Detecting Local Clusters of Under-5 Malnutrition in the Province of Marinduque, Philippines Using Spatial Scan Statistic

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ABSTRACT: Underweight and overweight among under-5 children continue to persist in the island Province of Marinduque, Philippines. Local spatial cluster detection provides a spatial perspective in understanding this phenomenon, specifically in which areas the double burden of malnutrition occurs. Using data from a province-wide census conducted in 2014-2016, we aimed to identify spatial clusters of different forms of malnutrition in the province and determine its relative risk. Weight-for-age z score was used to categorize the malnourished children into severely underweight, moderately underweight, and overweight. We used the multinomial model of Kulldorff's elliptical spatial scan statistic, adjusting for age and socioeconomic status. Four significant clusters across municipalities of Boac, Buenavista, Gasan, and Torrijos were found to have high risk of overweight and underweight simultaneously, indicating existence of double burden of malnutrition within these communities. These clusters should be targeted with tailored plans to respond to malnutrition, at the same time maximizing the resources and benefits.

KEYWORDS: Multinomial model, Kulldorff's elliptical spatial scan statistic, Philippines, spatial analysis, under-5 malnutrition, double burden of malnutrition

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Introduction

Under-5 malnutrition continues to persist in the Philippines, particularly in the island Province of Marinduque, with prevalence of some forms of malnutrition even worsening in recent years.[1] The National Nutrition Council (NNC) through its *Operation Timbang* (OPT)—an annual measurement of weight and height of all children under 6 years old in the community—reported that prevalence of underweight across municipalities in the province ranged from 4% to 12.3% in 2014 and 3.4% to 10.7% in 2015, while overweight 0.5% to 1.3%. Nonetheless, double burden of malnutrition is an emerging issue in the province. The World Health Organization (WHO) describes the double burden of malnutrition as a phenomenon in which there is a "coexistence of undernutrition along with overweight and obesity, or diet-related noncommunicable diseases, within individuals, households and populations, and across the life course."[2]

The role of spatial context in health has long been recognized,[3,4] but only in recent decades in which the use of spatial analysis and GIS have been incorporated in different studies.[3-5] Central to spatial analysis is Tobler's First Law of Geography (TFL),[6] in which in the context of malnutrition, it means that nutritional status of children in neighboring units may tend to be alike than those further apart leading to spatial clusters. One of the commonly used spatial analysis methods is the detection of local spatial clusters.[4] A spatial cluster is defined as an unusual number of cases that occurs within a population in a geographic area over a time period.[7,8] Identifying the clusters where double of burden of malnutrition exists is vital in the formulation of programs and interventions tailored on specific forms of malnutrition and targeted in specific areas. Given that resources are limited, geographic targeting ensures that benefits from interventions or programs are maximized.[8,9]

In the Philippines, only a few studies have used cluster detection techniques in public health.[10-12] One study was conducted to examine global and local spatial clustering of underweight children at the village level in the Province of Marinduque.[13] Yet, no studies have applied local spatial cluster detection methods, particularly at the individual- or household-level and on double burden of malnutrition. This study aimed to locate spatial clusters with double burden of under-5 malnutrition across the province by employing the Kulldorff's elliptical spatial scan statistic in multinomial model.

Methods

Data source

Our study used a cross-sectional design using secondary data from the Community-Based Monitoring System (CBMS) conducted by the Provincial Government of Marinduque in 2014-2016. Community-Based Monitoring System is a household-based local census aimed to collect several information that would support local planning, program design, and implementation. Detailed information on the CBMS methodology can be found elsewhere.[14] Approval on the use of secondary data was obtained from the Provincial Government of Marinduque and CBMS Network Office. The study population focused on malnourished children 0 to

59 months old residing in the province during the data enumeration, which included 1084 children in 987 households.

