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Research Article

Spatial Modeling of Overweight and Obesity among Non-Pregnant Women of Reproductive Age in Malawi

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Abstract

The prevalence of overweight (including obesity) among non-pregnant women of reproductive age (WRA) in Malawi substantially increased from 10% in 1992 to 21% in 2016. The main objective of this study was to assess significant factors of overweight (including obesity) among non-pregnant WRA in Malawi using spatial models implemented in R version 4.0.4. The 2015-16 Malawi Demographic and Health Survey (MDHS) datasets were used in this study. Significant determinants of overweight (including obesity) ranged from socio-demographic characteristics to sedentary lifestyle of non-pregnant WRA. Total number of children ever born had significant nonlinear effects on overweight (including obesity) among non-pregnant WRA. Furthermore, we observed significant structured spatial effects on childhood overweight (including obesity) among non-pregnant WRA. To achieve the sustainable development goals 2.2 and 3 (SDG 2.2 and SDG 3) by 2030 in Malawi, the existing nutrition programmes and nutrition policy makers in this country may as well consider interventions based on socio-demographic determinants and spatial variations presented in this paper.

Keywords: Bayesian Inference; Body Mass Index; Obesity; Overweight; Spatial Models; Women of Reproductive Age

Abbreviations

BMI: Body Mass Index; DFID: Department for International Development; DHS: Demographic and Health Survey; DNHA: Department of Nutrition, HIV and AIDS; EU: European Union; FAO: Food and Agriculture Organization; INLA: Integrated Nested Laplace Approximations; LGM: Latent Gaussian Model; LMIC: Low- and Middle-Income Countries; LUANAR: Lilongwe University of Agriculture and Natural Resources; MDHS: Malawi Demographic and Health Survey; MCMC: Markov Chain Monte Carlo; NCD: Non-Communicable Diseases; OR: Odds Ratio; RPL: Rab Processors Limited; SDG: Sustainable Development Goal; SSA: Sub-Saharan Africa; SUN: Scaling up Nutrition; UN: United Nations; UNICEF: United Nations Children's Fund (Formerly United Nations International Children's Emergency Fund); UNIMA: University of Malawi; USAID: United States Agency for International Development; VI: Valid International; WFP: World Food Programme; WHO: World Health Organisation; WRA: Women of Reproductive Age

Introduction

The global prevalence of overweight (including obesity) among women aged 18 years and over was reported as 40% in 2016 [1]. The national prevalence of overweight (including obesity) among non-pregnant women of reproductive age (WRA) in Malawi was about 10% in 1992 and 21% in 2016 [2,3]. Though the prevalence in Malawi was about half the global prevalence in 2016, being one of the low- and middle-income countries (LMIC), it was viewed worthy to assess the nutritional status of non-pregnant women in Malawi because their prevalence of overweight (including obesity) dramatically increased between 1992 and 2016 (about 10% in 1992, 11% in 2000, 13% in 2004, 19% in 2010, and 21% in 2016) [3]. According to World Health Organisation (WHO), a woman is overweight whenever her body mass index (BMI) is at least 25 kg/m^2 and obese whenever her BMI is at least 30 kg/m^2 [1]. Overweight and obese women have higher risk of suffering from diabetes, asthma, sleep disorder, high blood pressure, liver disease, musculoskeletal disorders like osteoarthritis, some cancers like endometrial cancer, and other diet-related non-communicable diseases (NCD) [1]. Consequently, a nation struggles to meet its full potential through loss in productivity, cognitive capacity, and increased health care costs [4].

The United Nations (UN) 2030 agenda is characterized by the 17 sustainable development goals (SDG) which includes SDG 2.2 that by 2030, all forms of malnutrition must be ended and that no one else must be left behind [5]. Furthermore, related to SDG 2.2, SDG 3 focuses on good health and wellbeing for all people by 2030 [5].

The Government of Malawi established the Department of Nutrition, HIV and AIDS (DNHA) in August 2004 to be responsible for nutritional programmes in the country [6]. In 2011, chaired by DNHA, Malawi joined the scaling-up nutrition (SUN) movement [6]. The SUN task force in Malawi is supported by DNHA (Chair); nine line ministries including health, agriculture, education, gender, local government and civic education; UN agencies including United Nations Children's Fund (UNICEF), World Food Programme (WFP), World Health Organization (WHO) and Food and Agriculture Organization (FAO); donors including technical experts from Irish Aid, United States Agency for International Development (USAID), UK Department for International Development (DFID), the European Union (EU) and the GIZ; Civil society; Business community including Valid International (VI), Rab Processors Limited (RPL), Illovo Sugar Company and Consumer Association of Malawi; Academia including the University of Malawi (UNIMA), and Lilongwe University of Agriculture and Natural Resources (LUANAR) to address all forms of malnutrition in Malawi [6].

