district is at least 19.6 % and at most 98.6 %. The percentage of LBW babies (X3) in each sub-district is at least 0 % and at most 23.1 %. The percentage of anemic pregnant women (X4) in each sub-district is at least 0 % and at most 101.4 %. The percentage of babies aged 6 months who receive exclusive breastfeeding (X5) in each sub-district is at least 0 % and at most 98.6 %. The percentage of children under five with complete basic immunization (X6) in each sub-district is at least 0 % and at most 201.7 %. The percentage of children under five who receive vitamin A (X7) in each sub-district is at least 0 % and at most 168.1 %. The percentage of postpartum mothers receiving vitamin A (X8) in each sub-district is at least 17.9 % and at most 157.1 %. The percentage of active "Posyandu" (X9) in each sub-district is at least 0 % and at most 100 %. The percentage of visits by pregnant women K4 (X10) in each sub-district is at least 23.7 % and at most 145 %. The percentage of children under five suffering from pneumonia (X11) in each sub-district is at least 0 % and at most is 166.7 %. The percentage of children under five suffering from diarrhea (X12) in each sub-district is at least 0 % and at most is 161.3 %. Based on the results of descriptive analysis, it is known that there is a maximum value that exceeds 100 %, then the distribution of the number of stunting and wasting cases varies from a minimum value of 0 to a maximum value. This shows that there are several areas that do not have the number of cases. However, data 0 on the number of stunting and wasting cases only reached 5.4 % for stunting, and 12.2 % for wasting and a total of 22.5 %. This percentage does not exceed 30 %, so it is still considered sufficient for further data processing and analysis.

Trivariate Poisson distribution test from variable response

Testing trivariate Poisson distribution variable response aims for know is third variable response distribute Poisson trivariate using Crockett's test. Testing trivariate Poisson distribution variable response shared into 17 groups based on residency area that is Bau-Bau, Bombana, South Buton, Central Buton, North Buton, Buton, Kendari, East Kolaka, North Kolaka, Kolaka, Konawe Islands, South Konawe, North Konawe, Konawe, West Muna, Muna and Wakatobi. The calculation results testing trivariate Poisson distribution variable response presented in Table 2.

Table 2 shows that all Regency/City areas have a test statistic value (T) that is smaller than 7.815 so that H0 fails to be rejected. This means that the random variables (Y1, Y2, Y3) for each Regency/City area have a trivariate Poisson distribution.

Correlation test between response variables

The correlation test between response variables is used to determine whether there is a significant correlation between response variables so that the data is suitable for multivariate analysis. The correlation values between response variables are as follows (Table 3):

According to [28] and Table 3, to test whether there is a correlation between response variables, the Sphericity test is carried out as follows:

a. Formulation Hypothesis

$$H_0 : \boldsymbol{\Sigma} = \sigma^2 \mathrm{I}$$
$$\mathrm{H}_1 : \boldsymbol{\Sigma} \neq \sigma^2 \mathrm{I}$$

Table 4
Correlation Values between variable predictor.

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
X1	1.00	−0.02	−0.04	0.01	−0.01	0.12	0.14	−0.07	0.06	−0.17	0.05	0.15
X2	−0.02	1.00	−0.04	0.01	0.01	0.17	0.42	0.25	0.18	0.09	0.12	0.13
X3	−0.04	−0.04	1.00	0.00	−0.09	0.09	−0.10	0.00	0.00	0.05	0.03	0.18
X4	0.01	0.01	0.00	1.00	−0.30	0.07	−0.17	−0.03	0.04	−0.03	−0.06	−0.15
X5	−0.01	0.01	−0.09	−0.30	1.00	−0.10	0.27	0.02	0.05	0.18	0.10	0.03
X6	0.12	0.17	0.09	0.07	−0.10	1.00	0.18	0.08	−0.07	−0.04	−0.01	−0.02
X7	0.14	0.42	−0.10	−0.17	0.27	0.18	1.00	0.07	0.07	−0.01	0.03	0.08
X8	−0.07	0.25	0.00	−0.03	0.02	0.08	0.07	1.00	0.13	0.60	0.12	0.06
X9	0.06	0.18	0.00	0.04	0.05	−0.07	0.07	0.13	1.00	0.13	−0.09	0.06
X10	−0.17	0.09	0.05	−0.03	0.18	−0.04	−0.01	0.60	0.13	1.00	−0.05	0.08
X11	0.05	0.12	0.03	−0.06	0.10	−0.01	0.03	0.12	−0.09	−0.05	1.00	0.14
X12	0.15	0.13	0.18	−0.15	0.03	−0.02	0.08	0.06	0.06	0.08	0.14	1.00

Table 5
R^2 value, VIF variable predictor.

Variable	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
R^2	0.891	0.705	0.922	0.863	0.764	0.886	0.688	0.559	0.912	0.548	0.892	0.868
Variance Inflation Factor (VIF)	1.122	1.419	1.085	1.159	1.309	1.129	1.453	1.788	1.096	1.826	1.121	1.152

b. Significant Level $(\alpha) = 0.05$
c. Test Statistics

$$W = -n \ln \left[\frac{|\mathbf{S}|}{(trace(\mathbf{S})/p)^p} \right] \sim \chi^2_{\frac{1}{2}p(p+1)-1}$$

Where

$$\mathbf{S} = \frac{1}{n-1} \sum_{j=1}^{n} (\mathbf{X}_j - \bar{\mathbf{X}})(\mathbf{X}_j - \bar{\mathbf{X}})^T$$

Computing

$$\mathbf{S} = \begin{bmatrix} 41.4928 & 7.5473 & 20.3650 \\ 7.54733 & 3.3475 & 5.1000 \\ 20.3650 & 5.1000 & 17.7428 \end{bmatrix}$$

$$W = -222 \ln \left[\frac{553.955}{(62.5831/3)^3} \right] = 620.8375$$

d. Critical Area : $H0$ rejected if $W > \chi^2_{(0.05;5)} = 11.07$
e. Conclusion

Based on the computational results, $W = 620.8375 > \chi^2_{(0.05;5)} = 11.07$ so H_0 rejected, so can concluded that There is correlation between response variable.

Multicollinearity test

Multicollinearity cases are detected based on the correlation coefficient values between predictor variables. The correlation values between variables are presented in Table 4.

Analysis results correlation between variable predictor show that no there is very high correlation between variables causal predictor exists case multicollinearity. Correlation highest occurs in variables predictors X8 and X10 of 0.60. Apart from correlation between variable predictor, identification case multicollinearity is also possible done with consider VIF value. VIF value for each variable predictor as following:

Table 5 shows that the largest VIF value for variable X10 is 1.826 and the smallest VIF value for variable X3 is 1.085. Overall, the VIF value for each predictor variable is less than 10, so it can be concluded that there are no cases of multicollinearity between the predictor variables. Thus, all predictor variables can be included in the MPR and GWMPR models.

Modeling with multivariate Poisson regression

Multivariate Poisson regression modeling of the number of stunting, wasting and underweight produces estimated values that are global or the same for each sub-district in Southeast Sulawesi. Simultaneous parameter testing in the MPR model with covariance being a function of the independent variable is carried out using the LRT method, which is formulated as follows:

$H_0 : \beta_{h1} = \beta_{h2} = ... = \beta_{h12} = 0$
H_1 : there is at least one $\beta_{hl} \neq 0; h = 0, 1, 2, 3; l = 1, 2, ..., 12$

The statistical value of the simultaneous test obtained based on calculations with the Python program is G2a = 10,307 which is greater than $\chi^2_{0,05;40} = 55.76$, so H0 is rejected. This means that there is at least one independent variable that has a significant effect on the response variable.

