Public Health in Practice 3 (2022) 100224

Contents lists available at ScienceDirect

Public Health in Practice

journal homepage: www.sciencedirect.com/journal/public-health-in-practice

Shared geographic spatial risk of childhood undernutrition in Malawi: An application of joint spatial component model

A. Ngwira

Basic Sciences Department, Lilongwe University of Agriculture and Natural Resources, P.O Box 219, Lilongwe, Malawi

ARTICLE INFO

Keywords:
Joint model
WinBUGS
Malnutrition
Bayesian
Spatial risk

ABSTRACT

Objectives: This study aimed at assessing shared spatial risk of childhood undernutrition indicators in Malawi.
Study design: Cross-sectional design.
Methods: The shared spatial component model was fitted to childhood undernutrition indicators, namely: stunting, wasting and underweight, using 5066 child records of the 2015/16 Malawi demographic health survey data. The spatial components were districts, and were modeled by the convolution prior, with the structured components being assigned the conditional autoregressive distribution.
Results: There is significant clustering of shared spatial risk of stunting and wasting (Moran I = 0.464, p-value = 0.009), and wasting and underweight (Moran I = 0.392, p-value = 0.026), and the risk maps show southern districts, followed by central districts being at greater risk of jointly having stunting and wasting, wasting and underweight, compared to the northern region districts. The shared spatial risk of stunting and underweight is randomly dispersed across the country (Moran I = - 0.044, p-value = 0.539).
Conclusion: Interventions to reduce the shared risk of child undernutrition should focus on the southern region districts and those in the central region, and a suggestion is made to address the issue of overpopulation and effects of climate change.

1. Introduction

Child undernutrition is a form of malnutrition resulting from eating less. Some forms of undenutrition are stunting, wasting and underweight. Stunting is measured by height-for-age z-score (HAZ) and is a sign of chronic food inadequacy. Wasting is measured by weight-for-height z-score (WHZ) and is a manifestation of acute situation related to illness or lack of food. Underweight is measured by weight-for-age z-score (WAZ) and it is a result of either wasting or stunting or both. Child undernutrition is said to be associated with poor survival, poor physical and cognitive development [1] and obesity, later in life [2]. The global burden of childhood malnutrition as of 2020 [3] was 21.3% for stunting, 6.9% for wasting and 5.6% for overweight. In Malawi, it is estimated that 37% of under-five children are stunted, 3% are wasted, 12% are underweight and 5% are overweight, according to the 2015/16 Malawi demographic health survey (MDHS) report [4].

Malnutrition has generally been decreasing from 1992 to 2015/16 in Malawi [4,5]. In this case, stunting has decreased from 55% to 37%, underweight from 24% to 12%, wasting from 6% to 3% and overweight from 9% to 5%. The decrease is claimed to be due to the decreasing poverty levels [6] and increase in women autonomy [7]. Nevertheless, malnutrition problem has remained persistent in Malawi due to the fact that some factors that contribute to malnutrition have not changed significantly. For example, poverty is still considered to be a contributing factor of childhood malnutrition [8]. Other contributing factors include: small sized children at birth, episodes of sicknesses during infancy and HIV mothers [9,10]. Persistent malnutrition in Malawi has also been attributed to differential in community characteristics like availability of facilities in different communities, differential in marriage culture (matrilineal versus patrilineal communities) [11]. In this case, communities with better facilities, like, dairy markets, and those with patrilineal marriages are associated with better nutritional status than those with poor facilities and with matrilineal marriages. Poor education of mothers, being male child, children of rural residence and poor access to clean water are other determinants of malnutrition in Malawi [12] that might have been left unattended. Furthermore, non-exclusive breast feeding is another potential factor of persistent malnutrition in Malawi [13]. Contextual geographical factors, like climatic factors such as high rainfall and temperature may also be playing part in the risk of having childhood malnutrition in Malawi [14].