However, spatial models have not been adequately considered to assess overweight and obesity among non-pregnant WRA in Malawi to provide these nutrition programmes and nutrition policy makers with sufficient evidence-based information to enhance implementation of their nutrition interventions.

In the current study, the main aim was to use spatial models implemented in integrated nested Laplace approximations (INLA) package [7] in R version 4.0.4 to analyse determinants of overweight and obesity among non-pregnant WRA in Malawi. This model was preferred because it appropriately assesses potential risk factors of an outcome of interest (in this study, overweight and obesity) having adjusted for structured spatial effects.

The rest of this paper is arranged as follows. The study population, sources of data, spatial model, posterior inference, and INLA approach are introduced in section 2. The results and their discussions are presented in section 3 and section 4, respectively. Finally, conclusions and recommendations are given in section 5.

Materials and Methods

Study population

The target population for this study was the entire country of Malawi located in the warm heart of Africa. The country comprises of 3 political regions: Northern Malawi, Central Malawi, and Southern Malawi and 28 political districts: Chitipa, Karonga, Nkhatabay, Rumphi, Mzimba, Likoma, Kasungu, Nkhotakota, Ntchisi, Dowa, Salima, Lilongwe, Mchinji, Dedza, Ntcheu, Mangochi, Machinga, Zomba, Chiradzulu, Blantyre, Mwanza, Thyolo, Mulanje, Phalombe, Chikwawa, Nsanje, Balaka, and Neno.

Data sources

Using two-stage cluster sampling design, Malawi Demographic and Health Surveys (MDHS) routinely collect demographic, anthropometric, and biomarkers data on WRA (15 - 49 years) in Malawi since 1992. So far, only five MDHS datasets are available; 1992, 2000, 2004, 2010, and 2015-16. For this reason, the most recent MDHS datasets 2015-16 were used to analyse overweight (including obesity) among non-pregnant WRA in Malawi.

Spatial model

Spatial data refer to trajectories of stochastic processes indexed on the continuum $Y(s) \equiv \{y(s), s \in D\}$ where D is the prescribed subset of $\mathbb{R}^d$. For simplicity, we can represent actual spatial data as a set of outcomes $y = \{y(s_1), y(s_2), y(s_3), \cdots, y(s_n)\}$, with $(s_1, s_2, s_3, \cdots, s_n)$, being a finite collection of n spatial units where measurements are taken. It is worthy to note that $d \in \mathbb{N}$ represents the finite number of dimensions of each of the spatial unit s_i where i = 1, 2, 3, ... n. For instance, if we are interested in using only longitude and latitude as 2-dimensions of a given spatial location s_i, then d = 2 so that $s_i \in D \subseteq \mathbb{R}^2$. Furthermore, note that if D is a continuous surface, then we obtain a spatially continuous stochastic processes whereas if D is a countable set of d-dimensional locations, then we end up with spatially discrete stochastic processes [8].

For simplicity, a generalized additive spatial model is formulated as in the equation:

$$\eta = \hat{\beta}_0 + \sum_i \hat{\beta}_i X_i + \sum_j f_j(Y_j) + f_s(S) + \varepsilon \quad ....(1)$$

Where n is a linear predictor (as a latent variable) based on family of model response variable e.g. mean μ for Gaussian response models and log(odds) for binary response models, $\hat{\beta}_0$ is the overall model intercept estimate, $\hat{\beta}_i$ is an i^{th} fixed effects parameter estimate, X_i is an i^{th} fixed effects covariate as a dummy variable, f_j is the j^{th} nonlinear smoothing function of the j^{th} nonlinear covariate Y_f, f_s is the smoothing function for structured spatial effects attributable to some spatial covariate S, and ε is the residual term including unstructured spatial effects.

