Iranian J Publ Health, Vol. 42, No.6, Jun 2013, pp. 581-587

Original Article

Mapping the Obesity in Iran by Bayesian Spatial Model

Maryam FARHADIAN [1], *Abbas MOGHIMBEIGI* [1,2], *Mohsen ALIABADI* [3]

1. Dept. Of Biostatistics and Epidemiology, School of Public Health, Hamadan University of Medical Science, Hamadan, Iran
2. Research Center for Behavioral Disorders and Substance Abuse, Hamadan University of Medical Science, Hamadan, Iran
3. Dept. Of Occupational Health, School of Public Health, Hamadan University of Medical Science, Hamadan, Iran

***Corresponding Author:** Tel: +98 811 8380090 Email: moghimb@yahoo.com

(Received 25 Dec 2012; accepted 17 Mar 2013)

Abstract

Background: One of the methods used in the analysis of data related to diseases, and their underlying reasons is drawing geographical map. Mapping diseases is a valuable tool to determine the regions of high rate of infliction requiring therapeutic interventions. The objective of this study was to investigate obesity pattern in Iran by drawing geographical maps based on Bayesian spatial model to recognize the pattern of the understudy symptom more carefully.

Methods: The data of this study consisted of the number of obese people in provinces of Iran in terms of sex based on the reports of non-contagious disease's risks in 30 provinces by the Iran MSRT disease center in 2007. The analysis of data was carried out by software R and Open BUGS. In addition, the data required for the adjacency matrix were produced by Geo bugs software.

Results: The greatest percentage of obese people in all age ranges (15-64) is 17.8 for men in Mazandaran and the lowest is 4.9 in Sistan and Baluchestan. For women the highest and lowest are 29.9 and 11.9 in Mazandaran and Hormozgan, respectively. Mazandaran was considered the province of the greatest odds ratio of obesity for men and women.

Conclusion: Recognizing the geographical distribution and the regions of high risk of obesity is the prerequisite of decision making in management and planning for health system of the country. The results can be applied in allocating correct resources between different regions of Iran.

Keywords: Mapping, Obesity, Bayesian Spatial Model, Iran

Introduction

Obesity and overweight are regarded be the most common metabolic disorders and an important disease of the recent decades. Obesity is the predisposing factor of most non-contagious diseases, which allotted a considerable contribution of diseases and disabilities. Since 1977, WHO has announced obesity as a major problem in developed and developing countries (1). Different studies have been carried out to examine the dimensions and spread of this phenomenon. These studies indicate the high incidence of obesity, overweight, and abdominal obesity in different parts of Iran with obesity rate reported greater for women than man (2-5).

To prevent most diseases and obesity-induced disorders in nationwide, we have felt that implementation of applied researches to recognize the prevalence patterns of this phenomenon as the most important rubric in health science researches. Drawing the geographic maps to recognize the grounding reasons and related data for obesity can be the first stop. In fact, disease mapping is a collection of statistical methods, which is applied to gain careful estimates of incidence of mortality or disease, and to compile them in geographic maps (6). Disease mapping has a long history in epidemiology, which may be defined as the estimation and presentation of summary measures of health outcomes. Disease mapping are valuable tools to determine the regions with high risk of infliction, which need therapeutic or intervention programs. In the problems of disease mapping, disease distribution has a spatial form. To find the deviation from the expected value of disease in the society and determine the regions, which have risk higher than the expected one, are the goals of mapping. Traditionally, Standardized Mortality Ratio (SMR) was used for the disease map presentation, but has many drawbacks. It is the ratio estimate of observed and expected, which yield produce large changes in estimate while small changes in expected value. Furthermore, when a minimum expectation is found, the SMR will be very large, so this SMR is a saturated estimate of relative risk (7). Therefore, crude risks are not trusty values to map the diseases since they are inaccurate in very small regions, also rates with large chance variation tend to highlight the map and such map does not yield meaningful/useful interpretation(8). Disease mapping has a long history in epidemiology as part of the classic triad of person/place/time. John snow, 19th century used point map technique to investigate the epidemics of plague in London(9). The scattering of data and possible correlation of the observed data in adjacent regions is a great barrier for which formulating data in Bayesian hierarchical model has been proposed. Model-based disease mapping (Bayesian) predict the local area risks ensemble in an optimal way, separate systematic variability from random noise and produce clean maps from random noise and any outcomes of population variation (10).