E-mail address: alfngwira@yahoo.com.

https://doi.org/10.1016/j.puhip.2021.100224
Received 7 March 2021; Received in revised form 19 October 2021; Accepted 16 December 2021
Available online 22 December 2021

Not many epidemiological studies in Malawi on childhood malnutrition have considered geographical contextual spatial risk of childhood malnutrition [14,15]. In addition, these few studies have not considered the shared contextual geographical spatial risk common to multiple malnutrition indicators. In this case, both Ngwira [14] and Kandala et al. [15], investigated the divergent contextual geographical spatial risk, specific to each malnutrition indicator. The shared geographical spatial risk to malnutrition indicators can be described as the risk to indicators due to similar unmeasured or unobserved factors, for example, similar socio-economic, climatic or environmental factors, all influencing the indicators. Some of the studies that have investigated the shared geographic contextual spatial risk of childhood malnutrition on the global scale are Sartorius et al. [16], Takele et al. [17] and Kinyoki et al. [18]. The investigation of shared geographic spatial risk of multiple disease outcomes usually benefit from joint shared spatial component model. The use of this model is based on the assumption that outcomes are correlated, like malnutrition indicators which are found to be pairwise correlated [19–21]. Correlation of malnutrition indicators is based on the fact that they usually share the same biomarkers of the same child, like age, weight and height.

The aim of this study was to investigate shared geographical spatial risk of childhood undernutrition indicators, so as to determine geographical regions (districts) where the indicators are strongly correlated and to hypothesize possible common or shared contextual risk factors for further epidemiological investigation.

2. Methods

2.1. Study area

The study used data of 2015/16 Malawi demographic and healthy survey (MDHS) which covered the whole nation of Malawi. Malawi is in the Southern Africa between latitudes, 9°22'S and 17°03'S and longitudes, 33°40'E and 35°55'E [22]. It has an area of 118480 km^2, length of 900 km and width of about 250 km. It is bordered by Mozambique to the south, south east, and south west, Zambia to the central west and north west and Tanzania to the north and north east. It has three main regions, namely: northern, central and southern region. There are a total of twenty eight districts and the northern region has six districts, that is, Karonga, Rumphi, Chitipa, Mzimba, Nkhata-bay and Likoma. The central region has nine districts, namely: Kasungu, Dowa, Ntchisi, Nkhota-kota, Mchinji, Salima, Dedza, Lilongwe and Ntcheu. There are thirteen districts located in the southern region and they are: Mulanje, Chiradzulu, Blantyre, Balaka, Mangochi, Machinga, Phalombe, Chikwawa, Nsanje, Mwanza, Thyolo, Neno and Zomba. There are four major cities in Malawi which are: Blantyre, Lilongwe, Mzuzu and Zomba. The total population size based on the latest census conducted in 2018 is 17563749 [23]. The southern and central regions are relatively highly populated than the northern region with the population sizes 7750629, 7523340 and 2289780 respectively [23].

2.2. Sampling design and data collection

The 2015/16 MDHS study according to National Statistical Office of Malawi [4], used a two stage cluster sampling with stratification where clusters were stratified by residence (urban/rural) and then in each cluster, households were randomly selected. In the first stage, 850 clusters, comprising of 173 clusters in urban areas and 677 clusters in rural areas were selected by probability proportional to size (PPS) cluster sampling method. In the second stage, 30 households from each urban cluster and 33 households from each rural cluster were selected by systematic sampling. The data from households was then collected using four questionnaires that is, household, woman, man and biomarker questionnaire. The household questionnaire was used to collect information on household characteristics such as type of dwelling unit, source of drinking water, type of toilet, type of house flooring material and ownership of durable goods. The individual woman and man questionnaires were administered to women aged 15–49 years and men aged 15–54 years in the selected households and were used to collect information on background characteristics such as age and education, marriage and sexual activity, maternal and child health, nutrition, fertility preferences, sexually transmitted diseases (STDs) and human immunodeficiency virus (HIV), among others. Biomarker questionnaires were used to collect information on anthropometric measurements such as height and weight, anemia and HIV testing. Anthropometric measurements were recorded for 0–59 months old children and whose mothers were 15–49 years of age.

2.3. Data variables

The study used MDHS child data set, where the unit of analysis is a child less than 5 years (0–59 months). The data set contains information on under-five children such as age, sex, anthropometric measurements (height, weight), anthropometric z-scores such as HAZ, WHZ and WAZ. Furthermore, the data set has information on child health indicators such as immunization coverage, vitamin A supplementation, recent occurrence of illnesses such as diarrhea, fever, cough and treatment of childhood diseases. The data set also contains information on maternal and household characteristics such as maternal education and wealth status, among others.