Study setting

The Province of Marinduque is an island located southeast of Manila with a land area of 959.3 km^2. It has 6 municipalities—Boac, Buenavista, Gasan, Mogpog, Sta Cruz, and Torrijos—with Boac as its capital, and subdivided into 218 villages. The island's terrain is predominantly hilly and mountainous, with fishing and farming as the primary source of income.[13]

Study variables

Due to limited data availability, we only used the results of the OPT on weight-for-age z scores according to sex. Malnourished children were classified into 3 types—severely underweight, moderately underweight, and overweight. A child was considered severely underweight (ie, child's weight was severely low for his or her age) if his or her weight-for-age z score was greater than 3 standard deviations below the median of the WHO reference population, while moderately underweight if greater than 2 and less than 3 standard deviations below the said median. The child was considered overweight if his or her weight was high for his or her age, with weight-for-age z score greater than 2 standard deviations above the median of the WHO reference population. Age and membership to *Pantawad Pamilyang Pilipino Program* (4Ps) or Bridging Program for the Filipino Family were included as covariates. The age refers to the child's age at last birthday and grouped into either 0 to 24 or 25 to 59 months old. Membership of 4Ps is a proxy variable to indicate socioeconomic status, which refers to household's membership to the conditional cash transfer program for the poor in the past 12 months from the conduct of the data collection. Using the 2 covariates, 4 subpopulations were created: 0 to 24 months old who are members of 4Ps and those who are non-members and 25 to 59 months old who are members of 4Ps and those who are non-members.

This study was reviewed and approved (UPMREB -2018-127-01) by the University of the Philippines Manila (UPM) Research Ethics Board.

Data processing and analysis

Non-spatial data were checked for completeness and consistency using Stata Software (Version 12, College Station, TX, USA). Notably, there were no missing non-spatial data. Spatial data were checked and visualized using QGIS version 2.18.19. Two-dimensional Cartesian coordinates were used for all household locations. All spatial data used the same coordinate reference system (CRS) which is World Geodetic System (WGS) 84, European Petroleum Survey Group (EPSG): 4326.

Descriptive statistics such as frequencies and percentages were computed to describe the under-5 malnourished children included in the study. Local spatial cluster detection at the province level, regardless of municipal boundaries, was done using the multinomial model of Kulldorff's elliptical spatial scan statistic.[15-18] The spatial scan statistic considered each malnourished child as a case that is belonging to severely underweight, moderately underweight, or overweight. Considering all possible groupings of these categories, it identified clusters where the distribution of these types of malnutrition among malnourished children may be significantly different from the remaining areas of the study region.[15] This is done by creating an elliptical window (z), of varying size, shape, angle, and centroid, that moves across the study region. For each window at any given position, the relative risk or the ratio of the proportions of the number of children categorized in each type of malnutrition out of the total number of malnourished children inside the window versus outside the window is compared using the likelihood ratio test. The null hypothesis is that the relative risk is the same inside and outside the window, while the alternative hypothesis is that there is an increased risk within the window as compared with outside. The log likelihood ratio (LLR) test statistic for a window z is given below:

$$log\lambda_z = \sum_k \left\{ \begin{array}{l} c_k(z)\log\dfrac{c_k(z)}{C(z)} \\ +(c_k - c_k(z))\log\dfrac{c_k - c_k(z)}{C - C(z)} \end{array} \right\} - \sum_k c_k log\left(\frac{c_k}{C}\right)$$

where c_k is the total number of observations in category k and C is the total number of observations in the whole study area.

The window with the highest LLR (or maximum of log λ_z) is the most likely cluster and the rest are called secondary clusters.[15,18] To determine which of these clusters are statistically significant, the P-values were generated using 999 Monte Carlo simulations.[16,18,19] Clusters with P-value less than .05 were identified as statistically significant.

Maximum geographical cluster size for all analysis using SaTScan™ was set to 50% of the total population.[16,18] The number of angles used were 4, 6, 9, 12, and 15 for shapes 1.5, 2, 3, 4, and 5, respectively.[17,18] To avoid long and narrow clusters and favoring compact clusters, a medium strength non-compactness penalty was used.[17,18] The multiple data sets feature was used to adjust for covariates. Only all significant clusters were reported. The results of the data analysis done in SaTScan™ were imported in QGIS, and all cartographic displays were carried out in the same software.

Results

A total of 1084 under-5 children who are malnourished—either underweight or overweight—were included in the study. Moderately underweight was the most prevalent (75%) across the province. The prevalence of overweight and severely underweight were 13.7% and 10.9% among malnourished children,

Table 1. Prevalence of types of malnutrition among malnourished children under-5 years old in the Province of Marinduque, 2014-2016.