Clayton and Kaldor proposed the hierarchical models and related empirical Bayesian inference for standardized mortalities when there is a spatial correlation between the observations in neighboring regions (11). In the recent years, different spatial models have been proposed for hidden hierarchical levels. Since the nearby regions have the same rates of disease or mortality, the spatial pattern must be considered in map parameter's estimation. Therefore, to evaluate such cases, Bayesian method has been proposed, which incorporates the information related to deaths and the cases observed in each region and that related to relative risks of the whole region in terms of the prior distribution (6). In another word, in the Bayesian spatial models, the purpose is to obtain the smooth estimates of odds ratio (OR). Bayesian hierarchical models are typically used to produce such maps, where the spatial pattern in disease risk is represented by a set of random effects. These random effects are often assigned by a conditional autoregressive (CAR) prior (12-13). There have been carried out some studies via Bayesian methods like mapping geographical variations related to acute heart infarcts, Parkinson, the diabetes type I (6).

Due to the lack of specific mapping health symptoms such as obesity through spatial Bayesian methods, we have set out to draw a geographical map based on Bayesian spatial method to recognize the pattern of obesity in Iran. The aim of this study was to produce accurate map of obesity based on estimated odds ratio in Iran.

Materials and Methods

The data on this study consist of the number of obese people in the population of provinces in terms of gender based on the latest published report of risk factors of non contagious diseases in 30 provinces in 2007 presented by the disease center of health, treatment and medical education of Iran (14). Obesity and overweight evaluation have been, based on the criterion of WHO, the body mass index (BMI), obtained by dividing weight (kg) on height squared (m2). The index greater than 30 is considered the represent of obesity, in addition, the data on the location of each province expressed as the adjacency matrix, was used. The population of men (women) was shown in each province by N_i and the number of people with BMI>30 as y_i. Assume that the number found obese people at the location i is y_i out of N_i

sampled, then y_i *is* a binomial random variable, $y_i \sim Bin\,(N_i, p_i)$, where p_i is the proportion infected at each location. The ordinary logistic model is given by

$$\log(\frac{p_i}{1-p_i}) = \alpha_0 + b_i$$

Where α_0 (the intercept) indicates the logarithm of global mean odds of the entire country. b_i is the random effect specific to the region which shows the logarithm of remaining or unexplained odds ratio of obesity in the i-th province. In fact, b_i is considered to be the hidden risk factor effect. In addition, to consider spatial correlation between spatial effects of bi in neighboring provinces, the conditional auto regression was used and Monet Carlo Markov Chain (MCMC) algorithm and gibes and Metropolis Hasting sampling was used for prior distribution. In these conditions, the estimation of prevalence of obesity in the i-th province was calculated by:

$$p_i = \frac{\exp(\alpha_0 + b_i)}{1 + \exp(\alpha_0 + b_i)}$$

We refer to $OR = \exp(b_i)$ an odds ratio, which is a ratio of the local area odds over the global mean odds (10). The results of a Bayesian disease-mapping analysis are presented in the form of a map displaying a point estimate of the odds ratio for each province. The data analysis was carried by R and Open BUGS software. In addition, the required data in adjacency matrix were generated by Geo bugs software.

Also we assessed MCMC convergence of all model parameters by trace plots and autocorrelation plots of the MCMC output after burn-in. Furthermore, we look at different diagnostics to check the convergence of an MCMC algorithm such as the Geweke's convergence diagnostic (Z-score). This is supported in the coda package in R. the result showed that the MCMC algorithm is convergent.