The response variables of interest considered were childhood undernutrition status indicators: stunting (yes, if HAZ<-2/no, if HAZ≥-2), wasting (yes, if WHZ<-2/no, if WHZ≥-2) and underweight (yes, if WAZ<-2/no, if WAZ≥-2). This definition of the childhood undernutrition indicators was based on WHO 2006 child growth standards [24]. The independent variables considered were child age (in months), mother body mass index (kg/m^2), child sex (male/female), education (no education/primary/secondary/higher), wealth quantile (poorest/poor/rich/richer/richest) and geographical location of the child which was district. The use of these independent variables was based on the literature [15]. Missing values in the response variables were dealt with automatically through Bayesian inference by sampling from their posterior distributions [25]. A few missing values for child age were dealt with, by deleting all records where child age was missing. The standard approach though, was to define the prior distribution for child age and then use posterior estimates for missing values, but this paused a challenge on initializing the Markov chain Monte Carlo (MCMC) chains. The final total number of cases used were 5066.

2.4. Statistical analysis

Bivariate scatter plots were made between two of the three childhood undernutrition indicators to asses correlation. A multiple variable joint shared heterogeneity model of any of the two childhood undernutrition status indicators was then fitted. Specifically, a joint shared spatial model of stunting and wasting, stunting and underweight, and wasting and underweight were fitted. Theoretically, a bivariate shared spatial model of the two Bernoulli distributed health outcomes is defined as follows according to Manda et al. [26]: Let π_{ij1} be the probability of child i in area j of having disease of the first kind, and π_{ij2} the probability of child i in area j of having disease of the second kind. Then the joint shared spatial model of the two diseases is defined as: $\text{logit}(\pi_{ij1}) = \alpha_1 + X^T\beta_1 + \varnothing_j\gamma + \varphi_{j1}$ and $\text{logit}(\pi_{ij2}) = \alpha_2 + X^T\beta_2 + \frac{\varnothing_j}{\gamma} + \varphi_{j2}$, where X is a vector of fixed effects and $\varnothing_j$ is the area level shared spatial component and $\varnothing_{j1}$ and $\varnothing_{j2}$ are the two area level spatial effects which are disease specific. The parameter γ represents the differential gradient of the shared spatial component of the two diseases. The ratio of the scaling parameters, γ to $\frac{1}{\gamma}$ compares the weight of disease 1 relative to disease 2 associated with the shared component. The shared spatial effect, $\varnothing_j$ represents the proxy of the area level unmeasured risk factors influencing both diseases and the disease specific spatial effects, $\varnothing_{j1}$ and $\varnothing_{j2}$,

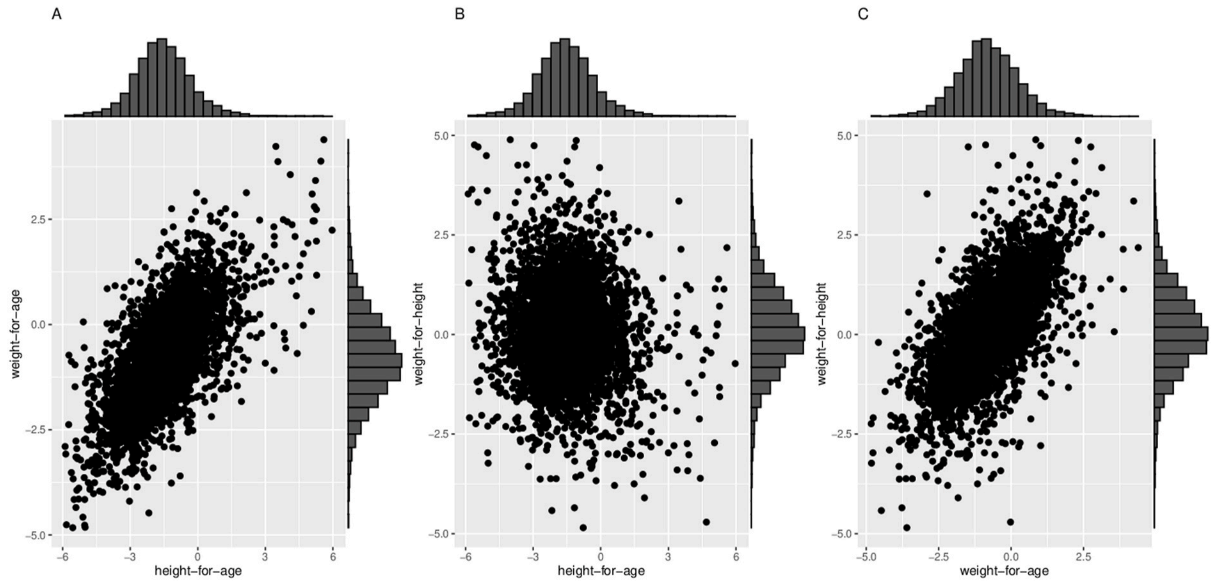

Fig. 1. Pairwise scattered plots of the z-scores for the childhood undernutrition indicators. A (HAZ and WAZ), B (HAZ and WHZ) and C (WAZ and WHZ).