SUBPOPULATION	WEIGHT-FOR-AGE CLASSIFICATION			TOTAL
	OVERWEIGHT	MODERATELY UNDERWEIGHT	SEVERELY UNDERWEIGHT	
0-24 months old with 4Ps	15 (10.1%)	80 (9.8%)	13 (11.0%)	108
0-24 months old without 4Ps	42 (28.4%)	125 (15.3%)	14 (11.9%)	181
25-59 months old with 4Ps	28 (18.9%)	246 (30.1%)	46 (39.0%)	320
25-59 months old without 4Ps	63 (42.6%)	367 (30.1%)	45 (38.1%)	475
Total	148 (13.7%)	818 (75.5%)	118 (10.9%)	1084

respectively. Across subpopulations, higher proportion of those non-4Ps members regardless of age were overweight, while 30% to 39% of the children aged 25 to 59 months old without 4Ps were underweight (Table 1).

In this study, double burden of malnutrition in communities is characterized by the presence of both overweight and underweight. Using the multinomial purely spatial SaTScan™ analysis adjusted by age and 4Ps membership, we determined spatial clusters where the distribution of the forms of malnutrition is significantly different from the remaining areas. The results show 6 spatial clusters, but only 5 were statistically significant as shown in Table 2 and Figure 1.

The primary cluster was in Gasan covering east of Barangay Pingan, south of Barangay Dawis, and west of Barangay Banuyo. The cluster is relatively small, with an area of 3.1 km^2 including 31 malnourished under-5 children. All children inside the cluster had high risk of being overweight, ranging from 2.9 to 13.7 times higher than those outside the cluster. At the same time, all children inside the cluster except for those 25 to 59 months without 4Ps were also at risk of severely underweight. However, the pattern of relative risk within the cluster was different across groups. For instance, 0 to 24 months old children regardless of 4Ps membership were twice as much at risk of being overweight than moderately underweight, while children aged 25 to 59 months without 4Ps had nearly double risk of being severely underweight than being overweight.

The first secondary cluster (cluster 2) was elongated in shape with an area of 229.8 km^2 which contained the inner and mountainous villages of both Boac and Torrijos. All 52 malnourished children had the foremost risk of being severely underweight, with relative risk ranging from 2.9 to 9.9. Children with 4Ps, regardless of age, who are residing inside the cluster, were simultaneously at risk of being overweight and severely underweight. Among those with 4Ps, those aged 0 to 24 months were 4 times and those aged 25 to 59 months were 1.2 times more likely to be severely underweight than overweight within the cluster.

The secondary cluster 3 covered an area of about 115 km^2 including majority of Gasan and areas west of Boac. It had 214 malnourished children. Apart from 0 to 24 months old without 4Ps, all children within the cluster had 1.1 to 1.3 times higher risk of being moderately underweight compared with those outside. It is evident, however, that overweight and severely underweight at the same time posed risks among 0 to 24 months old children without 4Ps living inside the cluster. Although relative risks are lower, 25 to 59 months old with 4Ps were at risk of both overweight and moderately underweight at the same time.

Another significant cluster with an area of 17.5 km^2 was found in northern part of Boac covering 22 barangays including the town center. Within the cluster, there were 69 malnourished children. However, this cluster did not demonstrate the presence of double burden as the most dominant type of malnutrition was moderately underweight only but affecting all subpopulations.

Discussion

The results revealed the presence of double burden of malnutrition in 4 of the 5 statistically significant clusters located across 4 municipalities in southwest of the island. All 4 clusters exhibited simultaneous existence of overweight and severely underweight but affected different population groups depending on where it is located. Only one of these clusters had higher relative risk for overweight and moderately underweight at the same time.

We found that clusters with dual burden of malnutrition exist in both generally poor and non-poor areas. For instance, clusters 1 and 3 mostly cover coastal villages and some upland villages. There is marked poverty in these areas, with low access to sanitary toilet and safe drinking water and had one of the highest proportions of households who experienced hunger due to food shortage.[20] Intuitively, the general profile of the villages within the clusters suggests the presence of undernutrition. These areas have high relative risk of moderately and severely underweight. However, there is also high relative risk for overweight. In cluster 1, it is even higher than the underweight risk. In the Philippines, among children of households headed by fisherfolks, undernutrition is more pronounced but still overnutrition was observed.[21] Therefore, there could also be other factors related to overnutrition among under-5 children in the cluster, regardless of their age and income status. Furthermore, cluster 2 is composed mostly of upland rural

Table 2. Results of multinomial[a] cluster detection analysis showing the significant clusters for types of malnutrition adjusted for age and 4Ps membership, Province of Marinduque, 2014-2016.

