Correlation between the spatial distribution of leprosy and socioeconomic indicators in the city of Vitória, State of ES, Brazil

POLIANE BARBOSA Sampaio*, ADELMO INÁCIO BERTOLDE**, ETHEL LEONOR NOIA MACIEL* & ELIANA ZANDONADE*

*Graduate Program in Public Health, Federal University of Espírito Santo (Universidade Federal do Espírito Santo (UFES)), Vitória, ES, Brazil
**Exact Sciences Center of the UFES (Centro de Ciências Exatas da UFES), Vitória, ES, Brazil

Accepted for publication 15 October 2013

Summary

Introduction: Leprosy is a disease that is directly linked to poverty. The number of cases in Vitória, the capital city of Espírito Santo, has been decreasing in recent years, but the disease remains highly endemic. This research aimed to identify relationships between the epidemiological status of leprosy and socioeconomic indicators during the period from 2005 to 2009.

Methods: An ecological study was performed based on the spatial distribution of leprosy in Vitória, Espírito Santo, between 2005 and 2009. The source data used were records available at the Secretary of State for Health of the Espírito Santo. We used the Urban Quality Index (IQU) as the leprosy-associated socioeconomic variable. The data were analysed with covariate and spatial effects by the WinBugs programme (Version 1.4) and R (Version 2.12).

Results: The spatial distribution of leprosy in the district is not uniform. By studying the geographic distribution of leprosy cases, and the risks estimated by the complete Bayesian model, it was possible to gain further insight into the distribution of leprosy cases. It was noted that neighbourhoods with a low IQU have a higher leprosy case detection rate than neighbourhoods with a higher IQU. This result reinforced the theory that a low IQU is associated with the emergence of leprosy.

Conclusion: The model methodology adopted enabled the verification of the effect of the influence of covariates related to the social determinants of health as well as the spatial structure, in contrast to the gross rate method that does not aggregate this information. The results obtained suggest that leprosy control may be promoted by improving the socioeconomic indicators of neighbourhoods, and highlights the need for further study.
Introduction

Leprosy is caused by *Mycobacterium leprae*, which is also known as Hansen’s bacillus. This disease can infect large numbers of individuals within a community, although only a few will become ill.\cite{1,2,3} It remains a serious public health problem due to its ability to cause disability.\cite{4}

Brazil is among the countries with the highest numbers of leprosy cases. In 2010, according to World Health Organization (WHO) estimates, the country had 34,894 new cases of Hansen’s disease.\cite{3,5}

In 2010, the Ministry of Health conducted a study in Brazil to identify 10 clusters with the highest leprosy case detection.\cite{6} The state of Espírito Santo is one of these 10 areas of greatest risk, and the case detection rates for leprosy during the period from 2004 to 2009 placed the State in the category of ‘very high’ to ‘hyperendemic’. The mean case detection rate during this period was approximately 37.08 cases per 100,000 inhabitants and was thus classified as very high, making the state a priority for national disease control programmes.\cite{7}

Vitória, the capital of Espírito Santo, is currently divided into 79 districts, and the municipal disease dynamics resemble those of the state, with a decreasing trend in recent years. However, endemicity remains very high, according to the Ministry of Health parameters. In 2008, the incidence rate of leprosy in Vitória was 26.12 cases per 100,000 inhabitants, which is well above the target set by WHO.\cite{5,8}

Leprosy is directly linked to poverty, sanitation and housing conditions because overcrowding is responsible for increased airborne spread of the bacillus.\cite{9} According to the Health Ministry, ‘leprosy transmitted by Hansen’s bacillus is influenced by the cultural and economic relationships between groups in the community. At this ecological approach level, many factors interact to determine morbidity and various health problems.’\cite{10}

Geographic Information Systems (GIS) are tools that are used primarily in ecological studies and in which the unit of analysis is a geographic area or region. This technique facilitates the mapping of the living conditions of a population to identify the existing needs for increased capacity with regard to the health situation in the region.\cite{11} The Pan American Health Organization (PAHO) recommends the use of this tool in countries with large regional differences and territorial extensions, such as Brazil and India.\cite{12}

An analysis of the factors that might influence the occurrence and distribution of leprosy was conducted to identify relationships between the epidemiological status of the disease and socioeconomic indicators. Mapping the occurrence of leprosy might contribute to an understanding of disease epidemiology in Vitória and thus assist the processes of formulation, implementation and reorientation of disease control and reduction measures.