denote the proxies for the unmeasured risk factors specific to the two diseases. The focus of this study was on the investigation of the shared spatial component which represents the shared latent risk between the two diseases. In this case, the shared spatial component was the district of the child, where the shared risk would be observed per district. The rest of the independent variables were used as control variables. Model estimation was fully Bayesian using the Gibbs sampling where model parameters were assigned prior distributions. All fixed effect parameters were assigned the normal distribution with a large variance assuming prior ignorance. All the spatial components were assigned the convolution prior where they were split into structured and unstructured, that is, $u+v$. The unstructured spatial components were assigned the normal distribution with zero mean, that is, $u \sim N(0, \delta_u^2)$, and the structured spatial effects were modeled by the following intrinsic conditional autoregressive (ICAR) normal distribution [27]:

$v_i \middle| v_{j\in\Theta_i} \sim N\left(\frac{\sum_{j\in\Theta_i} v_j w_{ij}}{\sum_{j\in\Theta_i} w_{ij}}, \frac{\delta_v^2}{\sum_{j\in\Theta_i} w_{ij}}\right)$, where w_{ij} was the weight relating adjacent areas, that is, if $w_{ij}=1$, then the adjacent areas i and j were neighbors and if $w_{ij}=0$, then the adjacent areas were not neighbors. The idea behind the ICAR prior for the area spatial effect is that the spatial effect of the geographical location is the average of spatial effects of the neighbors of the given location. The variance parameters were assigned the gamma distribution. Since model inference was Bayesian, design based analysis was not necessary as this is not common in Bayesian inference [28]. According to Kang & Bernstein [29], a true Bayesian analyst does not use survey weights as the focus is on reliable statistical models rather than on assessing the degree to which their estimates are nationally representative or not. The models were fitted by WinBUGS using R2WinBUGS package in R. A total number of 25000 iterations were used and after a burn in of 10000 iterations and thinning of every 30th iteration, 500 iterations were left for posterior analysis. Before posterior analysis, the Markov chain Monte Carlo (MCMC) chains for all parameters were assessed for convergence to the posterior distribution by CODA package in R. The Geweke, Gelman-Rubin and Heidelberger-Welch diagnostic tests confirmed the convergence of MCMC chains. Posterior analysis involved the mapping of the posterior mean of the shared spatial component. Posterior probability that the shared spatial risk for each district was greater than one (i.e. Prob. (RR > 1)) was also plotted to highlight areas with increased risk.

Table 1
Variance parameters of the shared spatial component model.

Model	δ^2 (Shared pattern)	δ^2 (Specific pattern)	% (Shared pattern)
Stunting and wasting			
Stunting	0.007 (0.001, 0.021)	0.008 (0.001, 0.022)	0.439 (0.101, 0.906)
Wasting	0.018 (0.000, 0.074)	0.061 (0.023, 0.116)	0.186 (0.003, 0.592)
Stunting and underweight			
Stunting	0.008 (0.001, 0.026)	0.009 (0.002, 0.020)	0.457 (0.086, 0.842)
Underweight	0.015 (0.001,0.057)	0.019 (0.003, 0.044)	0.399 (0.024, 0.895)
Underweight and wasting			
Wasting	0.174 (0.042, 0.397)	0.029 (0.003, 0.077)	0.842 (0.610, 0.978)
Underweight	0.033 (0.004, 0.103)	0.013 (0.002, 0.058)	0.706 (0.331, 0.966)

2.5. *Ethical issues*

The data used in this study was downloaded from DHS website (www.dhsprogram.com/data) after being granted permission. The MDHS study was approved by Malawi Health Sciences Research Committee and Institutional Review Board of ICF Macro in Calverton, Maryland, USA. Participants gave consent to take part in the study after enumerators asked for their permission.