For know variable It's up to you which one has influence significant to variable response, done parameter testing Partial. For test in a way partial parameters $\beta_{hl} (h = 0, 1, 2, 3; l = 1, 2, ..., 12)$ are formulated as follows:

$H_0 : \beta_{hl} = 0$
$H_1 : \beta_{hl} \neq 0$

The results of calculating parameter estimates and *Z test statistics* in Table 6 show that several independent variables have values $|Z| > Z_{0.025} = 1.96$ or p- value < 0.05 which indicates that this variable has a significant effect on the response variable.

MPR model for factors that influence Stunting (Y1), Wasting (Y2), and Underweight (Y3) based on results parameter estimates in the table above can written down as following:

a. Number of Stunting Cases
The significant predictor variables for the number of stunting cases (Y1) with a significance level of 5 % are the percentage of toddlers aged 12–59 months (X2), the percentage of LBW babies (X3), the percentage of anemic pregnant women (X4), the percentage of babies aged <6 months receiving Exclusive breastfeeding (X5), percentage of toddlers with complete basic immunization (X6), percentage of postpartum mothers receiving vitamin A (X8), Active Posyandu ratio (X9), percentage of K4 visits by pregnant women (X10) and percentage of toddlers suffering from pneumonia (X11).
b. Number of wasting cases
Variable significant predictor to amount wasting case (Y2) with level 5 % significance is percentage toddler age 12–59 months (X2), percentage LBW babies (X3), percentage of anemic pregnant women (X4), percentage toddler with Immunization base complete (X6), percentage toddler got vitamin A (X7), percentage Mother postpartum got vitamin A (X8), ratio Integrated Healthcare Center Active (X9), percentage visit Mother pregnant K4 (X10) and percentage toddler suffering from pneumonia (X11).
c. Number of underweight cases

Variable significant predictor to amount underweight case (Y3) with level 5 % significance is percentage toddler type sex male (X1), percentage toddler age 12–59 months (X2), percentage of anemic pregnant women (X4), percentage toddler with Immunization base complete (X6), percentage toddler got vitamin A (X7), percentage Mother postpartum got vitamin A (X8), ratio Integrated Healthcare Center Active (X9), percentage visit Mother pregnant K4 (X10), percentage toddler suffering from pneumonia (X11) and percentage toddler suffer diarrhea (X12).

Spatial heterogeneity testing

The next step is to test spatial heterogeneity as a requirement for GWMPR modeling to identify spatial variation in data on the number of cases of stunting, wasting and underweight. To determine the existence of spatial heterogeneity, it can be done by testing the equality of variance-covariance matrices for each observational data or location using the Glejser (G) test with the following hypothesis:

$H_0 : \Sigma_1 = \Sigma_2 = ... = \Sigma_n = \Sigma$ (No heterogeneity spatial)
H_1 : at least there is one $\sum_i \neq \sum$; $i = 1, 2, \ldots, n$ (heterogeneity spatial)

Test result heterogeneity spatial data on Stunting (Y1), Wasting (Y2), and Underweight (Y3) with the Glejser test, obtained mark test statistic $G = 47.210$ which is more than $\chi^2_{(0,05;30)} = 43.77$, so that H_0 rejected. That matter means There is heterogeneity spatial data on Stunting (Y1), Wasting (Y2), and Underweight (Y3).

Modeling number of stunting, wasting and underweight with GWMPR

The GWMPR model is a statistical technique that is local because of the diversity in regional relationships which is called spatial heterogeneity. To determine the existence of spatial heterogeneity, you can test the equality of the variance-covariance matrices for each observational data or location. Next, modeling Stunting (Y1), Wasting (Y2), and Underweight (Y3) with GWMPR. Stunting (Y1), Wasting (Y2), and Underweight (Y3) modeling begins by estimating the GWMPR model parameters using the MLE method and solving iteratively using the Newton Raphson algorithm. The optimum bandwidth value for the Gaussian kernel adaptive weighting function, parameter estimation results, standard error, and Z test statistical values for each location were obtained based on the minimum generalized cross-validation (GCV) value.

Table 6
Results of MPR parameter estimation.

Variable Response 1 (Stunting)		Variable Response 2 (Wasting)			Variable Response 3 (Underweight)									
Par	Estimated Value	Standard Error	Z	P-value	Par	Estimated Value	Standard Error	Z	P-value	Par	Estimated Value	Standard Error	Z	P-value
$\beta_{1.0}$	3.3180	0.0697	47.605	0.000	$\beta_{2.0}$	2.5839	0.1280	20.184	0.000	$\beta_{2.0}$	3.1845	0.0801	39.734	0,000
$\beta_{1.1}$	0.0001	0.0007	0.092	0.926	$\beta_{2.1}$	−0.0006	0.0013	−0.454	0.649	$\beta_{2.1}$	0.0017	0.0009	1.976	0.048
$\beta_{1.2}$	0.0172	0.0006	29.500	0.000	$\beta_{2.2}$	0.0108	0.0011	10.076	0.000	$\beta_{2.2}$	0.0159	0.0007	22.500	0.000
$\beta_{1.3}$	0.0103	0.0022	4.798	0.000	$\beta_{2.3}$	0.0213	0.0039	5.451	0.000	$\beta_{2.3}$	−0.0025	0.0029	−0.877	0.380
$\beta_{1.4}$	−0.0037	0.0002	−16.898	0.000	$\beta_{2.4}$	−0.0012	0.0004	−3.023	0.002	$\beta_{2.4}$	−0.0042	0.0003	−15.91	0.000
$\beta_{1.5}$	−0.0085	0.0003	−25.317	0.000	$\beta_{2.5}$	−0.0046	0.0006	−7.225	0.000	$\beta_{2.5}$	−0.0002	0.0004	−0.542	0.587
$\beta_{1.6}$	0.0024	0.0003	8.869	0.000	$\beta_{2.6}$	−0.0004	0.0005	−0.727	0.466	$\beta_{2.6}$	−0.0040	0.0003	−12.02	0.000
$\beta_{1.7}$	−0.0007	0.0004	−1.878	0.060	$\beta_{2.7}$	0.0038	0.0007	5.448	0.000	$\beta_{2.7}$	−0.0017	0.0004	−3.850	0.000
$\beta_{1.8}$	0.0021	0.0005	3.949	0.000	$\beta_{2.8}$	−0.0005	0.0010	−0.546	0.584	$\beta_{2.8}$	−0.0022	0.0006	−3.367	0.001
$\beta_{1.9}$	0.0065	0.0002	31.523	0.000	$\beta_{2.9}$	0.0021	0.0004	5.538	0.000	$\beta_{2.9}$	0.0046	0.0002	18.687	0.000
$\beta_{1.10}$	−0.0050	0.0005	−9.710	0.000	$\beta_{2.10}$	−0.0060	0.0010	−6.239	0.000	$\beta_{2.10}$	0.0028	0.0006	4.578	0.000
$\beta_{1.11}$	0.0092	0.0004	20.742	0.000	$\beta_{2.11}$	0.0073	0.0008	8.756	0.000	$\beta_{2.11}$	0.0030	0.0006	5.308	0.000
$\beta_{1.12}$	0.0004	0.0004	1.091	0.275	$\beta_{2.12}$	0.0071	0.0006	11.221	0.000	$\beta_{2.12}$	−0.0013	0.0005	−2.525	0.012

Significance with level α=5 %.

Table 7
Grouping based regions variable significant predictors of the number of stunting cases.