Posterior inference

The intuitive method for estimating Bayesian posterior marginal distribution is Markov chain Monte Carlo (MCMC). The alternative method is integrated nested Laplace approximations (INLA) [7]. We used INLA method because it is generally faster and that the solution converges quickly than MCMC for quantile models [7,9].

INLA approach

The INLA [7] package of R software [10] was used for all data analyses. This package implements the INLA method, which performs the direct computation of the marginal posterior densities in a large latent Gaussian model (LGM) sub-class of the fully Bayesian hierarchical models, instead of using the time-consuming MCMC simulation technique. The package is appropriate for all hierarchical models that have the following form:

Level 1: $(y_i|x, \vartheta) \sim \pi(y_i \,|\eta_i, \vartheta)$ ....(2)

Level 2: $(x|\vartheta) \sim N(0, Q^{-1}(\vartheta))$ ....(3)

Level 3: $\vartheta \sim \pi(\vartheta)$ ....(4)

Where ϑ is a set of hyperparameters, x is a latent Gaussian field, $y = (y_1, y_2, y_3, \cdots, y_n)^T$ is a vector of responses, η_i is a linear predictor for an i^{th} individual, and Q(ϑ) is the precision matrix to the latent filed x conditioned on ϑ.

Basically, INLA method is used to approximate a desired marginal posterior density of ϑ using a Gaussian approximation $\tilde{\pi}(x|\vartheta, y)$ for the posterior on the latent field evaluated at posterior mode, x*

$$\pi(\vartheta|y) \propto \left.\frac{\pi(x,\vartheta,y)}{\pi(x|\vartheta,y)}\right|_{x=x^*(\vartheta)} \approx \left.\frac{\pi(x,\vartheta,y)}{\tilde{\pi}(x|\vartheta,y)}\right|_{x=x^*(\vartheta)} \quad ......(5)$$

And is called the Laplace approximation [11-14]. The algorithm uses numerical optimisation to find the mode of the required posterior distribution. The marginal posterior of each x_j and ϑ_k are then calculated using numerical integration over hyperparametric set ϑ, with another Laplace approximation (hence nested Laplace) involved in two marginal posterior computations:

$$\pi(x_j\,|y) \approx \int \tilde{\pi}(x|\vartheta, y)\tilde{\pi}\,(\vartheta|y)d\vartheta \quad .... (6)$$

$$\pi(\vartheta_k\,|y) \approx \int \tilde{\pi}(\vartheta|y)d\vartheta_{-k} \quad ....(7)$$

Where ϑ_{-k} is the vector of all hyperparameters ϑ but with the k-th hyperparameter ϑ_k removed.

Results

This section presents the most significant findings of the current study. It begins with national prevalence trends for overweight (including obesity) among non-pregnant WRA from 1992 to 2016, followed by potential risk factors for overweight (including obesity) among non-pregnant WRA, then concludes with an analysis of spatial model for overweight (including obesity) among non-pregnant WRA.

National prevalence of overweight and obesity among non-pregnant WRA in Malawi

Table 1 shows the trends for national overweight (including obesity) among non-pregnant WRA from 1992 to 2016. The national prevalence slightly increased from 10.2% in 1992 to 11.8% in 2000 and then to 13.4% in 2004. However, the national prevalence dramatically increased from 13.4% in 2004 to 19.5% in 2010 and then to 21.3% in 2016 [3]. Clearly, though the national prevalence in Malawi was about half the global prevalence (about 40%) in 2016 [1], it is worthy to appropriately research more on nutritional status of WRA in Malawi to enhance timely nutrition interventions in Malawi to achieve both SDG 2.2 and SDG 3 by 2030.

Potential risk factors for overweight and obesity among non-pregnant WRA in Malawi

Table 2 summarises the results obtained from bivariate analysis (crosstabulations) between the prevalence of overweight (including obesity) and each of its potential risk factors. All the percentages presented in parentheses were calculated by dividing the cell-specific number by total number within the given variable category. Based on Pearson Chi-square values and their associated p-values (all p-values < 0.01), all the factors presented in table 2 were significantly associated with prevalence of overweight (including obesity) among non-pregnant WRA in Malawi in 2016 at 1% significance level (99% confidence level).

Year	Prevalence (%)
1992	10.2
2000	11.8
2004	13.4
2010	19.5
2016	21.3

Table 1: National prevalence trends for overweight (including obesity) among non-pregnant WRA in Malawi from 1992 to 2016.