Methodology

This was an ecological study with a spatial analysis of new leprosy cases during the period from 2005 to 2009. Census and epidemiological data were used to explain how the occurrence of the disease is influenced by socioeconomic context.
Vitória has a population of 320,156 inhabitants and an area of 104.3 km². The municipality is currently divided into 79 districts. The 2000 territorial divisions were used for the study. At that time, the city was divided into 78 districts and these were adopted as the unit of analysis. Population information, which included the 2000 Census, was acquired from the Vitória Municipal Health Secretariat (Secretaria Municipal de Saúde de Vitória (SEMUS)) and the Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatística (IBGE)).

The Urban Quality Index (IQU) was obtained for each neighbourhood in the municipality to analyse the socio-economic situation. The IQU was developed by the Institute for Studies, Training and Consultancy in Social Policies (Instituto de Estudos, Formação e Assessoria em Políticas Sociais (POLIS)). The index is based on IBGE source data that were organised by the city of Vitória. The study period duration was 5 years, from 2005 to 2009, and IQU data were used from the territorial divisions that were in effect in 2000.

The IQU is a descriptive and compound quantitative index and is the result of the agglomeration of other simple indicators. It comprises 11 simple indicators that are divided into four dimensions as follows: the Educational dimension indicates the level of education, including the percentage of those over 15 years who are illiterate, the percentage of those responsible for the household who have fewer than 4 years of study and the percentage of those responsible for the household with 15 years or more of study; the Housing dimension includes the average number of people per household and the average number of bathrooms per household; the Environmental Dimension includes the percentage of households with an adequate water supply, the percentage of households with proper sanitation and the percentage of households with adequate garbage collection; and the Income dimension includes the average income of those responsible for the household in terms of the minimum wage, the percentage of those responsible for the household who earn up to twice the minimum wage and the percentage of those responsible for the household who earn more than 10 times the minimum wage.

The calculation of case detection rates was performed by dividing the sum of new cases per neighbourhood by the sum of the population during the years of 2005 to 2009 and multiplying the result by 100,000, according to the SVS/MS (Secretariat for Health Surveillance/Ministry of Health) methodology. The gross case detection rate and data tabulation from the Information System for Notifiable Diseases (Sistema de Informações de Agravos de Notificação (SINAN)) were performed with a Microsoft Excel spreadsheet (Microsoft, Redmond, WA, USA).

The scale used to categorise the levels of disease endemicity, which were based on parameters established by the Ministry of Health, was as follows: the detection coefficient was considered hyperendemic when the detection rate was greater than 40.00 cases per 100,000 inhabitants; very high when there were 20.00 to 39.99 cases per 100,000 inhabitants; high when there were 10.00 to 19.99 cases per 100,000 inhabitants; medium when there were 2.00 to 9.99 cases per 100,000 inhabitants; and low when there were fewer than 2.00 cases per 100,000.

STATISTICAL ANALYSIS

Spatial epidemiology includes the analysis of geo-referenced data from the health area and its relationships to several aspects that are measurable in space, such as environmental, behavioural, socioeconomic, genetic and infectious factors.
Using language more appropriate to statistical concepts, one can interpret the occurrence of a localised event as a spatial stochastic process in which the probability associated with an event can be modified to consider the location of event occurrence.\textsuperscript{15}

With regard to the maps used to evaluate the spread of disease, the classical measure used to estimate the risk of a disease in an area \( i \) is the gross rate of incidence, herein called \( t_i \) and expressed as follows:

\[
t_i = \frac{n_i}{N_i} \times 1000,
\]

where \( n_i \) is the total number of disease occurrences or cases, and \( N_i \) is the exposed population of area \( i \). One limitation associated with use of the gross rate occurs when the event of interest is rare or when localities have small populations; both of these situations generate high instability when estimating the risk of an event occurrence.\textsuperscript{16} One alternative is to use a complete Bayesian method. This estimates the risk in an area \( i \) while considering the spatial effects of a particular neighbourhood structure.\textsuperscript{17}