Subdistrict	Variable Significant	Group
Buke, Landono, Mowila, Sabulakoa	X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12	1
Marobo, Andoolo, West Andoolo, Baito, Tinanggea, East Kabaena, Maginti	X1, X2, X3, X4, X5, X6, X7, X9, X10, X11, X12	2
Anggalomoare, Besulutu, Bondoala, Kapoiala, Lalonggasumeeto, Morosi, Sampara, Ranomeeto, West Ranomeeto, Lembo, Motui, Sawa, Kadia, West Kendari, Mandonga, Puuwatu, Wua-Wua	X1, X2, X4, X5, X6, X7, X8, X9, X10, X11, X12	3
Kapontori, Lasalimu, South Lasalimu, Wajo Market, Siontapina, Wabula, Wolowa, Batukara, Bone, Duruka, Lohia, Parigi, Pasi Kolaga, Pasir Putih, Tongkuno, South Tongkuno, South Wakorumba, Lambuya, Meluhu, Oneembute, Pondidaha, Puriala, West Wongeduku, Samaturu, Wolo, Angata, Benua, Wangi-Wangi, South Wangi-Wangi, Bonegunu, Kambowa, Kulisusu, Dangia, Ladongi, Poli-Polia, Gu, Lakudo, Mawasangka, Central Mawasangka, East Mawasangka, Sangia Wambulu, Batauga, Kadatua, Lapandewa, Sampolawa, Siompu, West Siompu, Batupoaro, Betoambari, Bungi, Kokalukuna, Lea-Lea, Murhum, Sorawolio, Wolio	X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11	4
Towea, East Kolono, Laonti, Moramo, Kabaena, West Kabaena, South Kabaena, Central Kabaena, North Kabaena, North Wakorumba, West Wawonii, South Wawonii, Central Wawonii, Southeast Wawonii, East Wawonii, North East Wawonii, North Wawonii	X1, X2, X3, X4, X5, X6, X9, X10, X11, X12	5
Soropia, Konda, Palangga, Wolasi, Abeli, Baruga, Kambu, Kendari, Poasia	X1, X2, X4, X5, X6, X7, X9, X10, X11, X12	6
Batalaiworu, Kabangka, Kabawo, Katobu, Kontukowuna, Kontunaga, Lasalepa, Maligano, Napabalano, Watopute, Basala, Lalembuu, Lantari Jaya, West Kulisusu, Aere, Lambandia, Barangka, Kusambi, Lawa, Napano Kusambi, Sawerigadi, Tiworo Islands, South Tiworo, Central Tiworo, Wa Daga, Talaga Raya	X1, X2, X3, X4, X5, X6, X7, X9, X10, X11	7
Abuki, Anggaberi, Tongauna, North Tongauna, Uepai, Unaaha, Baula, Kolaka, Latambaga, Wundulako, Lalolae, Loea, Mowewe, Tinondo, Tirawuta, Uluiwoi	X2, X3, X4, X5, X6, X7, X8, X9, X10, X11	8
Amonggedo, Anggotoa, Konawe, Wawotobi, Wongeduku, Binongko, Kaledupa, South Kaledupa, Togo Binongko, Tomia, East Tomia, Batu Atas	X1, X2, X3, X4, X5, X6, X8, X9, X10, X11	9
Latoma	X1, X2, X3, X5, X6, X7, X8, X9, X10, X11	10
Routa, Iwoimendaa, Batu Putih, Katoi, Kodeoha, Lambai, Lasusua, Ngapa, Pakue, Pakue Tengah, Pakue Utara, Porehu, Ranteangin, Tiwu, Tolala, Watunohu, Wawo, Lasolo, Wawolesea, Ueesi	X1, X2, X4, X5, X6, X7, X8, X9, X10, X11	11
Kolono, Laeya, Lainea, North Moramo, South Palangga, Kep. Masaloka Raya, Mata Oleo, Southeast Poleang, Rarowatu, Rumbia, Central Rumbia, North Tiworo, Nambo	X1, X2, X4, X5, X6, X9, X10, X11, X12	12
Asinua	X2, X3, X5, X6, X7, X8, X9, X10, X11	13
Padangguni, Andowia, Landawe, Langgikima, Lasolo Islands, Molawe, Oheo, Wiwirano	X2, X4, X5, X6, X7, X8, X9, X10, X11	14
Polinggona, Pomalaa, Tanggetada	X2, X3, X4, X5, X6, X7, X9, X10, X11	15
Mata Usu, Jenisunu	X1, X2, X4, X5, X6, X7, X9, X10, X11	16
North Kulisusu	X1, X2, X3, X4, X5, X6, X9, X10, X11	17
Asera	X1, X2, X5, X6, X7, X8, X9, X10, X11	18
Toari, Watubangga, West Poleang	X2, X4, X5, X6, X7, X9, X10, X11	19
South Poleang, Central Poleang, East Poleang, North Poleang, North Rarowatu	X1, X2, X4, X5, X6, X9, X10, X11	20
Poleang	X2, X4, X5, X6, X9, X10, X11	21

To find out which independent variables have a significant effect on the response variable for each location, partial parameter testing was carried out. GWMPR testing produces parameters for each sub-district for the number of stunting and wasting cases. Grouping of regions based on significant predictor variables in the number of cases of stunting, wasting and underweight is presented in Tables 7–9.

The grouping of the number of significant predictor variables based on the map on the number of stunting cases can be seen in Fig. 1.

The grouping of the number of significant predictor variables based on the map on the number of stunting cases can *be* seen in Fig. 2.

Grouping the number of significant predictor variables based on the map on the number of *underweight cases* can be seen in Fig. 3.

Fig. 1 shows that there are 21 sub-district area segmentations based on significant variables. Group 7 contains 10 variables (X1,X2,X3,X4,X5,X6,X7,X9,X10,X11) that are significant in dominating several sub-districts. Fig. 2 shows that there are 10 sub-district area segmentations based on significant variables. Group 4 contains 9 variables (X1,X2,X3,X4,X7,X9,X10,X11,X12) that are significant in dominating several sub-districts. Fig. 3 shows that there are 37 sub-district area segmentations based on significant variables. Group 2 has 11 variables (X1,X5,X6,X7,X9,X10,X11,X12) which is significant in dominating several districts, and likewise in group 9 there are 10 variables (X2,X3,X4,X5,X6,X7,X9,X10,X11,X12).

To find out which independent variables have a significant effect on the response variable for each location, partial parameter testing is carried out. As an example, parameter testing will be presented at the research location, namely Barangka District.

The GWMPR model for factors influencing the average number of Stunting cases (Y1), the average number of Wasting cases (Y2), and the average number of Underweight cases (Y3) for Barangka District based on the parameter estimation results in Table 10 can

Table 8
Grouping based regions variable significant predictor of the number of wasting cases.