Results

The result of this study related to prevalence of obesity and obesity rank of the provinces are presented in Table 1. Based on the findings, the greatest percentage of the obese people in all age ranges (15-64 yr) was in Mazandaran (17.8) and the lowest in Sistan and Baluchestan (4.0) for men. The figure for women was 29.4 and 1.9 for women in Mazandaran and Hormozgan, respectively.

The odds ratio of obesity in various provinces of the country is shown in terms of men and women in the Table1. Based on the results, Mazandaran (OR=1.71), Tehran (1.56) and Gilan (1.51) was recognized to be the provinces of the greatest odds ratio for women followed by Khozestan (1.48), east Azerbaijan (1.47), west Azerbaijan(1.44), Ardabil (1.34) and Kermanshah (1.26) as high risk provinces and Qom(1.23), Ghazvin (1.22), Golestan (1.17), Zanjan (1.04), Kordestan (1.02), Semnan (1.01) and Yazd (1.00) as medium risk and other provinces as low risk.

For men, Mazandaran (2.02) was the province of the greatest odds ratio followed by Tehran (1.57) and Ardabil (1.50), Qom (1.48), Zanjan (1.36), west Azerbaijan (1.32), Yazd (1.27), Khozestan (1.26), Semnan (1.24), east Azerbaijan (1.20), Golestan (1.19), Esfahan (1.19), Gilan (1.08), Razavi Khorasan (1.00), Ghazvin (1.00) and respectively and other provinces have low risk.

The mapping of estimation of the obesity OR for men and women in the provinces, based on Bayesian spatial method and the results of Table 1 are presented in Fig.1 and Fig.2. The results show that Bayesian spatial method can illustrate the odds ratio of obesity in the country geographically. The estimates of Bayesian spatial model are taken from 10000 iterations and the map is drawn through the mean of iterative estimates.

Discussion

With the emerge of medical and health data expressed in terms of geographical areas, the study of mapping diseases in small areas has been suggested as a new technique in geographical epidemiology (7). As the geographical areas usually consist of populations with different sex and age structure, using crude estimates in drawing geographical maps is misleading.

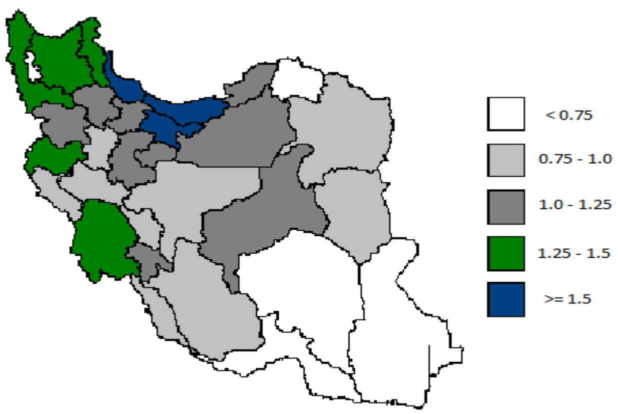

Fig. 1: The distribution of the obesity prevalence among females in Iran in 2007 using Bayesian spatial model

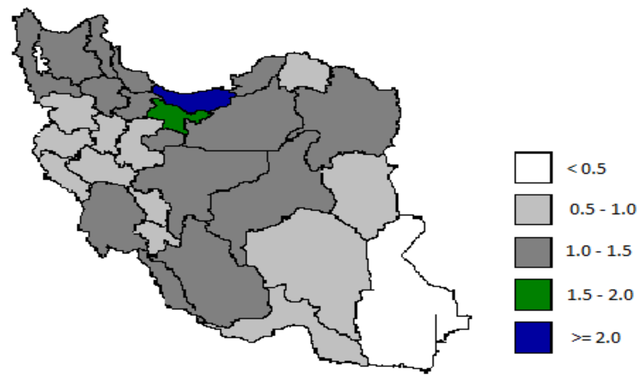

Fig. 2: The distribution of the obesity prevalence among males in Iran in 2007 using Bayesian spatial model

Table1: Odds ratio estimated of obesity and obesity rank by province in Iran in 2007

