A Structured-additive modeling of Diabetes and Hypertension in Northeast India

Introduction

Despite the diversity in terms of dietary food habits and cultural practices, to our knowledge, studies on diabetes and hypertension in Northeast India have not investigated the geographical heterogeneity in diabetes and hypertension causes (17,18). According to Koissi et al, ignorance of heterogeneity in the model may lead to biased parameter estimates (19). It is important to note here that geographical heterogeneity can be an effect of unobserved factors which may consist of contextual factors. Geographical differences in the causes of diabetes and hypertension can be explained by large-scale variability in term of environmental factors like availability of green space (20) the level of urbanization and westernization (21) differences in dietary food pattern (15,16) level of poverty and access to medical facilities (22). Studies have shown that obesity which causes diabetes and hypertension is known to be associated with the availability of green space or park (20,23). A study by Haynes-Maslow et al, explained that an increase in the number of fast-food restaurants in a county is associated with an increasing prevalence of diabetes in that particular county (24). There are a number of studies from India and abroad (13,15,16) that have considered geographical heterogeneity while modelling diabetes and hypertension, however these studies have ignored the non-linear effect due to continuous variables (i.e. the approach of using bivariate spline) in modelling geographical heterogeneity.

This paper contributes to the knowledge of understanding the spatial variation of diabetes and hypertension in Northeast India by adopting the Bayesian spatial mixed model approach based on the Markov Chain Monte Carlo (MCMC) simulation technique. Furthermore, the study would be the first to map diabetes and hypertension in Northeast India in term of residuals spatial effect. The map would have important implications in understanding on how diabetes and hypertension are spatially distributed, and it will help the health promotion programmes to allocate the resources equitably and efficiently.

Material and Methods

Study area and data

The study focused on Northeast India and used the standard national representative Indian Demographic Health Survey (IDHS) data which is also known as the National Family Health Survey (NFHS-4).

Study Sample for North-East India region

The study sample comprised of 112, 062 respondents (both females and males) of aged 15-49 years. Out of the total sample 13,360 were males and 98,702 were female respondents.

Dependent variables

The outcome variables in this study are diabetes and hypertension status of the respondent. The outcomes variables are binary with a value of 1 for a “Yes” (meaning presence) and 0 for a “No” (meaning absence).

Explanatory variables

The explanatory variables chosen for this study were guided by existing literature. Demographic variables considered are age and sex. Socioeconomic variables include the respondent’s caste, marital status, level of education, place of residence and household wealth. The variable of lifestyle behaviour includes current cigarettes smoking, tobacco consumption and alcohol consumption. To capture the effect of dietary eating habits on chronic diseases, we include the types of food consumed by an individual, such as consumption of milk, pulses, vegetables, fish, fruits, eggs, chicken, aerated drinks and fried food.

Statistical Analysis

The data were fitted using the Geo-additive logistic regression models to understand fixed as well as spatial effects of diabetes and hypertension (Chronic disease was used to represent diabetes and hypertension). Respondent status of chronic disease is a binary outcome; it is being distributed as *Bernoulli* (p_{ij}) where p_{ij} is the probability that respondent *j* in district *i* is having chronic disease. The district of the respondent was labelled as $s_i \in$ (1, 2, 3….,82) were the label was matching to the label in the map.

The spatial effect is split up into two parts, the spatially correlated (structured) and an uncorrelated (unstructured) effect.