Subdistrict	Variable Significant	Group
South Palangga	X1, X2, X3, X4, X5, X6, X7, X9, X10, X11, X12	1
Napabalano, Towea, East Kolono, West Kabaena, North Kabaena, Kep. Masaloka Raya, Mata Oleo, Southeast Poleang, Rumbia, Central Rumbia, North Kulisusu, North Wakorumba, Napano Kusambi, North Tiworo	X1, X2, X3, X4, X5, X7, X9, X10, X11, X12	2
Laeya, Lainea, Lalembuu, Palangga, Tinanggea	X2, X3, X4, X5, X6, X7, X9, X10, X11, X12	3
Kapontori, Lasalimu, South Lasalimu, Wajo Market, Siontapina, Wabula, Wolowa, Batalaiworu, Batukara, Bone, Duruka, Kabangka, Kabawo, Katobu, Kontukowuna, Kontunaga, Lasalepa, Lohia, Maligano, Marobo, Parigi, Pasi Kolaga, Pasir Putih, Tongkuno, South Tongkuno, South Wakorumba, Watopute, Kabaena, South Kabaena, Central Kabaena, East Kabaena, Binongko, Kaledupa, South Kaledupa, Togo Binongko, Tomia, East Tomia, Wangi-Wangi, South Wangi-Wangi, Bonegunu, Kambowa, Kulisusu, West Kulisusu, Barangka, Kusambi, Lawa, Maginti, Sawerigadi, Tiworo Islands, South Tiworo, Central Tiworo, Wa Daga, Gu, Lakudo, Mawasangka, Central Mawasangka, East Mawasangka, Sangia Wambulu, Talaga Raya, Batauga, Batu Atas, Kadatua, Lapandewa, Sampolawa, Siompu, West Siompu, Batupoaro, Betoambari, Bungi, Kokalukuna, Lea-Lea, Murhum, Sorawolio, Wolio	X1, X2, X3, X4, X7, X9, X10, X11, X12	4
Amonggedo, Anggalomoare, Besulutu, Bondoala, Lalonggasumeeto, Morosi, Pondidaha, Puriala, Sampara, Wonggeduku, Andoolo, West Andoolo, Angata, Baito, Basala, Benua, Buke, Konda, Landono, North Moramo, Mowila, Ranomeeto, West Ranomeeto, Sabulakoa, Wolasi, Abeli, Baruga, Kadia, Kambu, Kendari, West Kendari, Mandonga, Nambo, Poasia, Puuwatu, Wua-Wua	X2, X3, X5, X6, X7, X9, X10, X11, X12	5
Routa, Iwoimendaa, Batu Putih, Katoi, Kodeoha, Lambai, Lasusua, Ngapa, Pakue, Pakue Tengah, Pakue Utara, Porehu, Ranteangin, Tiwu, Tolala, Watunohu, Wawo, Asera, Oheo, Wiwirano, Ueesi	X1, X2, X3, X5, X7, X9, X10, X11, X12	6
Polinggona, Toari, Watubangga, Kolono, Laonti, Moramo, Lantari Jaya, Mata Usu, Poleang, West Poleang, South Poleang, Central Poleang, East Poleang, North Poleang, Rarowatu, North Rarowatu, Jenisunu, West Wawonii, South Wawonii, Central Wawonii, Southeast Wawonii, East Wawonii, Northeast Wawonii, North Wawonii	X2, X3, X4, X5, X7, X9, X10, X11, X12	7
Abuki, Anggaberi, Anggotoa, Kapoiala, Konawe, Lambuya, Meluhu, Oneembute, Padangguni, Soropia, Tongauna, North Tongauna, Uepai, Unaaha, Wawotobi, West Wongeduku, Baula, Pomalaa, Tanggetada, Wundulako, Andowia, Landawe, Langgikima, Lasolo, Lasolo Islands, Lembo, Molawe, Motui, Sawa, Wawolesea, Aere, Dangia, Ladongi, Lalolae, Lambandia, Loea, Poli-Polia, Tirawuta	X2, X3, X5, X7, X9, X10, X11, X12	8
Latoma, Samaturu, Wolo	X1, X2, X3, X5, X7, X10, X11, X12	9
Asinua, Kolaka, Latambaga, Mowewe, Tinondo, Uluiwoi	X2, X3, X5, X7, X10, X11, X12	10

be written as follows:

$$\widehat{\lambda}_1 = \exp\left(2.9141 + 0.0062X_1 + 0.0172X_2 + 0.0142X_3 - 0.0052X_4 - 0.0055X_5 + 0.0029X_6 + 0.0017X_7 + 0.0012X_8 + 0.0088X_9 - 0.0067X_{10} + 0.0089X_{11} - 0.0008X_{12}\right) \quad (40)$$

$$\widehat{\lambda}_2 = \exp\left(2.3190 + 0.0054X_1 + 0.0095X_2 + 0.0279X_3 - 0.0021X_4 - 0.0009X_5 + 0.0007X_6 + 0.0037X_7 - 0.0002X_8 + 0.0035X_9 - 0.0085X_{10} + 0.0061X_{11} + 0.0064X_{12}\right) \quad (41)$$

$$\widehat{\lambda}_3 = \exp\left(2.0468 + 0.0140X_1 + 0.0182X_2 - 0.0013X_3 - 0.0048X_4 + 0.0035X_5 - 0.0021X_6 + 0.0022X_7 - 0.0023X_8 + 0.0073X_9 - 0.0013X_{10} + 0.0039X_{11} - 0.0007X_{12}\right) \quad (42)$$

Based on Table 10 and Eqs. (40)–(42) it can be interpreted as follows.

1. The percentage of male toddlers (X1) influences the average number of stunting cases (Y1), the average number of wasting cases (Y2), and the average number of underweight cases (Y3). This can be shown from each Z value of (Y1=4.9244, Y2=2.9336, Y3=8.0712) which is greater than Z table = 1.96. This can be interpreted that every 1 % addition to the percentage of male toddlers (X1) in Barangka District will increase the average number of stunting cases (Y1) by exp(0.0062) = 1.0062 times assuming other variables are constant, increasing the average number of wasting cases (Y2) is exp(0.0054) = 1.0054 times assuming other variables are constant, and increases the average number of underweight cases (Y3) by exp(0.014) = 1.0141 times assuming other variables are constant.
2. The percentage of toddlers aged 12–59 months (X2) influences the average number of stunting cases (Y1), the average number of wasting cases (Y2), and the average number of underweight cases (Y3). This can be shown from the respective Z values of (Y1=22.6685, Y2=7.7757, Y3=19.8364) which are greater than Z table = 1.96. This can be interpreted as every 1 % addition to the percentage of toddlers aged 12–59 months (X2) in Barangka District will increase the average number of stunting cases (Y1) by exp(0.0172) = 1.0173 times assuming other variables are constant, increasing the average number of wasting cases (Y2) is exp(0.0095) = 1.0095 times assuming other variables are constant, and increases the average number of underweight cases (Y3) by exp(0.0182) = 1.0184 times assuming other variables are constant.

Table 9
Grouping based regions variable significant predictors of the number of underweight cases.