	Province	Observed number BMI>30 Y_i		Population size N_i		Rank of province based on estimated OR		Spatial estimate of OR along with SEs			
		Female	Male	Female	Male	Female	Male	Female		Male	
1	Zanjan	69433	41439	337051	326288	12	5	1.04	0.004	1.36	0.007
2	Yazd	65461	43777	327307	364812	17	7	1.00	0.004	1.27	0.006
3	west Azerbaijan	253466	121205	960099	977463	6	6	1.44	0.003	1.32	0.004
4	Tehran	1344702	731511	4802508	5079939	2	2	1.56	0.001	1.57	0.002
5	Sistan	90709	34420	697764	702443	29	30	0.60	0.002	0.48	0.002
6	Semnan	41307	25292	204489	216174	15	10	1.01	0.005	1.24	0.008
7	Qom	82958	50706	353013	370120	9	4	1.23	0.004	1.48	0.007
8	Ghazvin	92729	39840	396278	410719	10	16	1.22	0.004	1.00	0.005
9	Mazandaran	318862	188357	1066428	1058188	1	1	1.71	0.003	2.02	0.005
10	Markazi	94194	37952	470972	474396	16	22	1.00	0.003	0.81	0.004
11	Lorestan	97342	39670	586399	592089	21	25	0.80	0.002	0.67	0.003
12	Kordestan	99867	44944	491954	493893	14	20	1.02	0.003	0.93	0.004
13	Boyerahmad	43471	13115	212053	211527	13	29	1.03	0.005	0.61	0.005
14	Khozestan	383712	175026	1421156	1470809	4	8	1.48	0.002	1.26	0.003
15	South Khorasan	32306	13552	204467	205328	25	27	0.75	0.004	0.66	0.005
16	Razavi Korasan	300973	182323	1904893	1879617	24	15	0.75	0.001	1.00	0.002
17	North Khorasan	39588	16792	274920	258337	28	28	0.67	0.003	0.65	0.005
18	Kermanshah	157202	61919	655008	665797	8	18	1.26	0.003	0.96	0.004
19	Kerman	130954	60522	873024	903317	27	26	0.70	0.002	0.67	0.002
20	Eilam	32089	13876	189873	192720	20	23	0.81	0.004	0.72	0.006

Table 1: Cond…

21	Hamadan	110216	41276	595762	589657	19	24	0.91	0.003	0.70	0.003
22	Golestan	127641	62534	564785	553394	11	12	1.17	0.003	1.19	0.005
23	Gilan	238229	88273	869449	848779	3	14	1.51	0.003	1.08	0.003
24	Fars	244915	163214	1521210	1554416		13	0.77	0.001	1.09	0.002
25	Esfahan	310010	190093	1606271	1682241	18	11	0.96	0.001	1.19	0.003
26	East Azerbaijan	335408	147349	1251521	1292538	5	10	1.47	0.003	1.20	0.003
27	Char mahal Bakhteyari	46981	26931	291807	289582	22	19	0.77	0.003	0.96	0.006
28	Boshehr	45562	31908	290206	332370	26	17	0.74	0.003	0.99	0.005
29	Ardabil	105462	57365	421849	415690	7	3	1.34	0.004	1.50	0.006
30	Hormozgan	52408	41064	440405	471998	30	21	0.54	0.002	0.89	0.004

BMI= Body Mass Index, OR=Odds Ratio, SE=Standard Error

Today, mapping diseases are of great interest for health authorities, due to its significance to diagnose the risk factors. If we know a special disease occurs in some areas more than in others, we want to provide better medical facilities in these areas. Mapping spatial distributions of disease occurrence can serve as a useful tool for recognizing exposures of public health concern (13). Application of lately developed Bayesian hierarchical models facilitates the prediction of spatial patterns for recognizing areas in need and the estimation of risk associations for informed health service plan and resource allocation. In this article, we present such an application. Bayesian Conditional Autoregressive model is a disease mapping method, which is used for smoothening of the odds ratio. This model gives some shrinkage and spatial smoothing of the crud estimate, which gives a more stable estimate of the pattern of underlying risk of disease than that provided by the raw estimates. This method efficiently lends information from neighboring areas than from areas far away and smoothing local rates toward local, neighboring values. This reduces the variance in the related estimates and allows for the spatial effect of regional differences in Province populations (8).