Variable	Overweight (%)	Not overweight (%)	Total	Chi-square (p-value)
Age of woman				
15-24	388 (14.52)	2285 (85.48)	2673	233.8 (< 0.001)
25-34	2100 (26.04)	5965 (73.96)	8065	
35-49	3294 (28.96)	8082 (71.04)	11376	
Region of residence				
Northern region	1347 (32.63)	2781 (67.37)	4128	117.9 (< 0.001)
Central region	1953 (25.71)	5592 (74.29)	7527	
Southern region	2500 (23.90)	7959 (76.10)	10459	
Type of residence				
Rural residence	4197 (22.50)	14457 (77.50)	18654	821.3 (< 0.001)
Urban residence	1585 (45.81)	1875 (54.19)	3460	
Marital status				
Never married before	54 (17.25)	259 (82.75)	313	80.2 (< 0.01)
Currently married	4884 (27.12)	13125 (72.88)	18009	
Formerly married	844 (22.26)	2948 (77.74)	3792	
Ethnicity of woman				
Other tribes	1608 (23.80)	5149 (76.20)	6757	245.8 (< 0.001)
Chewa tribe	644 (29.30)	1554 (76.28)	2198	
Tumbuka tribe	956 (23.72)	3074 (76.28)	4030	
Lomwe tribe	227 (29.67)	538 (70.33)	765	
Tonga tribe	642 (24.03)	2030 (75.97)	2672	
Yao tribe	204 (19.79)	827 (80.21)	1031	
Sena tribe	73 (27.24)	195 (72.76)	268	
Nkhonde tribe	862 (31.97)	1834 (68.03)	2696	
Mang'anja tribe	108 (19.85)	436 (80.15)	544	
Ngoni tribe	164 (37.79)	270 (62.21)	434	
Nyanja tribe	294 (40.89)	425 (59.11)	719	
Education level of woman				
No formal education	982 (21.85)	3512 (78.15)	4494	326.1 (< 0.001)
Primary education	3451 (24.54)	10611 (75.46)	14062	

Secondary education	1202 (36.51)	2090 (63.49)	3292	
Higher education	147 (55.26)	119 (44.74)	266	
Wealth index quintile				
Poorest	590 (13.69)	3719 (86.31)	4309	1600.2 (< 0.001)
Poorer	753 (16.99)	3678 (83.01)	4431	
Middle	999 (22.41)	3458 (77.59)	4457	
Richer	1402 (30.29)	3226 (69.71)	4628	
Richest	2038 (47.52)	2251 (52.48)	4289	
Contraceptive method				
None or natural method	2420 (24.45)	7479 (75.55)	9899	115.7 (< 0.01)
Artificial method	3362 (27.52)	8853 (72.48)	12215	
Watching Television				
None or not everyday	4048 (22.26)	14135 (77.74)	18183	925.9 (< 0.001)
Almost daily	1734 (44.11)	2197 (55.89)	3931)	
Work category				
Not working at all	1471 (27.12)	3954 (72.88)	5425	568.3 (< 0.001)
Sedentary office work	1314 (31.24)	2892 (68.76)	4206	
Physically active work	2997 (24.01)	9486 (75.99)	12483	

Table 2: Potential risk factors for overweight (including obesity) among non-pregnant WRA in Malawi.

The age-specific prevalence rates revealed that older non-pregnant women aged 35 - 49 were highly prevalent (about 29%) whereas younger non-pregnant women aged 15 - 24 were least prevalent (about 15%). This finding implied that prevalence of overweight (including) obesity among non-pregnant WRA significantly increased with age. The region of residence was significantly associated with overweight (including obesity) with highest prevalence in the Northern region (about 33%) and least in the Southern region (about 24%).

The non-pregnant WRA were more prevalent in urban residence (about 46%) than in rural residence (about 23%). The most overweight non-pregnant WRA were those who were currently married (about 27%) whereas those never married before were least overweight (about 17%).

Ethnicity was significantly associated with overweight (including obesity) among non-pregnant WRA in Malawi in 2016. The most overweight belonged to Nyanja tribe (about 41%) and Ngoni tribe (about 38%) whereas the least overweight belonged to Yao tribe (about 19.8%) and Mang'anja tribe (about 19.9%).

The level of education was significantly positively associated with overweight (including obesity) among non-pregnant WRA (no formal education 22%, primary education 25%, secondary education 37%, and higher education 55%). This finding revealed that the prevalence of overweight (including obesity) significantly increased with their levels of education.