Subdistrict	Variable Significant	Group
Baula, Pomalaa, South Palangga, Lantari Jaya, Dangia, Poli-Polia	X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12	1
Wajo Market, Wabula, Wolowa, Amonggedo, Anggaberi, Anggotoa, Konawe, Lambuya, Meluhu, Oneembute, Pondidaha, Puriala, Tongauna, Uepai, Unaaha, Wawotobi, Wonggeduku, West Wongeduku, Angata, Lasolo, Lembo, Molawe, Wawolesea, Ladongi, Lalolae, Loea, Tirawuta, Lapandewa, Sampolawa	X1, X2, X3, X4, X5, X6, X7, X9, X10, X11, X12	2
Maligano, West Kulisusu, North Wakorumba	X1, X2, X4, X5, X6, X7, X8, X9, X10, X11, X12	3
Andoolo, West Andoolo, Baito, Basala, Benua, Buke, Lalembuu, Palangga, Tinanggea, Aere, Lambandia	X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12	4
Katoi, Kodeoha, Lambai, Lasusua, Ngapa, Pakue, Porehu, Ranteangin, Tiwu, Tolala, Watunohu	X1, X2, X3, X4, X6, X7, X8, X9, X10, X11, X12	5
Poleang, West Poleang, Central Poleang, North Poleang, Rarowatu, North Rarowatu, Jenisunu	X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X12	6
Kulisusu	X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11	7
Kapontori, Gu, Lakudo, Sangia Wambulu, Batauga, Batupoaro, Betoambari, Bungi, Kokalukuna, Lea-Lea, Murhum, Sorawolio, Wolio	X1, X2, X4, X5, X6, X7, X9, X10, X11, X12	8
Anggalomoare, Besulutu, Bondoala, Kapoiala, Lalonggasumeeto, Morosi, Sampara, Konda, Landono, Mowila, Ranomeeto, West Ranomeeto, Sabulakoa, Wolasi, Motui, Sawa, Baruga, Kadia, Kambu, West Kendari, Mandonga, Puuwatu, Wua-Wua	X2, X3, X4, X5, X6, X7, X9, X10, X11, X12	9
Batu Putih, Pakue Tengah, Pakue Utara, Wawo	X1, X2, X3, X4, X6, X7, X9, X10, X11, X12	10
North Kulisusu	X1, X2, X4, X5, X6, X8, X9, X10, X11, X12	11
Lasalimu, South Lasalimu, Siontapina	X1, X2, X3, X4, X5, X6, X7, X9, X10, X11	12
Batalaiworu, Batukara, Duruka, Katobu, Kontunaga, Lasalepa, Lohia, South Wakorumba, Bonegunu	X1, X2, X4, X5, X6, X7, X8, X9, X10, X11	13
Napabalano, Kusambi, Napano Kusambi	X1, X2, X4, X5, X6, X7, X8, X9, X11, X12	14
Abuki, Asinua, Padangguni, North Tongauna, Kolaka, Latambaga, Wundulako, Andowia, Lasolo Islands, Mowewe, Tinondo, Uluiwoi	X1, X2, X3, X4, X5, X6, X7, X9, X10, X12	15
Polinggona, Tanggetada, Watubangga, Mata Usu	X2, X3, X4, X5, X6, X7, X8, X9, X10, X12	16
Laeya	X1, X2, X3, X4, X5, X6, X7, X9, X11, X12	17
Rumbia, Central Rumbia	X1, X2, X3, X4, X5, X6, X8, X9, X10, X12	18
South Poleang	X1, X2, X3, X4, X5, X6, X7, X8, X9, X10	19
Pasi Kolaga, Pasir Putih, Tongkuno, South Tongkuno, Kambowa	X1, X2, X4, X5, X6, X7, X9, X10, X11	20
Latoma, Routa, Iwoimendaa, Samaturu, Wolo, Asera, Landawe, Langgikima, Oheo, Wiwirano, Ueesi	X1, X2, X3, X4, X6, X7, X9, X10, X12	21
Soropia, North Moramo, Abeli, Kendari, Nambo, Poasia	X2, X3, X4, X5, X6, X7, X9, X11, X12	22
Toari	X2, X3, X4, X6, X7, X8, X9, X10, X12	23
East Colono	X1, X2, X4, X5, X6, X8, X9, X10, X12	24
Moramo, Kadatua, Siompu	X1, X2, X4, X5, X6, X7, X9, X11, X12	25
Kabaena, West Kabaena, South Kabaena, Central Kabaena, East Kabaena, North Kabaena, Talaga Raya	X1, X2, X4, X5, X6, X8, X9, X10, X11	26
Binongko, Kaledupa, South Kaledupa, Tomia, East Tomia, Wangi-Wangi, South Wangi-Wangi	X1, X2, X3, X4, X5, X6, X9, X10, X11	27
Wawonii, East Wawonii, Northeast Wawonii	X1, X2, X4, X5, X6, X8, X9, X11, X12	28
Kabangka, Kontukowuna, Watopute, Barangka, Lawa, Maginti, Sawerigadi, Tiworo Islands, South Tiworo, Wa Daga	X1, X2, X4, X5, X6, X7, X8, X9, X11	29
Kep. Masaloka Raya, Mata Oleo, Southeast Poleang, East Poleang	X1, X2, X3, X4, X5, X6, X8, X9, X10	30
North Tiworo	X1, X2, X3, X4, X5, X6, X8, X9, X12	31
Kolono, Lainea	X1, X2, X4, X5, X6, X9, X11, X12	32
Bone, Kabawo, Marobo, Parigi, Mawasangka, Central Mawasangka, East Mawasangka	X1, X2, X4, X5, X6, X7, X9, X11	33
Towea, Laonti, West Wawonii, South Wawonii, Central Wawonii, North Wawonii	X1, X2, X4, X5, X6, X8, X9, X12	34
Togo Binongko, Batu Atas	X1, X2, X3, X4, X5, X6, X9, X11	35
Central Tiworo	X1, X2, X4, X5, X6, X8, X9, X11	36
West Siompu	X1, X2, X4, X5, X6, X9, X11	37

3. The percentage of LBW babies (X3) influences the average number of stunting cases (Y1), and the average number of wasting cases (Y2), while the average number of underweight cases (Y3) has no effect. This can be shown that the Z value of (Y1=3.5630, Y2=4.9459) is greater than Z table = 1.96, while the Z value of (Y3=−0.2379) is greater than Z table = −1.96. This can be interpreted as every 1 % addition to the percentage of LBW babies (X3) in Barangka District will increase the average number of stunting cases (Y1) by exp(0.0142) = 1.0143 times assuming other variables are constant, increasing the average number of cases wasting (Y2) was exp(0.0279) = 1.0283 times assuming other variables were constant, while the average number of underweight cases (Y3) did not decrease or increase.
4. The percentage of anemic pregnant women (X4) influences the average number of stunting cases (Y1), the average number of wasting cases (Y2), and the average number of underweight cases (Y3). This can be shown from each Z value of (Y1=−14.3904, Y2=−3.9819, Y3=−12.3651) which is smaller than Z table = −1.96. This can be interpreted as every 1 % addition to the