CLUSTER	OVERWEIGHT		MODERATELY UNDERWEIGHT		SEVERELY UNDERWEIGHT		LLR	P-VALUE
	NO. OF CASES	RR	NO. OF CASES	RR	NO. OF CASES	RR		
Primary cluster (1)							32.26	.000023
0-24 months old with 4Ps	4	6.18	0	0	2	3.09		
0-24 months old without 4Ps	5	2.92	2	0.35	1	1.66		
25-59 months old with 4Ps	5	13.7	0	0	0	0		
25-59 months old without 4Ps	7	4.82	4	0.43	1	8.3		
Secondary cluster (2)							32.62	.00004
0-24 months old with 4Ps	1	1.47	1	0.26	3	6.18		
0-24 months old without 4Ps	0	0	3	0.61	4	9.94		
25-59 months old with 4Ps	4	2.26	10	0.57	8	2.85		
25-59 months old without 4Ps	1	0.41	6	0.42	11	8.21		
Secondary cluster (3)							24.58	.003
0-24 months old with 4Ps	0	0	20	1.3	2	0.71		
0-24 months old without 4Ps	14	1.39	33	0.99	1	2.1		
25-59 months old with 4Ps	1	0.2	48	1.34	0	0		
25-59 months old without 4Ps	14	1.14	80	1.11	1	0.91		
Secondary cluster (4)							24.02	.0043
0-24 months old with 4Ps	3	5.15	2	0.53	0	0		
0-24 months old without 4Ps	5	3.94	1	0.24	0	0		
25-59 months old with 4Ps	4	2.37	11	0.67	16	2.14		
25-59 months old without 4Ps	13	4.31	10	0.46	4	1.62		
Secondary cluster (5)							22.45	.017
0-24 months old with 4Ps	1	0.28	20	1.3	1	0.33		
0-24 months old without 4Ps	3	0.5	20	1.25	1	0.5		
25-59 months old with 4Ps	0	0	61	1.32	3	0.28		
25-59 months old without 4Ps	2	0.19	65	1.25	3	0.41		

Abbreviations: LLR, log likelihood ratio; RR, relative risk of being either overweight, moderately or severely underweight among malnourished under-5 children in the cluster compared with outside the cluster.
[a]Elliptical scan window; medium non-compactness penalty.

villages, which are also considered as hardly reached areas. Farming is the main source of income and poverty is a problem in these areas. All children in this cluster were highly at risk of severely underweight. However, non-beneficiaries of 4Ps regardless of age were at risk of overweight as well. This shows that specific populations in these areas are more vulnerable to experience double burden of malnutrition. On the contrary, cluster 4 is situated near the business district of the capital of the province. The areas it covers had relatively good socioeconomic profile in terms of income, access to potable water, access to sanitary toilet, and employment.[20] These areas have the foremost risk of being overweight, but they are also equally at risk of being severely underweight. Even in relatively urban areas, pockets of poverty are also present in which underweight would still be a challenge.

This study has several limitations that should be acknowledged. First, the SaTScan™ does not generate corresponding confidence interval for the relative risk, which could provide