Similarly, the prevalence of overweight (including obesity) significantly increased with their levels of household wealth index quintiles (poorest 14%, poorer 17%, middle 22%, richer 30%, and richest 48%).

Among the non-pregnant WRA, those who used artificial contraceptive methods were more overweight (about 28%) than those who used natural contraceptive methods (about 24%). The non-pregnant WRA who watched Television almost daily were more overweight (about 44%) than those who either never watched Television at all or watched Television only in some days of the week (about 22%).

Finally, occupation of non-pregnant WRA was significantly associated with their nutritional status. The most overweight were those either with sedentary office work (about 31%) or with no work at all (about 27%) whereas the least overweight were those with physically active work (about 24%).

Fixed effects on overweight and obesity among non-pregnant WRA in Malawi

Since all the variables presented in table 2 were found significantly associated with prevalence of overweight (including obesity), all of them were again included in subsequent spatial model. Table 3 shows the estimated fixed effects (stratum-specific adjusted log odds ratios) together with their standard errors and 95% credible intervals on overweight (including obesity) among non-pregnant WRA. The first category was arbitrarily chosen as the reference category in each of the variables except for region of residence where the Central region was arbitrarily chosen as the reference category. The corresponding stratum-specific odds ratios (OR) were easily computed by exponentiating the estimated log odds ratios.

Variable	Posterior log OR	Standard error	95% Credible interval
(Intercept)	-2.4876	0.1914	(-2.8689, -2.1173)
Age of woman			
15-24	Reference		
25-34	0.6212	0.0640	(0.4966, 0.7475)
35-49	0.8300	0.0635	(0.7064, 0.9554)
Region of residence			
Central region	Reference		
Northern region	0.2368	0.0697	(0.0999, 0.3736)
Southern region	-0.3141	0.0717	(-0.4548, -0.1734)
Type of residence			
Rural residence	Reference		
Urban residence	0.4302	0.0475	(0.3368, 0.5232)
Marital status			
Never married before	Reference		
Currently married	0.6557	0.1620	(0.3451, 0.9808)
Previously married	0.5142	0.1664	(0.1945, 0.8475)
Ethnicity of woman			
Other tribes	Reference		
Chewa tribe	-0.5576	0.1009	(-0.7553, -0.3592)
Tumbuka tribe	-0.5945	0.0940	(-0.7788, -0.4099)
Lomwe tribe	-0.5736	0.1065	(-0.7822, -0.3643)
Tonga tribe	-0.5757	0.1158	(-0.8035, -0.3490)
Yao tribe	-0.5767	0.1088	(-0.7900, -0.3630)
Sena tribe	-0.8492	0.1294	(-1.1037, -0.5958)
Nkhonde tribe	-0.8535	0.1636	(-1.1781, -0.5358)
Mang'anja tribe	-0.9731	0.1501	(-1.2697, -0.6803)
Ngoni tribe	0.2444	0.1047	(0.0387, 0.4497)
Nyanja tribe	0.2189	0.1362	(0.0478, 0.4868)

Education level of woman			
No formal education	Reference		
Primary education	-0.0048	0.0451	(-0.0930, 0.0838)
Secondary education	0.0464	0.0619	(-0.0753, 0.1678)
Higher education	0.3241	0.1422	(0.0456, 0.6038)
Wealth index quintile			
Poorest	Reference		
Poorer	0.2151	0.0607	(0.0961, 0.3344)
Middle	0.5117	0.0590	(0.3963, 0.6276)
Richer	0.8219	0.0582	(0.7081, 0.9364)
Richest	1.2180	0.0661	(1.0884, 1.3481)
Contraceptive method			
None or natural method	Reference		
Artificial method	0.0934	0.0335	(0.0276, 0.1592)
Watching Television			
None or not everyday	Reference		
Almost daily	0.4802	0.0574	(0.3674, 0.5928)
Work category			
Not working at all	Reference		
Sedentary office work	0.1689	0.0399	(0.0906, 0.2471)
Physically active work	-0.2301	0.0489	(-0.3261, -0.1341)

Table 3: Fixed effects on overweight (including obesity) among non-pregnant WRA in Malawi.