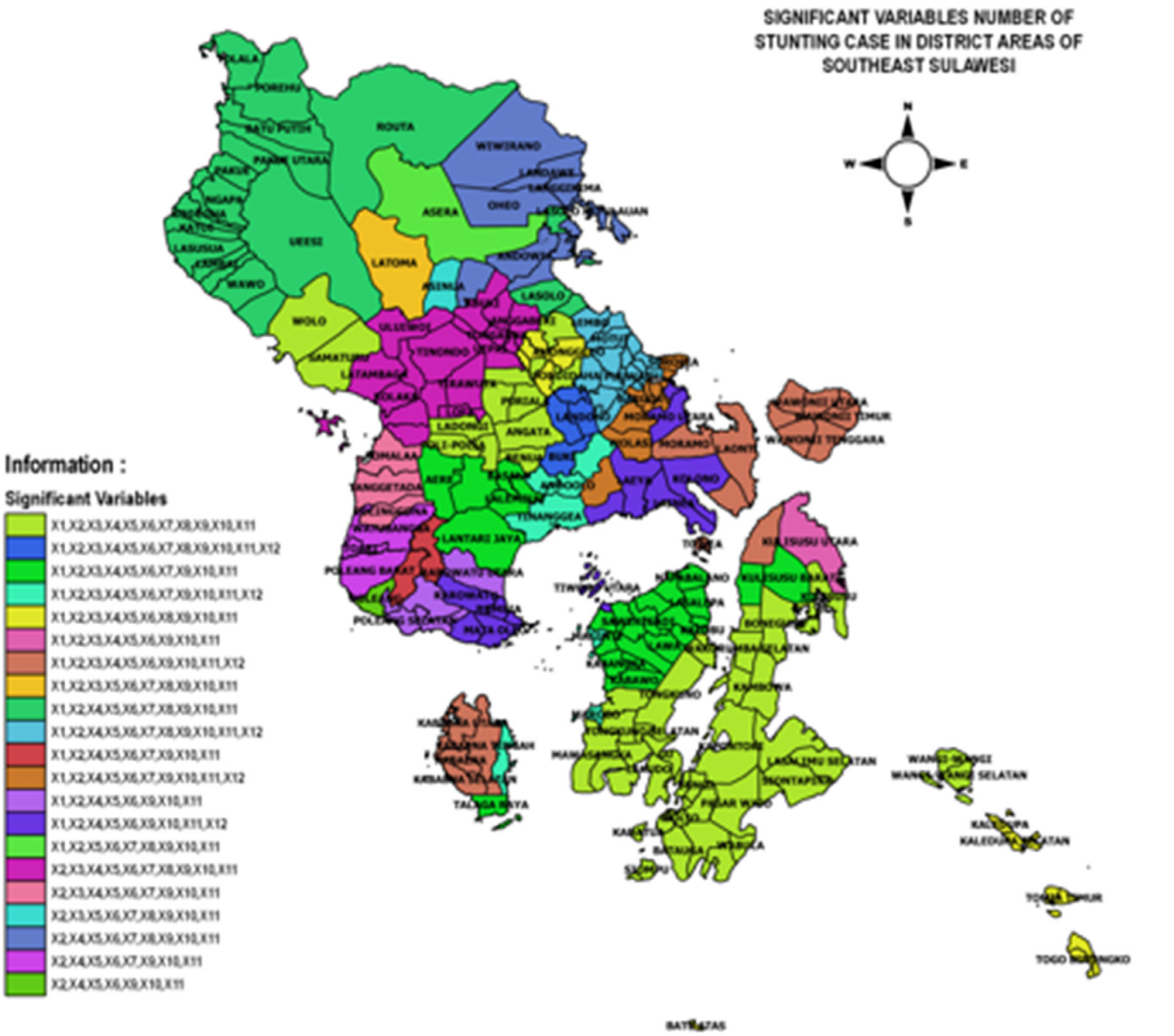

Fig. 1. Grouping map subdistrict based on amount significant predictor variable *of stunting*.

Table 10
Results of GWMPR parameter assessment in the District Barangka.

Variable Response 1 (Stunting)				Variable Response 2 (Wasting)				Variable Response 3 (Underweight)			
Par	Est	S.E	Z	Par	Est	S.E	Z	Par	Est	S.E	Z
$\beta_{1.0}$	2.9141	0.1266	23.0241	$\beta_{2.0}$	2.3190	0.1693	13.6999	$\beta_{3.0}$	2.0468	0.1308	15.6436
$\beta_{1.1}$	0.0062	0.0013	4.9244	$\beta_{2.1}$	0.0054	0.0019	2.9336	β_{31}	0.0140	0.0017	8.0712
$\beta_{1.2}$	0.0172	0.0008	22.6685	$\beta_{2.2}$	0.0095	0.0012	7.7757	$\beta_{3.2}$	0.0182	0.0009	19.8364
$\beta_{1.3}$	0.0142	0.0040	3.5630	$\beta_{2.3}$	0.0279	0.0056	4.9459	$\beta_{3.3}$	−0.0013	0.0054	−0.2379
$\beta_{1.4}$	−0.0052	0.0004	−14.3904	$\beta_{2.4}$	−0.0021	0.0005	−3.9819	$\beta_{3.4}$	−0.0048	0.0004	−12.3651
$\beta_{1.5}$	−0.0055	0.0006	−9.7426	$\beta_{2.5}$	−0.0009	0.0009	−1.0125	$\beta_{3.5}$	0.0035	0.0006	5.5124
$\beta_{1.6}$	0.0029	0.0004	6.5417	$\beta_{2.6}$	0.0007	0.0006	1.0588	$\beta_{3.6}$	−0.0021	0.0005	−4.5265
$\beta_{1.7}$	0.0017	0.0006	2.9409	$\beta_{2.7}$	0.0037	0.0008	4.3604	$\beta_{3.7}$	0.0022	0.0007	3.2117
$\beta_{1.8}$	0.0012	0.0008	1.5705	$\beta_{2.8}$	−0.0002	0.0012	−0.1246	$\beta_{3.8}$	−0.0023	0.0009	−2.4642
$\beta_{1.9}$	0.0088	0.0003	28.4106	$\beta_{2.9}$	0.0035	0.0005	7.1955	$\beta_{3.9}$	0.0073	0.0003	21.7542
$\beta_{1.10}$	−0.0067	0.0007	−9.0302	$\beta_{2.10}$	−0.0085	0.0012	−7.0532	$\beta_{3.10}$	−0.0013	0.0009	−1.3594
$\beta_{1.11}$	0.0089	0.0008	11.8290	$\beta_{2.11}$	0.0061	0.0010	5.9057	$\beta_{3.11}$	0.0039	0.0009	4.5283
$\beta_{1.12}$	−0.0008	0.0006	−1.4467	$\beta_{2.12}$	0.0064	0.0009	7.0676	$\beta_{3.12}$	−0.0007	0.0008	−0.8496

Significance with level α=5 %.

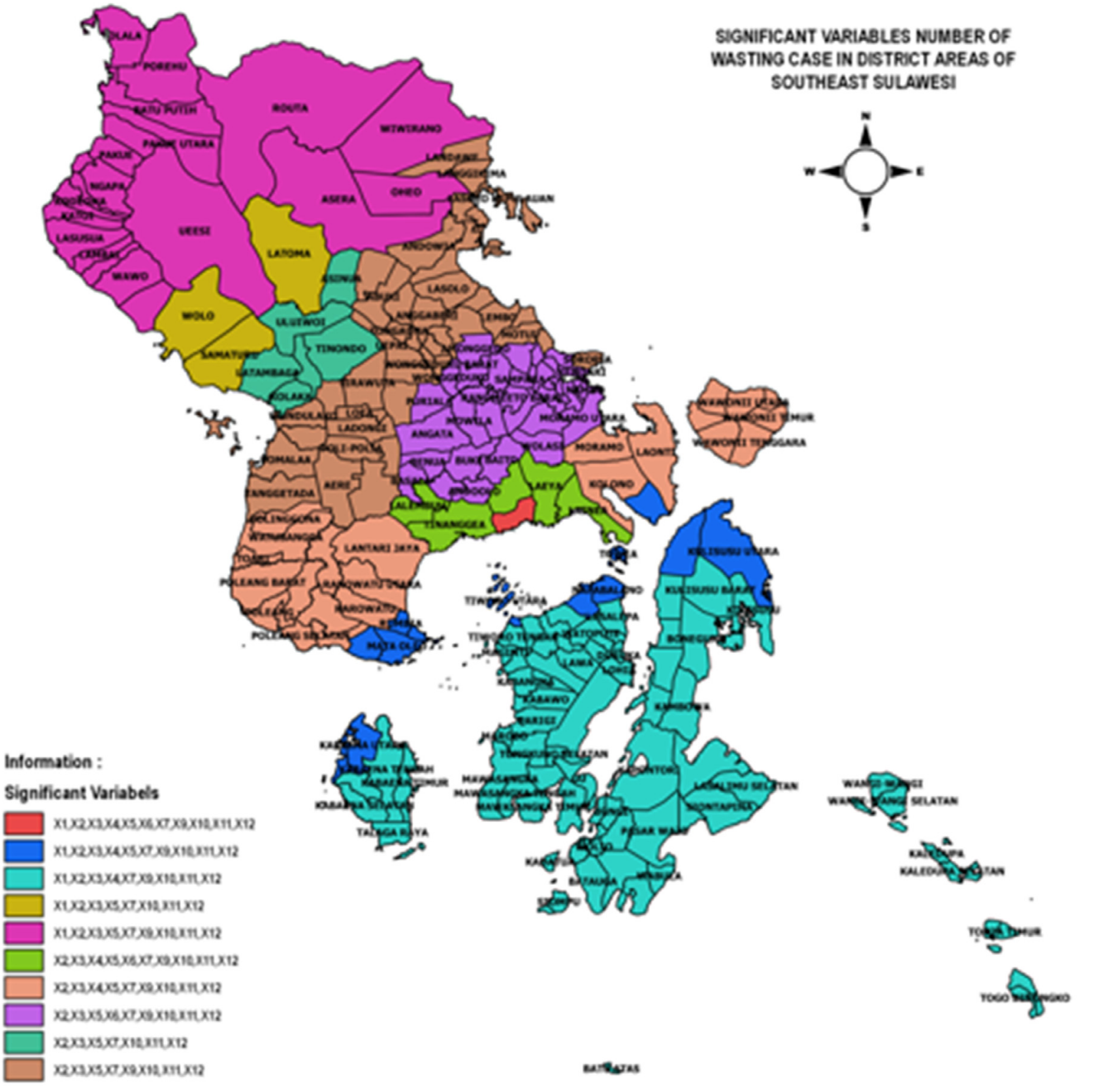

Fig. 2. Grouping map subdistrict based on amount significant predictor variable *of wasting*.

percentage of anemic pregnant women (X4) in Barangka District, it will reduce the average number of stunting cases (Y1) by exp(−0.0052) = 0.9948 times assuming other variables are constant, reducing the average the number of wasting cases (Y2) is exp(−0.0021) = 0.9979 times assuming other variables are constant, and reduces the average number of underweight cases (Y3) by exp(−0.0048) = 0.9952 times assuming other variables are constant.