3. Results

Fig. 1 presents pairwise scattered plots of the z-scores for the childhood undernutrition indicators, namely: the height-for-age, weight-for-age, and weight-for-height. There is linear correlation between weight-for-age and height-for-age z-score (Fig. 1A), and between weight-for-height and weight-for-age z-score (Fig. 1C), since the scatter plots form a linear pattern. There is a very weak correlation between weight-for-height and height-for-age z-score (Fig. 1B), since the pattern in a scatter plot cannot be clearly defined. A shared spatial model of stunting and wasting, stunting and underweight, and then wasting and underweight was then fitted.

Table 1 shows estimates of the variance parameters. The proportion of variance due to shared risk factors between the childhood

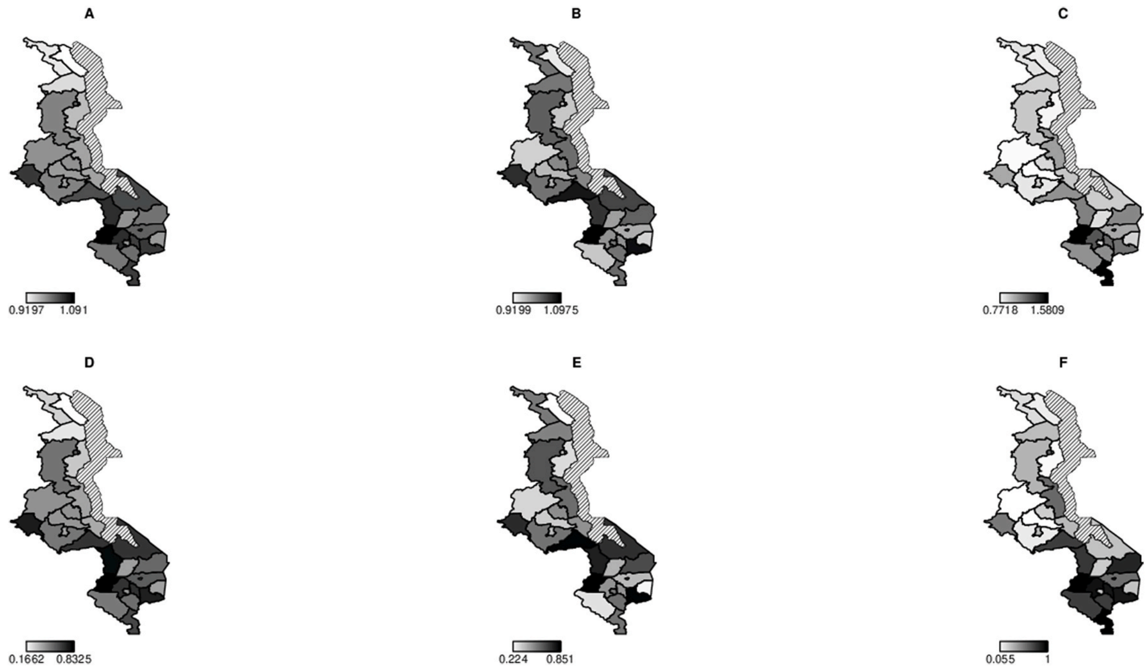

Fig. 2. The shared spatial risk of childhood undernutrition indicators (A–C). (A) Stunting and wasting, (B) stunting and underweight and (C) underweight and wasting. Probability that RR > 1 (D–F). (D) Stunting and wasting, (E) stunting and underweight and (F) underweight and wasting.

undernutrition indicators is very high for wasting and underweight (84% and 71%) and is moderate for stunting and wasting (44% and 19%), and stunting and underweight (46% and 40%). The scaled shared spatial variance parameters for wasting and underweight (0.174 and 0.033) are relatively higher than those of stunting and wasting (0.007 and 0.018) and stunting and underweight (0.008 and 0.015), which are close to zero. This is suggesting insignificant shared spatial variation regarding the latter two pairs of undernutrition status indicators.

