Mapping the Obesity in Iran by Bayesian Spatial Model

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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 infection, 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, 
\( y_i \sim Bin \left( N_i, p_i \right) \), where \( p_i \) is the proportion infected at each location. The ordinary logistic model is given by
\[
\log\left( \frac{p_i}{1-p_i} \right) = \alpha_0 + b_i
\]
Where \( \alpha_0 \) (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 \( b_i \) in neighboring provinces, the conditional auto regression was used and Metropolis Markov Chain (MCMC) algorithm and Gibbs 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 \( \text{OR} = \exp(b_i) \) 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 pre-sented 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

Table 1: Odds ratio estimated of obesity and obesity rank by province in Iran in 2007

| Province       | Observed number BMI > 30 | Population size | Rank of province based on estimated OR | Spatial estimate of OR along with SEs |
|----------------|--------------------------|-----------------|----------------------------------------|-------------------------------------|
|                | Yi                       | N<sub>i</sub>   | Female | Male | Female | Male | Female | Male | Female | Male |
| 1. Zanjan      | 69433                    | 41439           | 337051 | 32688 | 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 Azerbajan | 253466                    | 121205          | 960099 | 106812 | 6      | 6    | 1.44   | 0.003 | 1.32    | 0.004 |
| 4. Tehran      | 1347402                  | 731511          | 4802508 | 507939 | 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 | 407179 | 10     | 16   | 1.22   | 0.004 | 1.00    | 0.005 |
| 9. Mazandaran  | 318862                   | 188357          | 1064428 | 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 | 24     | 15   | 0.75   | 0.004 | 0.66    | 0.005 |
| 16. Razavi Khorasan | 300973                   | 182323          | 1904893 | 1879617 | 28     | 28   | 0.75   | 0.001 | 1.00    | 0.002 |
| 17. North Khorasan | 39588                    | 16792           | 274920 | 258337 | 8      | 18   | 1.26   | 0.003 | 0.96    | 0.004 |
| 18. Kerman     | 130954                   | 60522           | 873024 | 903317 | 27     | 26   | 0.70   | 0.002 | 0.67    | 0.002 |
| 19. Eilam      | 32089                    | 13876           | 189873 | 192720 | 20     | 23   | 0.81   | 0.004 | 0.72    | 0.006 |

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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 smoothing of the odds ratio. This model gives some shrinkage and spatial smoothing of the crude 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

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### Table 1: Conditional Autoregressive Prior

| Province       | Cases  | Deaths | Odds Ratio | 95% CI | SE  | Adjusted Odds Ratio | 95% CI | SE  |
|----------------|--------|--------|------------|-------|-----|---------------------|-------|-----|
| Hamadan        | 110216 | 41276  | 595762     | 589657| 16  | 0.91                | 0.003 | 0.70 | 0.003 |
| Golestane      | 127641 | 62534  | 564785     | 553394| 11  | 1.17                | 0.003 | 1.19 | 0.005 |
| Gilan          | 238229 | 88273  | 869449     | 848779| 3   | 1.51                | 0.003 | 1.08 | 0.003 |
| Fars           | 244915 | 163214 | 1521210    | 1554416| 13  | 0.77                | 0.001 | 1.09 | 0.002 |
| Esfahan        | 310010 | 190093 | 1606271    | 1682241| 18  | 0.96                | 0.001 | 1.19 | 0.003 |
| East Azerbayjan| 335408 | 147349 | 1251521    | 1292538| 5   | 1.47                | 0.003 | 1.20 | 0.003 |
| Char mahal     | 46981  | 26931  | 291807     | 289582| 22  | 0.77                | 0.003 | 0.96 | 0.006 |
| Bakhteyari     | 45562  | 31908  | 290206     | 332370| 26  | 0.74                | 0.003 | 0.99 | 0.005 |
| Boshehr        | 105462 | 57365  | 421849     | 415690| 7   | 1.34                | 0.004 | 1.50 | 0.006 |
| Ardabil        | 52408  | 41064  | 440405     | 471998| 30  | 0.54                | 0.002 | 0.89 | 0.004 |

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

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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.

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