5. The percentage of 6 months old babies who are exclusively breastfed (X5) influences the average number of stunting cases (Y1) and the average number of underweight cases (Y3), while the average number of wasting cases (Y2) has no effect. This can be shown by the Z value of (Y1= −9.7426) which is smaller than Z table = −1.96, and the Z value of (Y3=5.5124) which is greater than Z table = 1.96, while the Z value of (Y2= −1.0125) is greater than Z table = −1.96. This can be interpreted as every 1 % addition to the percentage of 6 month old babies receiving exclusive breast milk (X5) will reduce the average number of stunting cases (Y1) by exp(−0.0055) = 0.9945 times assuming other variables are constant, increasing the average number of underweight cases (Y3) is exp(0.0035) = 1.0035 times assuming other variables are constant. Meanwhile, the average number of wasting cases (Y2) did not decrease or increase.
6. The percentage of toddlers with complete basic immunization (X6) influences the average number of stunting cases (Y1) and the average number of underweight cases (Y3), while the average number of wasting cases (Y2) has no effect. This can be shown by the Z value of (Y1= 6.5417) which is greater than Z table = 1.96, and the Z value of (Y3=−4.5265) which is smaller than Z

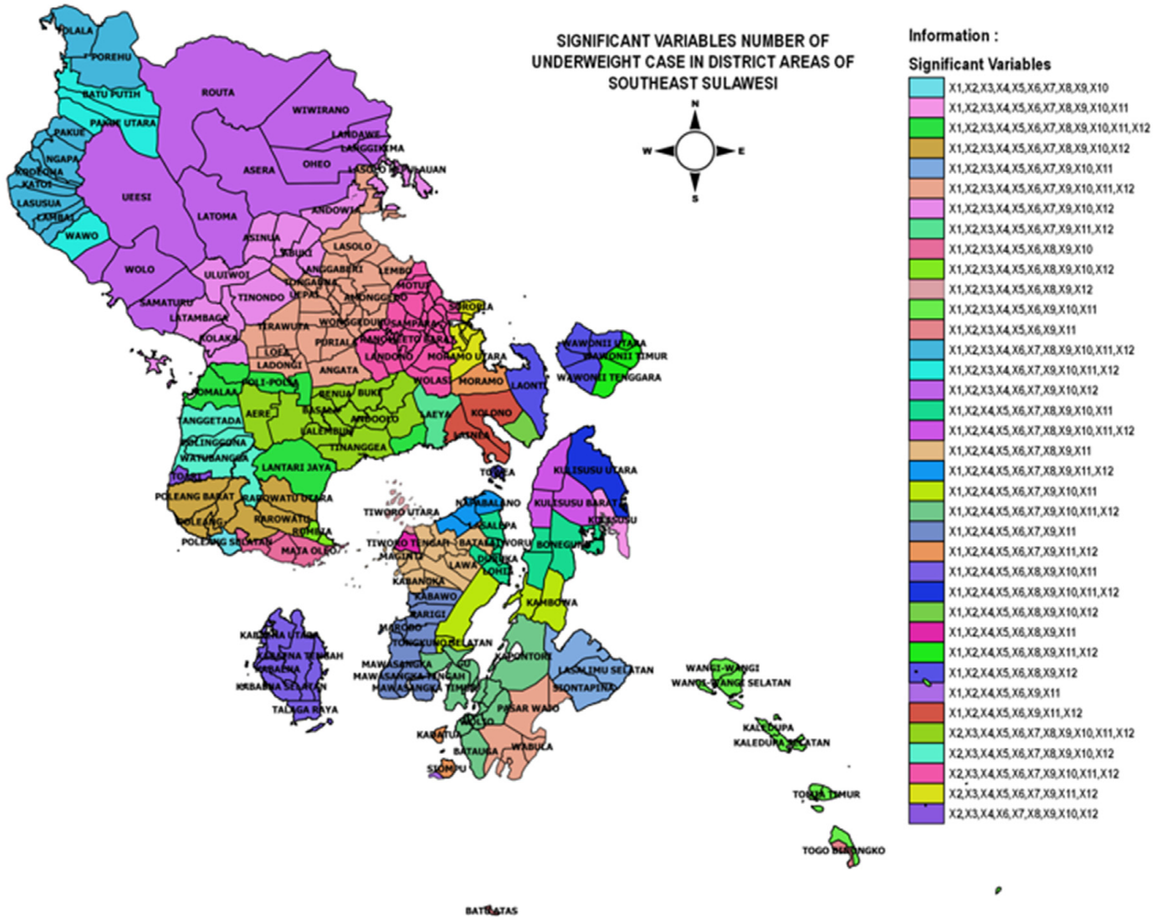

Fig. 3. Grouping map subdistrict based on amount significant predictor variable *of underweight.*

table = −1.96, while the Z value of (Y2=1.0588) smaller than Z table = 1.96. This can be interpreted as every 1 % addition to the percentage of toddlers with complete basic immunization (X6) will increase the average number of stunting cases (Y1) by exp(0.0029) = 1.0029 times assuming other variables are constant, reducing the average number of cases underweight (Y3) by exp(−0.0021) = 0.9979 times assuming other variables are constant. Meanwhile, the average number of wasting cases (Y2) did not decrease or increase.

7. The percentage of children under five who receive vitamin A (X7) influences the average number of stunting cases (Y1), the average number of wasting cases (Y2), and the average number of underweight cases (Y3). This can be shown from each Z value of (Y1=2.9409, Y2=4.3604, Y3=3.2117) which is greater than Z table = 1.96. This can be interpreted that for every 1 % increase in the percentage of children under five who receive vitamin A (X7) in Barangka District, it will increase the average number of stunting cases (Y1) by exp(0.0017) = 1.0017 times assuming other variables are constant, increasing the average number of wasting cases (Y2) is exp(0.0037) = 1.0007 times assuming other variables are constant, and increases the average number of underweight cases (Y3) by exp(0.0022) = 1.0022 times assuming other variables are constant.
8. The percentage of postpartum mothers receiving vitamin A (X8) only influences the average number of underweight cases (Y3), while the average number of stunting cases (Y1) and the average number of wasting cases (Y2) have no effect. This can be shown by the Z value of (Y3= −2.4642) which is smaller than Z table = −1.96, while the Z value of (Y1=1.5705) is smaller than Z table = 1.96, as well as the Z value of (Y2= −0.1246) is greater than Z table = −1.96. This can be interpreted that every 1 % addition to the percentage of postpartum mothers receiving vitamin A (X8) in Barangka District will reduce the average number of underweight cases (Y3) by exp(−0.0023) = 0.9977 times assuming other variables are constant, Meanwhile Therefore, the average number of stunting cases (Y1) and the average number of wasting cases (Y2) did not decrease or increase.
9. The percentage of active Posyandu (X9) influences the average number of stunting cases (Y1), the average number of wasting cases (Y2), and the average number of underweight cases (Y3). This can be shown from each Z value of (Y1=28.4106, Y2=7.1955, Y3=21.7542) which is greater than Z table = 1.96. This can be interpreted as every 1 % addition to the percentage of active Posyandu (X9) in Barangka District will increase the average number of stunting cases (Y1) by exp(0.0088) = 1.0088 times assuming other variables are constant, increasing the average number of cases wasting (Y2)

by exp(0.0035) = 1.0035 times assuming other variables are constant, and increasing the average number of underweight cases (Y3) by exp(0.0073) = 1.0073 times assuming other variables are constant.