Fig. 2 shows the shared spatial pattern of two of the three childhood undernutrition status indicators. The shared spatial risk pattern of stunting and wasting (Fig. 2A) shows many districts in the southern region being at increased risk to both stunting and wasting. One district in the north and west, called Mzimba is also at increased risk to both stunting and wasting. The shared unobserved risk pattern of stunting and underweight (Fig. 2B), shows the high risk areas being randomly distributed across the country. Similar to the shared risk pattern of stunting and wasting, the shared risk pattern of wasting and underweight (Fig. 2C) shows high risk areas being clustered in the south. The posterior probability map regarding stunting and wasting (Fig. 2D) that the estimated risk ratio is greater than one is showing many areas in the center and south having high probability that the risk ratio exceeds one. With regard to stunting and underweight (Fig. 2E), many districts across Malawi, regardless of region, have high probability that the risk ratio is greater than one. Regarding wasting and underweight (Fig. 2F), most districts in the southern region have a higher probability that the shared risk ratio is more than one. Spatial cluster analysis by the Moran I statistic, shows that there is significant clustering regarding shared risk to stunting and wasting (Moran I = 0.464, p-value = 0.009). There is also significant spatial autocorrelation regarding unobserved common risk to wasting and underweight (Moran I = 0.392, p-value = 0.026). The unobserved shared risk to both stunting and underweight is randomly dispersed across Malawi (Moran I = - 0.044, p-value = 0.539).

4. Discussion

The study aimed at exploring the bivariate shared spatial risk pattern of childhood undernutrition indicators in Malawi while using the shared spatial component model. The study has highlighted geographical regions (districts) with high and low contextual spatial risk shared by childhood undernutrition indicators pairwise. This will guide epidemiologist to know districts where the undernutrition indicators co-exists and hence forth investigate underlying risk factors causing the co-existence. The strength of the study is in the use of relatively novel analytical method as the routine methods tend to use separate models to investigate the spatial risk of individual undernutrition indicators.

The study finds that most districts in the southern region and including a few in the central region in Malawi are consistently being at increased risk to all the three pairs of childhood undernutrition indicators. The findings of the study are consistent with the literature [30,31], where it was found that the distribution of underweight and stunting separately, were more prevalent in the south and center than in the northern region. The observed spatial gradient may be due to the effect of common latent factors in play, and an explanation of such factors, is a matter of conjecture. One possible latent factor, could be population density. The southern region has the highest population density (244 people/km^2) seconded by the central region (211 people/km^2) and lastly the northern region with the lowest density (84 people/km^2) [14,23]. The observed spatial gradient of the shared risk to undernutrition indicators, where the high risk coincides with the high population density is supported by the Nube & Sonneveld [30], who also observed that underweight hot spots in Africa were also high population density areas. The population density though itself is not correlated with undernutrition, but the pressure on land and its deterioration in quality due to high population brings about poor nutrition conditions [32].

The other possible driver of the observed shared spatial structure would be the climate. The main factors of climate are rainfall and temperature. High temperature tends to be associated with increased risk of undernutrition [18]. The effect of temperature on malnutrition is due to the fact that temperature is directly linked to aridity according to Quan et al. [33], which in turn has an impact on malnutrition [34]. On the other hand, high rainfall has been found to be associated with increased risk of stunting and low rainfall is associated with increased risk of wasting and underweight [14,18]. The high risk to childhood undernutrition indicators manifested in the southern region in Malawi is therefore as expected since the south eastern part (Zomba, Mulanje and Thyolo) is associated with high rainfall and the south western part including the southern tip (Balaka, Chikwawa and Nsanje) is associated with high temperature and low rainfall [35]. The effect of climate change like flooding would also be the other contributing factor to the observed high risk in the southern region. Areas especially in the southern tip experience flooding from Shire River almost every year. Flooding has been documented to enhance food insecurity by reducing fish catch rates due to dilution of fish in greater volumes of water [36]. Flooding is also associated with child morbidity like diarrhea which in turn is associated with high risk to undernutrition [37].

The weakness of this study though is that the data is a little bit out dated and hence the actual shared spatial risk patterns might have changed over the last five years. Nonetheless, the observed shared risk patterns may still guide the policy makers regarding the areas with increased shared risk in the absence of up to date nationally representative data, as currently there is no up to date data to my knowledge. Furthermore, this study has not investigated the shared spatial risk of all the three childhood undernutrition indicators. This may be the future work to be done. Also, future work may consider shared spatial-temporal risk trends, to investigate shared risk pattern by both space and time.

5. Conclusion

The study finds non-random pattern of the shared risk to stunting and wasting, wasting and underweight, where the southern region is at increased risk compared to the central and northern region. There is no significant clustering regarding the shared risk to stunting and underweight. The observed south to north gradient of spatial risk pattern calls for epidemiologist to further investigate the actual shared risk factors bringing about this spatial risk gradient. In addition, it is suggested that nutrition intervention policies should include interventions to address the effects of climate change and overpopulation on childhood undernutrition status.