The odds for overweight (including obesity) among non-pregnant women aged 25 - 34 was about 1.86 times the odds for overweight (including obesity) among non-pregnant women aged 15 - 24 (log OR = 0.6212, OR = $e^{0.6212}$ = 1.86). An OR of 1.86 (above 1) implied that a non-pregnant aged 25 - 34 had significantly higher likelihood of being overweight (or obese) than the one aged 15 - 24. This finding was statistically significant with 95% credibility because the 95% credible interval for log OR entirely contained positive values only excluding zero (95% C.I. = (0.4966, 0.7475)). Similarly, the odds for overweight (including obesity) among non-pregnant women aged 35 - 49 was about 2.29 times the odds for overweight (including obesity) among non-pregnant women aged 15 - 24 (log OR = 0.8300, OR = $e^{0.8300}$ = 2.29). This result was also statistically significant with 95% credibility because the 95% credible interval for log OR entirely contained positive values only excluding zero (95% C.I. = (0.7064, 0.9554)). Clearly, these findings concurred with those in section 3.2 that prevalence of overweight (including obesity) among pregnant WRA significantly increased with age.

On one hand, the odds for overweight (including obesity) among non-pregnant WRA who resided in the Northern region was significantly about 1.27 times the odds for overweight (including obesity) among those who resided in the Central region (log OR = 0.2368, OR = $e^{0.2368}$ = 1.27, 95% C.I. = (0.0999, 0.3736)). On the other hand, the odds for overweight (including obesity) among those who resided in the Southern region was significantly about 0.73 times the odds for overweight (including obesity) among those who resided in the Central region (log OR = -0.3141, OR = $e^{-0.3141}$ = 0.73, 95% C.I. = (-0.4548, -0.1734)). An OR of 0.73 (below 1) implied that those who resided in the Southern region had significantly lower likelihood of being overweight (or obese) than those who resided in the Central region. Clearly, these findings concurred with those in section 3.2 that prevalence of overweight (including obesity) was significantly highest in the Northern region and significantly least in the Southern region.

Following similar fashion, the non-pregnant WRA who resided in urban areas had significantly higher likelihood of being overweight (or obese) than those who resided in rural areas (OR = 1.54). Those who were currently married had significantly higher likelihood of being overweight than those who were never married before (OR = 1.93) whereas those who were formerly married had significantly higher likelihood of being overweight (or obese) than those who were never married before (OR = 1.67).

All ethnic groups were significantly different from the reference ethnic group (other tribes) because all of them excluded zero in their 95% credible intervals. On one hand, only the non-pregnant WRA belonging to two ethnic groups had significantly higher likelihoods for overweight (including obesity) than those belonging to other tribes; Ngoni tribe (OR = 1.28) and Nyanja tribe (OR = 1.24). On the other hand, those belonging to the rest of the ethnic groups presented in table 3 had significantly lower likelihoods for overweight (including obesity) than those belonging to other tribes with Mang'anja tribe having the least likelihood (OR = 0.38).

The odds for overweight (including obesity) among non-pregnant WRA with primary education as their highest level of education was about 0.995 times the odds for overweight (including obesity) among those with no formal education (log OR = -0.0048, OR = $e^{-0.0048}$ = 0.995). However, this finding was not significant at 95% credibility because the OR is almost 1 and the 95% credible interval for log OR contained zero (95% C.I. = (-0.0930, 0.0838)). The odds for overweight (including obesity) among non-pregnant WRA with secondary education as their highest level of education was about 1.05 times the odds for overweight (including obesity) among those with no formal education (log OR = 0.0464, OR = $e^{0.0464}$ = 1.05). However, this finding was not significant at 95% credibility because the OR is almost 1 and the 95% credible interval for log OR contained zero (95% C.I. = (-0.0753, 0.1678)). The odds for overweight (including obesity) among non-pregnant WRA with higher education as their highest level of education was about 1.38 times the odds for overweight (including obesity) among those with no formal education (log OR = 0.3241, OR = $e^{0.3241}$ = 1.38). This result was significant at 95% credibility because the 95% credible interval for log OR entirely contained positive values only excluding zero (95% C.I. = (0.0456, 0.6038)).

For household wealth, the estimated log odds increased from poorer to richest index quintiles and all their 95% credible intervals for log OR entirely contained positive values only excluding zero implying that the prevalence of overweight (including obesity) among non-pregnant WRA significantly increased with their levels of household wealth index quintiles (poorer OR = 1.24, middle OR = 1.67, richer OR = 2.27, and richest OR = 3.38).