The model proposed in this paper assumes that the number of leprosy cases observed per neighbourhood can be represented by a Poisson distribution.\textsuperscript{18} Additionally, this model is intended to evaluate whether the IQU variable contributes to the model fit and hence to a better understanding of the leprosy distribution. Because this is a counting process of leprosy cases in which the exposed populations are relatively large, \( Y_i \) is defined as the number of leprosy cases observed per neighbourhood \( i \) by the following:

\[
Y_i | \theta_i \sim \text{Poisson} \left( E_i | \theta_i \right).
\]

In other words, the above formula indicates that, given \( \theta_i \), \( Y_i \) can be expressed as a Poisson distribution with a rate of \( E_i | \theta_i \); \( \theta_i \) is the relative leprosy risk in area \( i \), and \( E_i \) is the expected number of leprosy cases in each area \( i \) as obtained from the expression \( E_i = \frac{\sum \text{casos}}{\sum \text{população}} \).

Note that \( \theta_i \) is an unknown parameter of the model, while \( E_i \) is a measure that can be obtained directly from the disease reporting data.

The first level of the hierarchical model\textsuperscript{18} is given as

\[
Y_i | \theta_i \sim \text{Poisson} \left( E_i | \theta_i \right),
\]

with \( \theta_i \) expressed by the following relationship:

\[
\log \left( \theta_i \right) = \alpha IQU_i + u_i + b_i,
\]

where \( \alpha \) is the coefficient that represents the effect of covariates \( IQU_i \); \( u_i \) and \( b_i \) are the non-spatial and spatial random effect vectors, respectively.

In the second hierarchical level of the model, the following are attributed to the a priori distributions of each of the unknown parameters of the model, which are \( \alpha \), \( u_i \) and \( b_i \). For all analysed models, the a priori distribution for \( \alpha \) is given as \( \alpha \sim \text{Normal}(0, \tau_\alpha) \).

For component \( u_i \), a \( \text{Normal}(0, \tau_u) \) prior distribution is assigned. Component \( b_i \) considers the spatial effect of the neighbours, and in this case, the structure defined for the chosen neighbourhood matrix is binary and takes the value 1 when neighbouring areas are adjacent and the value 0 otherwise. Component \( b_i \) is given by the normal Conditional Auto-Regressive (CAR) distribution. The average is given by the arithmetic mean of the effects of its neighbours, and the variance is inversely proportional to the number of neighbouring areas.
The variances $\tau$, $\tau_u$ and $\tau_b$ are unknown and are termed hyperparameters and the values used for them was equal to 1000.

The estimates of risk for each area were obtained from the \textit{a posteriori} distribution of $\theta_i$ that resulted from the various models and their respective \textit{a priori} values. Due to the complexity of the model, the \textit{a posteriori} distribution was ascertained by the Markov Chain Monte Carlo (MCMC) stochastic simulation method.

The programme used for the Fully Bayesian modeling via MCMC was WinBugs (\textit{Win Bayesian inference Using Gibbs Sampling}; Version 1.4; The Bugs Project, Cambridge, UK; version available free for personal use at http://www.mrc-bsu.cam.ac.uk/bugs/winbugs/contents.shtml). The convergence of simulated chains was determined according to Gelman and Rubin’s method.\cite{19} The criterion used to choose the model was DIC (\textit{Deviance Information Criterion}), which indicates the best model fit as that with the lowest DIC value.\cite{20} The analysis was implemented with the following programmes to generate the maps and calculations of rates and indexes: Excel, R 2.6.2 (R Project for Statistical Computing; http://cran.r-project.org/bin/windows/base/old/2.6.2/), SPSS 11.5 (SPSS, Chicago, IL, USA) and TerraView 4.0.0 (available at http://www.dpi.inpe.br/terraview_eng/index.php).

\textbf{ETHICS}

The entire study was conducted according to Resolution No. 196/96 of the National Health Council (Conselho Nacional de Saude – CNS), and the project was approved by the Research Ethics Committee of the Federal University of Espirito Santo (Universidade Federal do Espirito Santo – UFES) under registration number 165/11.

\textbf{Results}

Figure 1 shows the spatial distribution of the detection coefficients of new leprosy cases for each neighbourhood in the city of Vitória between 2005 and 2009, as well as the IQU for the year 2000.