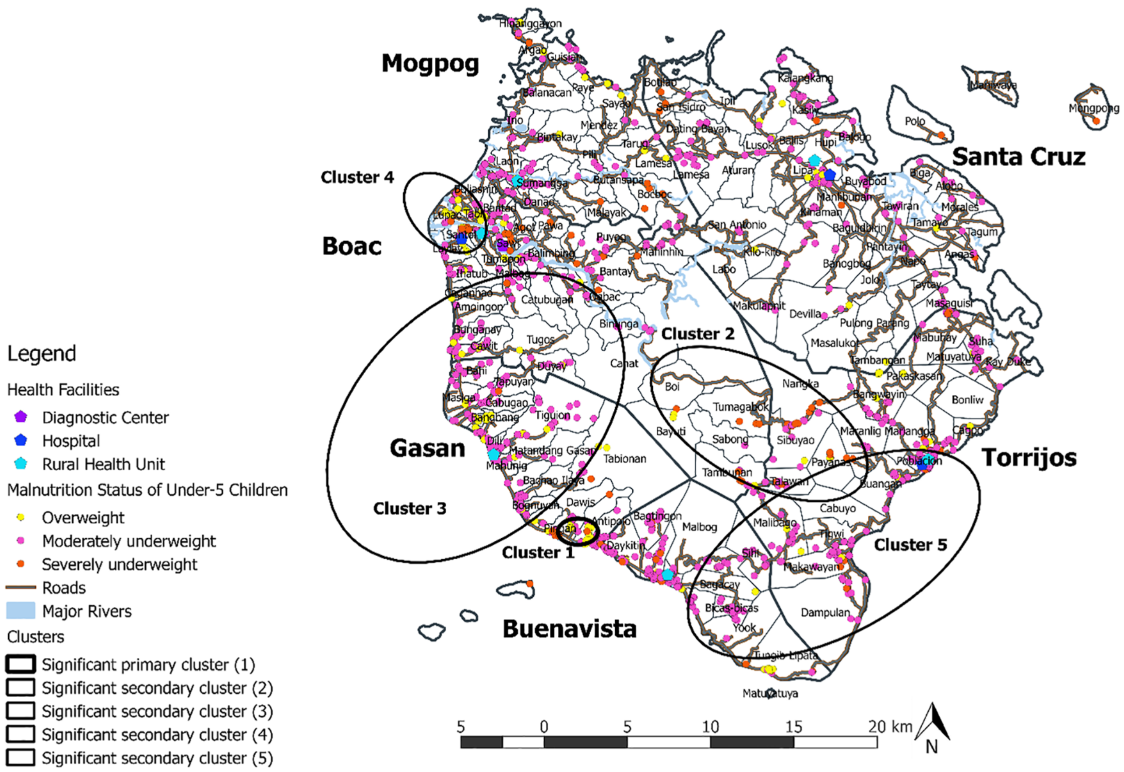

Figure 1. Location of clusters of types of malnutrition among under-5 malnourished children, by age and 4Ps membership status, Province of Marinduque, 2014-2016.

information about the range in which the true value lies with a certain degree of probability. Caution should be exercised when interpreting results. Second, the location data were obtained using the built-in GPS of tablets and mobile phones in which as its limitations, households very close to each other could have the same recorded location. This accuracy can affect the validity of the study results because inaccurate location could provide spurious spatial patterns. However, given that the study area is mostly rural, households are expected to be sparsely distributed. Third, as cluster morphology such as its shape and size are complex, geometric scanning window may not well represent its true morphology. In this study, the scanning window was limited to ellipse and circle only, as special case of ellipse, but true clusters which may appear irregular in shape might not be detected. However, based on the literature, elliptical scanning window has competitive power in detecting irregularly shaped clusters except for the extremely irregular ones.[9,22] Finally, as the data collection period lasted for almost a year from 2014 to 2015 and some in 2016, the nutritional status of the children was also based on these time points.

Considering the evidence of spatial clusters with coexistence of both overweight and underweight in this study, further investigation on factors affecting under-5 malnutrition in the identified clusters within the province could be conducted to provide a comprehensive picture. As this study is purely spatial in nature, further studies could also be done to explore clusters in both time and space as it is also important to consider the temporal trends in understanding public health phenomenon.

Conclusions/Recommendations

Using Kulldorff's elliptical spatial scan statistic in multinomial model, the study showed significant clusters of different forms of under-5 malnutrition among malnourished children, within and across municipalities, where there are both high risk of overweight and severely underweight, and overweight and moderately underweight. This manifests the existence of double burden of under-5 malnutrition in the Province of Marinduque. Variations in the patterns of risk of over and underweight affecting subpopulations differently may suggest underlying local causes at work that warrant further investigation.

The detection of significant clusters reinforces the need to investigate the spatial perspective of malnutrition to uncover specific areas with double burden of malnutrition. It also has important policy implications as availability of this information at the lowest level supports a more decentralized decision-making and planning process. For one, it supports the use of geographic targeting and targeting of specific populations based on some measure of risk. This also enables policymakers to give priority to identified high-risk areas and populations through developing policies and programs in line with local conditions and needs. This way benefits are maximized even with limited government resources.

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Author Contributions

NLCL: Conceptualization, Methodology, Software, Formal analysis, Writing- Original draft preparation. MCP: Methodology, Supervision, Writing- Reviewing and Editing. All authors reviewed and approved the final manuscript.

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