The non-pregnant WRA who used artificial contraceptive methods had significantly higher likelihood for overweight than those who used natural contraceptive methods (OR = 1.10). Those who watched Television almost daily had significantly higher likelihood for overweight than those who either never watched Television at all or watched Television only in some days of the week (OR = 1.62).

Finally, the non-pregnant WRA with sedentary office work were significantly more likely to be overweight (or obese) than those not working at all (OR = 1.18) whereas those with physically active work were significantly less likely to be overweight (or obese) than those not working at all (OR = 0.79).

Nonlinear effects on overweight and obesity among non-pregnant WRA in Malawi

Figure 1 displays the nonlinear effects of total number of children ever born on overweight (including obesity) in among non-pregnant WRA in Malawi in 2016. Clearly, the prevalence of overweight significantly decreased as the total number of children ever born increased from 0 to 5 and then significantly increased as the total number of children ever born increased from 5 onwards.

Figure 1: Nonlinear effects of total number of children ever born on overweight (including obesity) among non-pregnant WRA in Malawi.

Spatial effects on overweight and obesity among non-pregnant WRA in Malawi

Figure 2 displays the structured spatial effects on overweight (including obesity) among non-pregnant WRA in Malawi in 2016. The maps on the left (Figure 2a) show the posterior log odds ratios attributable to the structured spatial effects whereas those on the right (Figure 2b) show the significance of these effects with 95% credibility.

A range of colours from black (strongest negative) to yellow (strongest positive) were used to display the intensity of spatial effects within regions. Only three colours were used for discriminating significance of the effects. Firstly, black colour (-1) corresponded to significant negative structured spatial effects on overweight (including obesity). Secondly, yellow colour (+1) corresponded to significant positive structured spatial effects on overweight (including obesity). Lastly, purple colour (0) corresponded to non-significant structured spatial effects on overweight (including obesity).

The significant positive structured spatial effects were observed in four districts in the Northern region; Chitipa, Karonga, Nkhatabay, and Likoma; only Ntchisi district in the Central region; and only Blantyre district in the Southern region (Figure 2a and 2b).

The significant negative structured spatial effects were observed in three districts in the Central region; Mchinji, Dedza, and Salima; and in 6 districts in the Southern region; Mangochi, Chiradzulu, Phalombe, Mulanje, Chikwawa, and Nsanje; and none in the Northern region (Figure 2a and 2b).

Finally, the rest of the districts of Malawi were not associated with significant structured spatial effects in 2016.

Figure 2: Structured spatial effects and their significance on overweight (including obesity) among non-pregnant WRA in Malawi.

Discussion

The inference used in this study was fully Bayesian and the posterior marginal distributions were estimated using INLA package in R 4.0.4. The INLA approach was chosen because it is faster than MCMC approach for Bayesian models with high-dimensional hyperparametric space [7].

Most of the findings in this study were similar to published findings in related studies within sub-Saharan Africa (SSA). Firstly, a study on determination of factors associated with nutritional status of WRA in Nigeria was conducted in 2021 using quartile regression methods [15] and found similar results. Like the findings in this study, it also found that the age groups 25 - 34 and 35 - 49, total number of children ever born more than 6, urban residence, being either currently married or formerly married, attaining post-primary education, and belonging to middle or richer or richest household wealth index quintiles were significantly associated with increased likelihood of overweight (including obesity) among non-pregnant WRA in Nigeria in 2013 (the most recent DHS datasets that was available for Nigeria by then, currently 2018 datasets are available for Nigeria).

Secondly, a study on unhealthy bodyweight among women in Malawi was done in 2021 using multilevel multinomial logistic regression analysis on 2015-16 MDHS datasets [16] and found similar results. It also found that the age groups 25 - 34 and 35 - 49, urban residence, being either currently married or formerly married, attaining secondary or higher education, and belonging to middle or richest household wealth index quintiles, using oral contraceptive pills, belonging to Ngoni or Nyanja tribes, residing in the Northern region, and watching Television most frequently were significantly more likely to be overweight (or obese) among women in Malawi in 2016.