10. The percentage of visits by pregnant women K4 (X10) influences the average number of stunting cases (Y1), and the average number of wasting cases (Y2), while the average number of underweight cases (Y3) has no effect. This can be shown that the Z value of (Y1=−9.0302, Y2=−7.0532) is smaller than Z table = −1.96, while the Z value of (Y3=−1.3594) is greater than Z table = −1.96. This can be interpreted as every 1 % addition to the percentage of visits by pregnant women K4 (X10) in Barangka District will reduce the average number of stunting cases (Y1) by exp(−0.0067) = 0.9933 times assuming other variables are constant, increasing the average number of wasting cases (Y2) is exp(−0.0085) = 0.9915 times assuming other variables are constant, while the average number of underweight cases (Y3) does not decrease or increase
11. The percentage of children under five suffering from pneumonia (X11) influences the average number of stunting cases (Y1), the average number of wasting cases (Y2), and the average number of underweight cases (Y3). This can be shown from each Z value of (Y1=11.829, Y2=5.9057, Y3=4.5283) which is greater than Z table = 1.96. This can be interpreted as every 1 % addition to the percentage of children under five suffering from pneumonia (X11) in Barangka District will increase the average number of stunting cases (Y1) by exp(0.0089) = 1.0089 times assuming other variables are constant, increasing the average number wasting cases (Y2) by exp(0.0061) = 1.0061 times assuming other variables are constant, and increasing the average number of underweight cases (Y3) by exp(0.0039) = 1.0039 times assuming other variables are constant.
12. The percentage of children under five suffering from diarrhea (X12) only influences the average number of wasting cases (Y2), while the average number of stunting cases (Y1) and the average number of underweight cases (Y3) have no effect. This can be shown by the Z value of (Y2= 7.0676) which is greater than Z table = 1.96, while the Z value of (Y1=−1.4467, Y3=−0.8496) is greater than Z table = −1.96. This can be interpreted as every 1 % addition to the percentage of toddlers suffering from diarrhea (X12) in Barangka District will increase the average number of wasting cases (Y2) by exp(0.0064) = 1.0064 times assuming other variables are constant, meanwhile on average number of stunting cases (Y1) and the average number of underweight cases (Y3) did not decrease or increase.

Conclusions and recommendations

Based on the results of the analysis that has been carried out, several conclusions and suggestions are obtained as follows.

1. The average number of stunting cases is greater than the average number of wasting and underweight cases. The Pasarwajo sub-district area is the only area with the highest number of cases of stunting, wasting and underweight in Southeast Sulawesi Province.
2. Global estimates using the MPR approach show all predictor variables that influence the number of stunting cases in Southeast Sulawesi Province, except for the percentage of toddlers who are male (X1) and the percentage of toddlers suffering from diarrhea (X12). Likewise with the number of wasting cases, except for the percentage of male toddlers (X1) and the number of underweight cases is not influenced by the variables Percentage of LBW babies (X3) and Percentage of 6 months old babies receiving exclusive breast milk (X5).
3. Local estimates using the GWMPR approach on the number of stunting and wasting cases in Southeast Sulawesi province show that all predictor variables have a significant effect on the number of stunting, wasting and underweight cases. However, there are several regions with a number of significant predictor variables that dominate. For example, in Barangka sub-district, the number of stunting cases is influenced by 10 predictor variables, namely the percentage of male toddlers (X1), the percentage of toddlers aged 12–59 months (X2), the percentage of LBW babies (X3), the percentage of anemic pregnant women (X4)., Percentage of babies aged 6 months receiving exclusive breast milk (X5), Percentage of toddlers with complete basic immunization (X6), Percentage of toddlers getting vitamin A (X7), Percentage of active Posyandu (X9), Percentage of pregnant women visiting K4 (X10), Percentage of toddlers suffering from Pneumonia (X11). The number of wasting cases is influenced by 9 predictor variables, namely: Percentage of male toddlers (X1), Percentage of toddlers aged 12–59 months (X2), Percentage of LBW babies (X3), Percentage of anemic pregnant women (X4), Percentage of toddlers received vitamin A (X7), Percentage of active Posyandu (X9), Percentage of pregnant women visiting K4 (X10), Percentage of toddlers suffering from pneumonia (X11), Percentage of toddlers suffering from diarrhea (X12). The number of underweight cases is influenced by 9 predictor variables, namely the percentage of toddlers who are male (X1), the percentage of toddlers aged 12–59 months (X2), the percentage of anemic pregnant women (X4), the percentage of babies aged 6 months who receive exclusive breast milk (X5), Percentage of toddlers with complete basic immunization (X6), Percentage of toddlers getting vitamin A (X7), Percentage of postpartum mothers getting vitamin A (X8), Percentage of active Posyandu (X9), Percentage of toddlers suffering from Pneumonia (X11).
4. GWMPR model parameter estimates found 11 significant predictor variables for the number of stunting cases with the dominant variable being the ratio of active posyandu in South Wawaonii District, Konawe Islands Regency. 9 significant predictor variables for the number of wasting cases with the dominant variable being the percentage of 6 months old babies receiving exclusive breast milk in Padangguni District, Konawe Regency. 11 significant predictor variables for the number of underweight cases with the dominant variable being the ratio of active posyandu located in North Kulisusu District, North Buton Regency. The percentage of toddlers aged 12–59 months is the predictor variable that has the most significant influence on the number of stunting, wasting and underweight cases in the sub-districts of Southeast Sulawesi Province.
5. Segmentation of the number of stunting, wasting and underweight cases using the GWMPR approach which is based on significant predictor variables provides biased results. This is shown by the significant predictor variables, some of which have

a positive influence and a negative influence, but the regional groupings are still considered homogeneous. Therefore, further research needs to be carried out to overcome this, for example using the SEM-GWMPR, GWMPR – MARS methods.

Limitations

Not applicable.

Ethics statements

Data used is secondary data and primary. Secondary data from data from the Southeast Sulawesi Provincial Health Service in 2021, the collection of which was carried out by data management officers. Health Service data was obtained by applying for permission from the head of the Southeast Sulawesi Provincial Health Service. Deep data retrieval study This all data on stunting and wasting cases and nutrition bad in the Southeast Sulawesi Provincial Health Service in 2021 with analysis units sub-district in the district / city in 2021 there will be 222 sub-districts. Next, primary data with conducting Focus Group Discussions (FGD) to confirm and validate research data together Southeast Sulawesi Provincial Health Service.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Fitri Rachmillah Fadmi: Conceptualization, Visualization, Writing – original draft. **Bambang Widjanarko Otok:** Conceptualization, Visualization, Writing – review & editing. **Kuntoro:** Conceptualization, Visualization, Writing – review & editing. **Soenarnatalina Melaniani:** Conceptualization, Visualization, Writing – review & editing. **Riry Sriningsih:** Conceptualization, Visualization, Writing – review & editing.

Data availability

The authors do not have permission to share data.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.mex.2024.102736.

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