Ethics approval

The MDHS study was approved by Malawi Health Sciences Research Committee and the Institutional Review Board of ICF Macro in Calverton Maryland, USA.

Funding

No external sources of funding were received for this work.

Competing interests

The author declares that he has no competing interests.

References

[1] UNICEF, Improving child nutrition: the achievable imperative for global progress. https://data.unicef.org/resources/improving-child-nutrition-the-achievable-imperative-for-global-progress/, 2013. (Accessed 7 May 2020).
[2] WHO, Guidelines: assessing and managing children at primary health-care facilities to prevent overweight and obesity in the context of the double burden of malnutrition. https://www.who.int/publications/i/item/9789241550123, 2017. (Accessed 17 June 2020).
[3] UNICEF, WHO, World Bank, Levels and trends in child malnutrition: key findings of the 2020 edition of the joint child malnutrition estimates. https://www.who.int/publications/i/item/jme-2020-edition, 2020. (Accessed 13 October 2021).
[4] National Statistical Office of Malawi, Malawi demographic and health survey 2015-16. http://www.nsomalawi.mw/, 2017. (Accessed 22 August 2020).
[5] H. Doctor, S. Nkhana-Salimu, Trends and determinants of child growth indicators in Malawi and implications for the sustainable development goals, AIMS Public Heal. 4 (6) (2017) 590–614.
[6] G. Kumchulesi, Explaining the decline in child stunting in Malawi between 2010 and 2015. https://aercafrica.org/wp-content/uploads/2020/11/PB_711_Kumchulesi-Grace.pdf, 2020. (Accessed 15 October 2021).
[7] Z.B. Chilinda, M.L. Wahlqvist, M.S. Lee, Y.C. Huang, Higher maternal autonomy is associated with reduced child stunting in Malawi, Sci. Rep. 11 (2021) 3882.
[8] P.A.M. Ntenda, Y.C. Chuang, Analysis of individual-level and community-level effects on childhood undernutrition in Malawi, Pediatr Neonatol. 59 (2018) 380–389.
[9] K. Maleta, S.M. Virtanen, M. Espo, T. Kulmala, P. Ashorn, Childhood malnutrition and its predictors in rural Malawi, Paediatr. Perinat. Epidemiol. 17 (4) (2003) 384–390.
[10] P.A.M. Ntenda, Association of low birth weight with undernutrition in preschool-aged children in Malawi, Nutr. J. 18 (2019) 51.
[11] L.C. Chikhungu, N.J. Madise, S.S. Padmadas, How important are community characteristics in influencing children's nutritional status? Evidence from Malawi population-based household and community surveys, Heal. Place. 30 (2014) 187–195.
[12] L.K. Chilora, J. Duchoslav, Determinants of children's nutritional status in Malawi. https://ebrary.ifpri.org/digital/collection/p15738coll2/id/133799, 2020. (Accessed 18 October 2021).
[13] K. Machira, T. Chirwa, Dietary consumption and its effect on nutrition outcome among under-five children in rural Malawi, PLoS One 15 (9) (2020), e0237139.
[14] A. Ngwira, Climate and location as determinants of childhood stunting, wasting, and overweight: an application of semiparametric multivariate probit model, Nutrition 70S (2020) 100010, https://doi.org/10.1016/j.nutx.2020.100010.
[15] N.-B. Kandala, L. Fahmeir, S. Klasen, J. Priebe, Geo-additive models of childhood undernutrition in three sub-saharan african countries. https://doi.org/10.1002/psp.524, 2008. (Accessed 13 July 2020).
[16] B. Sartorius, K. Sartorius, R. Green, E. Lutge, P. Scheelbeek, F. Tanser, et al., Spatial- temporal trends and risk factors for undernutrition and obesity among children (<5 years) in South Africa, 2008–2017: findings from a nationally representative longitudinal panel survey, BMJ Open 10 (2020), e034476.
[17] K. Takele, T. Zewotir, D. Ndanguza, Spatial joint modelling of children under-five malnutrition in Ethiopia, J. Hum. Ecol. 70 (1–3) (2020) 132–142.