$$f_{spatial}(s_i) = f_{structured}(s_i) + f_{unstructured}(s_i)$$

Results

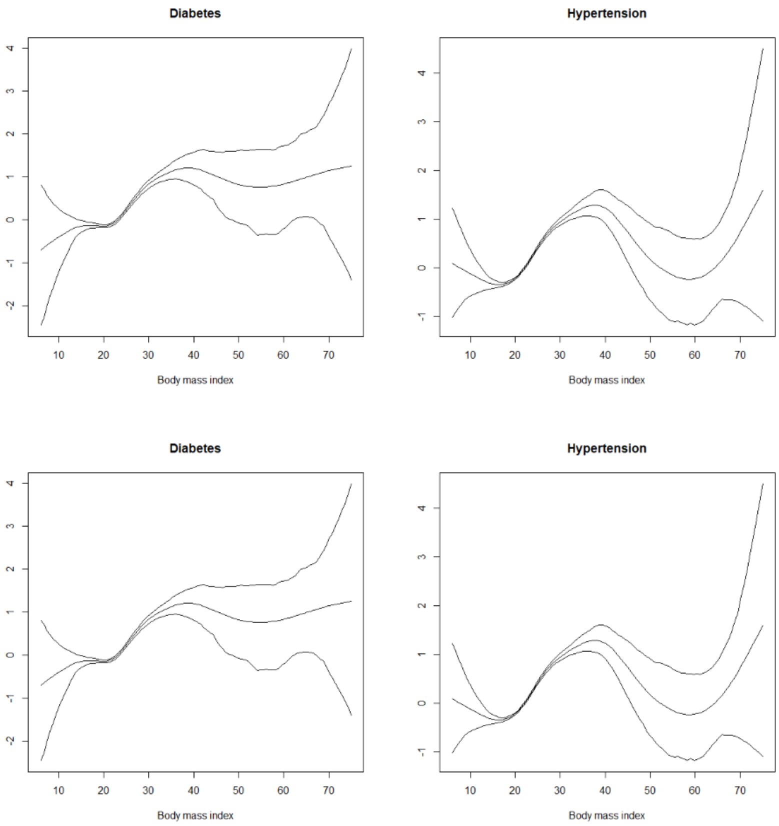
Fixed effects

In model M3 the effects of the categorical covariates are assumed fixed and jointly estimated with the continuous and spatial covariates. The posterior means and the corresponding 97.5% credible intervals of the fixed effect parameters are given in Table 3. The fixed effects covariates which are significant to diabetes are sex, current marital status, level of education and consumption of tobacco. The fixed effect coefficient for male is positive, which indicates that being male the risk of diabetes is high as compared to female. The coefficient for married is negative which means that married individuals have a reduced risk to diabetes as compared to never married individuals. Also, individuals who consume tobacco have reduced risk of diabetes.

Non-linear effects

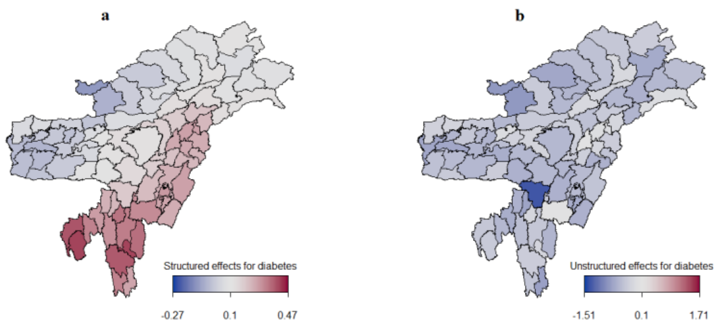
Another important advantage of using geo-additive model is the ability to incorporate the non-linear effect due to continuous covariates. In this study, we incorporated the non-linear effects of body mass index (BMI), wealth index score, and age of respondents.

Individual body mass index has a non-linear effect to diabetes and hypertension (Figure 1). It is evident from Figure 1 that as the BMI increases, its effect on diabetes and hypertension increases. The risk of diabetes and hypertension is lower at BMI value 20-25, but the risk starts to increase at BMI value from 50 and above.

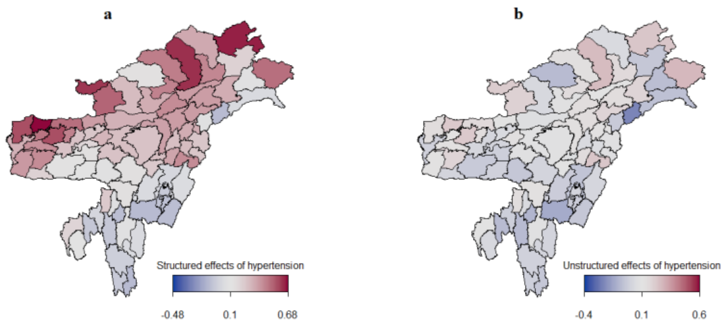


Spatial effects

The estimated spatial effects of diarrhea and hypertension, with color ranges from blue to maroon indicates low to high risk of diabetes and hypertension. The blue districts have a negative spatial effect and are therefore linked with lower odds of diabetes and hypertension. The maroon districts have a positive spatial effect and are therefore linked with higher odds of diabetes and hypertension. Spatial effects are surrogates of unknown influences, like environmental factors, climate, availability of good transport, access to good health care facilities. Figure 4a showed a clear indication of significant clustering of diabetes in Northeast India, with higher risk of diabetes occurring at the districts belonging to the states of Nagaland, Manipur, Mizoram, and Tripura, and low risk occurring at the district belonging to the states of Assam, Arunachal Pradesh and Meghalaya. However, the whole region of Northeast India is less affected by unstructured spatial effects of diabetes (Figure 4b). The structured spatial effects of diabetes which ranges from -0.27 to 0.47, was weak in comparison to the unstructured spatial effects which ranges from -1.51 to 1.71



The spatial clustering of hypertension, with higher risk of hypertension occurring at the district belonging to the states of Assam, Arunachal Pradesh, Nagaland and Meghalaya, while low risk of hypertension occurring at the district belonging to the states of Manipur, Mizoram, Tripura, and Hills and Barak valley of Assam. Further from Figure 5b, the unstructured spatial effect of hypertension was observed in some districts of Arunachal Pradesh such as Anjaw, Dibang valley and West Siang, this suggests that the spatial variation is due to the effects of unmeasured influences present locally within these districts. In the case of hypertension, the structured spatial effect which ranges from -0.48 to 0.68 is dominated over the unstructured spatial effects which ranges from -0.4 to 0.6.



Conclusion

In conclusion, it is evident that there are spatial effects to diabetes and hypertension in Northeast India. The results suggest that district specific factors (i.e. not related to neighbouring districts) are most likely to increase diabetes, however factors similar to close proximity districts are most likely to increase hypertension. Further, factors such as male, place of resident, level of education, household wealth status, BMI, consumption of egg and milk have been found to be significant in this study. Apart from the known factors, Non-communicable disease measures in Northeast India should also take into consideration the spatial heterogeneity, as well as take into account the local factors and non-local factors which contributes to the spatial heterogeneity. Effort in evaluating the district-specific factors of diabetes within the region should give more importance.