Thirdly, a study on overweight and obesity among women of reproductive age in Malawi was done in 2021 using 2-level multilevel multivariable logistic regression models on 2015-16 MDHS datasets [2]. It also found that white collar jobs, low exposure to community mass media, age groups 15 - 24 and 35 - 49, residing in the Northern region, urban residence, higher education, and richest households were significantly more likely to be overweight (or obese) among non-pregnant WRA in Malawi in 2016.

Lastly, a study on overweight and obesity among women in 32 SSA countries was done in 2016 using standardized pooling techniques on all DHS datasets for the 32 countries between January 2005 and December 2013 [17]. The main finding was that urban residence, higher education, and richest households were significantly more likely to be overweight (or obese) among women in these 32 SSA countries between 2005 and 2013.

Based on the findings in this study and the other similar studies [2,15-17], it is evident that either negligence or lack of awareness lead to high prevalence rates within SSA countries and other LMIC. For instance, some ethnic groups such as Ngoni and Nyanja tribes in Malawi do believe that being too fat with huge a belly is a symbol for being rich and a source of respect and honour within their communities such that they deliberately consume lots of meat, beers, and fatty diets. Most women who either attain higher education or belong to rich households do carelessly spend on purchasing unhealthy foods such as fast restaurant takeaways which gradually promotes overweight and obesity. Some women are not adequately guided on how to choose their right artificial contraceptive methods which might lead to hormonal imbalance that can eventually lead to overweight and obesity complications. Watching Television almost daily is viewed as one of the best ways to enhance awareness to desirable nutrition tips among women. However, staying tuned to Television more than 6 consecutive hours every day becomes a sedentary habit which can significantly lead to overweight and obesity complications. Finally, most white-collar job women do enjoy not doing any kind of manual work at all both at their workplaces and their homes. This mindset must be renewed and transformed because it is a sedentary behaviour which eventually leads to serious overweight and obesity complications. Therefore, all nutrition programs and nutrition policy makers must consider timely nutrition awareness campaigns on causes and consequences of overweight and obesity, food choices and healthy food habits, and minimum physical activity levels to circumvent sedentary behaviours.

The major strength of this study is that it appropriately modelled overweight (including obesity) among non-pregnant WRA in Malawi in 2016 using Bayesian spatial model which adequately accounted for structured spatial effects.

One of the limitations of this study was that the only most reliable source of data was the most recent 2015-16 MDHS datasets which was collected 5 years ago. The second limitation was that some important determinants of overweight and obesity among women were not collected by MDHS such as food choices, health habits, and physical activity levels. The last limitation was that all the associations reported in this paper were merely statistical such that no further biological or epidemiological theories were accounted for in the study design. Therefore, there a is need for further research to determine whether the significant determinants identified in this study were causal factors or merely confounding factors of overweight (including obesity) among non-pregnant WRA in Malawi. If they were merely proximate determinants, then there will be need for more research to identify the actual causes of overweight (including obesity) among non-pregnant WRA in Malawi.

Conclusion

The age groups 25 - 34 and 35 - 49, Northern region of residence, urban residence, being either currently married or formerly married, belonging to Ngoni or Nyanja tribes, attaining higher education, belonging to richer or richest household wealth index quintiles, using artificial contraceptive methods, watching Television almost daily, and sedentary occupation were significantly associated with increased likelihood of overweight (including obesity) among non-pregnant WRA in Malawi in 2016.

It was also noticed that the likelihood of being overweight (or obese) among non-pregnant WRA in Malawi in 2016 significantly reduced as the total number of children ever born increased from 0 to 5 whereas it significantly increased as the total number of children ever born increased from 5 upwards.

Furthermore, only six districts out of the 28 districts of Malawi; Chitipa, Karonga, Nkhatabay, Likoma, Ntchisi, and Blantyre were significantly associated with high prevalence rates of overweight (including obesity) among non-pregnant WRA in Malawi in 2016.

We recommend that scaling-up nutrition programs and nutrition policy makers should consider timely interventions based on significant socio-demographic factors, biomarkers, and spatial variations of overweight (including obesity) among non-pregnant WRA in Malawi as reported and discussed in this paper.

Availability of Data and Material

The datasets analysed during the current study are available in the "Measure DHS Program" repository, https://dhsprogram.com/data/available-datasets.cfm. Note that DHS datasets are publicly available on this website but that are downloadable only upon request to the Measure DHS Program.

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Authors' Contributions

OPLM was the principal investigator, conducted all statistical analyses, and wrote the entire draft manuscript alone.

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