This study discussed Bayesian spatial modeling and spatial smoothing of relative odds ratios where local information relevant to the rate odds for each individual province and global information relevant to the overall dispersion of the underlying spatial disease rates are integrated via a conditional autoregressive prior. We used Bayesian spatial model to draw the geographical map of obesity in Iran in which the data related to observed cases of obesity in each province were determined by Logistic distribution. We incorporated the data of prevalence of the country summarized in prior distribution with the spatial pattern of observations to provide more accurate estimates for odds ratio of obesity so that a more trustworthy map could be obtained. In fact, one of the benefits of Bayesian spatial models is to estimate the auto correlations simultaneously by using fitted regression model parameters (6-12). Many studies used classical and frequentist method to disease mapping (15, 16). The Bayesian allows the modeling of both sources of over dispersion, heterogeneity and spatial dependence or clustering in the model (17); however, it is not independent of selected prior distribution (15). The limitation of the study is absence of registered auxiliary variables such as lifestyle to adjust the odds ratio of obesity. We used, Open BUGS and R to calculate the items.

It is worthy to state that there is not any possibility of comparing our findings with other studies. The studies carried out in Iran have focused on the incidence of cardio-vascular diseases and obesity factors with a few paying attention to drawing geographical maps of disease based on statistical techniques.

Gharibzadeh et al., tried to draw the nationwide map of Acute Flaccid Paralysis by using mixture models (18). Mehrabi et al. drew the map of relative mortality of infants under one year in rural areas by using Bayesian methods and maximum likelihood (19). Kavoosi et al. drew the nationwide map of liver cancer by Bayesian spatial method (20). Mohebi et al. drew the geographical map of gastric cancer in the Caspian sea region by this method (21).

In Finland, Marjana et al. (2008) drew the geographical map of obesity by Bayesian hierarchical methods with GIS software (22). Johnson (2004) drew the incidence pattern of prostate cancer in New York by Bayesian hierarchical methods (23). In Ireland, Avril et al. (2010) used Bayesian spatial models of conditional auto regression and multiplied partition model to map cancer (24).

Conclusion

In this study, the geographical distribution of obesity was drowning so that regions at high risk of obesity are considered for the main prerequisite of managerial decision making and planning in health system. The results can be used to allocate the resources for different regions of the country to offer the health services more accurately. These maps can be used to determine the factors related to diseases in epidemiologic studies.

Ethical considerations

Ethical issues (Including plagiarism, Informed Consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, etc) have been completely observed by the authors.

Acknowledgements

The author would like to thank the Ministry of Health and Medical Education due to obesity data and one anonymous referee for valuable comments. The authors declare that there is no conflict of interest.