[18] D.K. Kinyoki, N.B. Kandala, S.O.M. Manda, E.T. Krainski, G.A. Fuglstad, G. M. Moloney, et al., Assessing comorbidity and correlates of wasting and stunting among children in Somalia using cross-sectional household surveys: 2007 to 2010, BMJ Open 6 (2016), e009854.
[19] A. Ngwira, E.C.S. Munthali, K.D. Vwalika, Analysis on the association among stunting, wasting and underweight in Malawi: an application of a log-linear model for the three-way table, J. Publ. Health Afr. 8 (1) (2017) 620.
[20] E.G.W. Kassie, D.L. Workie, Exploring the association of anthropometric indicators for under-five children in Ethiopia, BMC Publ. Health 19 (2019) 764.
[21] S.A. Richard, R.E. Black, R.H. Gilman, R.L. Guerrant, G. Kang, Z.A. Rasmussen, et al., Wasting is associated with stunting, J. Nutr. 142 (7) (2012) 1291–1296.
[22] Malawi Government & FAO, Country profile-Malawi. https://www.fao.org/3/i9753en/I9753EN.pdf, 2006. (Accessed 10 August 2021).
[23] National Statistical Office of Malawi, Population and housing census. http://www.nsomalawi.mw, 2018. (Accessed 14 October 2020).
[24] WHO, WHO Child Growth Standards: length/height-for-age, weight-for-age, weight-for-length, weight-forheight and body mass index-for-age. Methods and Development, 2006. https://apps.who.int/iris/handle/10665/43413. (Accessed 6 July 2020).
[25] Z. Ma, G. Chen, Bayesian methods for dealing with missing data problems, J. Korean Surg. Soc. 47 (2018) 297–313.
[26] S.O.M. Manda, R.G. Feltbower, M.S. Gilthorpe, Review and empirical comparison of joint mapping of multiple diseases, South Afr J Epidemiol Infect 27 (4) (2012) 169–182.
[27] J. Besag, J. York, A. Mollie, Bayesian image restoration, with two applications in spatial statistics (with discussion), Ann. Inst. Stat. Math. 43 (1) (1991) 1–75.
[28] A. Gelman, Struggles with survey weighting and regression modeling, Stat. Sci. 22 (2) (2007) 153–164.
[29] J. Kang, K. Bernstein, On bayesian inference with complex survey data, Biometrics Biostat Int J 3 (5) (2016), 00076.
[30] M. Nubé, B.G.J.S. Sonneveld, The geographical distribution of underweight children in Africa, Bull. World Health Organ. 83 (10) (2005) 764–770.
[31] D.K. Kinyoki, A.E. Osgood-Zimmerman, B.V. Pickering, L.E. Schaeffer, L. B. Marczak, A. Lazzar-Atwood, et al., Mapping child growth failure across low- and middle-income countries, Nature 577 (7789) (2020) 231–234.
[32] B.G.J.S. Sonneveld, M.A. Keyzer, Land under pressure: soil conservation concerns and opportunities for Ethiopia, Land Degrad. Dev. 14 (2003) 5–23.
[33] C. Quan, S. Han, T. Utescher, C. Zhang, Y.-S. Liu, Validation of temperature–precipitation based aridity index: paleoclimatic implications, Palaeogeogr. Palaeoclimatol. Palaeoecol. 386 (15) (2013) 86–95.
[34] K. Grace, F. Davenport, C. Funk, A.M. Lerner, Child malnutrition and climate in Sub-Saharan Africa: an analysis of recent trends in Kenya, Appl. Geogr. 35 (1–2) (2012) 405–413.
[35] K. Vincent, A.J. Dougill, D.D. Mkwambisi, T. Cull, L.C. Stringer, Analysis of existing weather and climate information for Malawi. https://futureclimateafrica.org/wp-content/uploads/2015/02/Malawi-existing-Analysis-of-existing-weather-and-climate-information-for-Malawi-final-with-disclaimer.pdf, 2014. (Accessed 5 February 2021).
[36] D. Tregidgo, J. Barlow, P.S. Pompeu, L. Parry, Tough fishing and severe seasonal food insecurity in Amazonian flooded forests, People Nat 2 (2) (2020) 468–482.
[37] G.G. Poda, C.Y. Hsu, J.C.J. Chao, Factors associated with malnutrition among children <5 years old in Burkina Faso: evidence from the Demographic and Health Surveys IV 2010, Int. J. Qual. Health Care 29 (7) (2017) 901–908.