References

1. World Health Organization (2000). WHO Technical Report Series 894. Obesity: preventing and managing the global epidemic. Available from: www.who.int/nutrition/publications/obesity/WHO_TRS_894/en/
2. Abdollahi AA, Behnampour N, Vaghari G (2010). The Correlation between Age, Gender and Education with Obesity in Urban Population of Golestan Province. *Iranian Journal of Endocrinology and Metabolism*, 12(3): 276-83.
3. Azizi F, Allahverdian S, Mirmiran P, Rahmani M, Mohammadi F (2001). Dietary factor and body mass index in a group of Iranian adolescents: Tehran lipid and glucose study. *Int J Vitam Nutr Res*, 71(2): 123-7.
4. Hosseini Esfahani F, Mirmiran P, Djazayeri S, Mehrabi Y, Azizi F(2008). Change in Food Patterns and its Relation to Alterations in Central Adiposity in Tehranian of District 13 Adults. *Iranian Journal of Endocrinology and Metabolism*, 10 (4): 299-312.
5. Fattahi F, kashkouli Behrouzi M, Zarrati M (2011). Relation of body mass index, abdominal obesity, some nutritional habits and hypertension in 25-65 year old population of Tehran. *Koomesh*, 12(3): 229-35.
6. Lawson A, Brown W, Vidal R (2003). *Disease mapping with WinBugs and MLwiN. UK: Wiley & Sons.*
7. Rao JNK (2005). *Small Area Estimation.* New Jersey: *Wiley & Sons.*
8. Venkatesan P, Srinivasan R, Dharuman C (2012). Bayesian Conditional Auto Regressive Model for Mapping Tuberculosis Prevalence in India. *IJPSR*, 3(1):1-3.
9. Gordis L (2008). *Epidemiology*, 4th ed, Saunders, Elsevier, Philadelphia, USA.
10. Ying C. Mac Nab (2003). Hierarchical Bayesian spatial modeling of small-area rates of non-rare disease. *Stat Med*, 22: 1761–73.
11. Clayton D, Kaldor J (1987). Empirical Bayes estimation of age standardized relative risks for use in disease mapping. *Biometrics*, 43: 671-81.
12. Besag J, York J, Molli A (1991). Bayesian image restoration with two applications in spatial statistics (with discussion). *Ann I Math Stat*, 43(1): 1-20.

13. Lee D (2011). A comparison of conditional autoregressive model used in Bayesian disease mapping. *Spat Spatiotemporal Epidemiol,* 2(2):79-89.
14. CDC of Iran (2007). Non-communicable Disease risk Factors Surveillance, Provincial Report. Center for Disease Control, Ministry of Health and Medical Education, Tehran, Iran.
15. Torabi M (2012). Spatial modeling using frequentist approach for disease mapping. *J App Stat*, 39(11): 2431-39.
16. Farhadian M, Mahjub H, Moghimbeigi A, Poorolajal J, Sadri GH(2012). Classification of death rate due to women's cancers in different countries. *Iranian J Publ Health*, 41(6): 58-64.
17. Ismaila AS, Angelo Canty A, Thabane L (2007). Comparison of Bayesian and frequentist approaches in modeling risk of preterm birth near the Sydney Tar Ponds, Nova Scotia, Canada. *BMC Med Res Methodol*, 7(39): 1-14.
18. Gharibzadeh S, Mahjub H, Moghimbeigi A, Sadri GH (2010). Disease Mapping of Acute Flaccid Paralysis in Iran Using Mixture Distributions. *Hakim Research Journal*, 12(4): 11.
19. Mehrabi Y, Maraghi E, AlaviMajd H, Motlagh ME (2010). Mapping of relative risk of rural infant mortality in 1380 and 1385: comparison of maximum likelihood and Bayesian methods. *Iran J Epidemiol*, 6(3): 1-7.
20. Kavousi A, Meshkani M, Mohammadzadeh M (2008). Spatial analysis of relative risk of lip cancer in Iran: a Bayesian approach. *Environmetrics*, 20: 347–59.
21. Mohebbi M, Mahmoodi M, Wolfe R , Nourijelyani K, Mohammad K, Zeraati H(2008). Geographical spread of gastrointestinal tract cancer incidence in the Caspian Sea region of Iran: Spatial analysis of cancer registry data. *BMC Cancer*, 8: 137.
22. Marjaana Lahti-Koski, Olli Taskinen, Minna Simila, Satu Mannisto, Tiina Laatikainen (2008). Mapping geographical variation in obesity in Finland. *Eur J Public Health*, 18(6): 637–43.
23. Johnson GD (2004). Small area mapping of prostate cancer incidence in New York State (USA) using fully Bayesian hierarchical modeling. *Int J Health Geogr*, 3(1): 29.
24. Hegarty AC, Carsin AE, Comber H (2010). Geographical analysis of cancer incidence in Ireland: A comparison of two Bayesian spatial models. *Cancer Epidemiology*, 34(4): 373–81.