Figure 1 (A), which shows the detection coefficients of new cases of leprosy, indicates that of the 78 districts, 18 (22.2%) were classified as hyperendemic, 20 (24.7%) as having very high endemicity and nine (11.1%) as having medium endemicity. All other districts had low endemicity.

Areas with high disease detection rates can be observed in the thematic map (Figure 1A), but few grouped areas were observed. Most areas on the eastern side of the municipality had the lowest leprosy detection coefficients during the study period.

Figure 1(B) shows that areas with a low IQU had higher leprosy detection rates than areas with higher IQU. A low IQU might be associated with poor living conditions. This result reinforces the theory that a low IQU is associated with the emergence of leprosy.

The mean IQU was 0.58 (standard deviation = 0.124), and the IQU values ranged from 0.34 to 0.84 with high inequality in the municipal centre.

In Figure 1, items A and B show an inverse trend between the detection coefficient of new leprosy cases and the IQU; in other words, the data are inversely proportional.

Table 1 shows the proposed models according to the Fully Bayesian approach and their respective DIC (\textit{Deviance Information Criterion}) values during the period from 2005 to 2009.
The models can be described as follows: Model 1 included only random effects \((u_i, b_i)\); Model 2 did not incorporate \(IQU_i\); Model 3 incorporated all variables used in this study, e.g., \(IQU_i\) and random effects \((u_i, b_i, IQU_i)\) and Model 4 included \(IQU_i\) but no random effects \((u_i, b_i)\).

Of the proposed models, it was found that Model 3 in Table 1 was the best fit because it had the smallest DIC value.

From the results of Model 3 (best fit), it was concluded that both the IQU and random effects contribute to an explanation of leprosy detection in Vitória.

Figure 2 shows the maps of spatial random effects \((b_i)\) and detection rate of leprosy cases according to the Fully Bayesian model estimates.

The model-adjusted coefficients map is very similar to the gross rates map. Furthermore, the component \(b_i\) (spatial random effect) map has a spatial cluster pattern such that negative values are typically observed in the neighbourhoods of northeast Vitória and positive values are observed in other districts; therefore, the distribution is homogeneous in the surrounding areas.

A spatial pattern, according to neighbourhood, can be observed between Figure 1A (top) and Figure 2A (below), and a similar pattern is observed between the IQU value and \(b_i\) spatial

---

**Table 1.** Regression models used to identify factors related to the Detection Coefficient of New Cases of Leprosy and their respective DIC values during the period from 2005 to 2009 in Vitória, State of Espírito Santo (ES), Brazil.

<table>
<thead>
<tr>
<th>Model</th>
<th>DIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) ( \log(\mu_i) = \log(E_i) + u_i + b_i )</td>
<td>339.79</td>
</tr>
<tr>
<td>(2) ( \log(\mu_i) = \log(E_i) + b_i )</td>
<td>353.98</td>
</tr>
<tr>
<td>(3) ( \log(\mu_i) = \log(E_i) + u_i + b_i + IQU_i )</td>
<td>336.04</td>
</tr>
<tr>
<td>(4) ( \log(\mu_i) = \log(E_i) + b_i + IQU_i )</td>
<td>344.82</td>
</tr>
</tbody>
</table>

DIC: Deviance Information Criterion.

\(u_i\): non-spatial random effect vectors.

\(b_i\): spatial random effect vectors.

\(IQU_i\): Urban Quality Index Variable.
effects. Typically, where there is a high (low) incidence of leprosy, there are accordingly low (high) IQU values and higher (lower) $b_j$ values.

Discussion

The study of the epidemiological status of leprosy and socioeconomic indicators in Vitória, State of Espírito Santo, Brazil during the period from 2004 to 2009 was conducted with thematic maps and epidemiological tools.

The statistical methods presented in the present study are useful for estimating variations and demonstrating patterns and spatial trends, and it is important to explore spatial dependence to show how these variations correlate in space.

To measure the spatial effect on the association of variables with new leprosy cases, a regression analysis was applied to count data according to a Fully Bayesian model. The R programme was used for risk mapping, and the free TerraView software programme was used to analyse the spatial correlations between new disease cases and the components of each district, as well as map construction.

The proposed statistical model represents a complex structure from a mathematical and computational modeling viewpoint but presents an advantage over simply using the gross rate and Bayesian Empirical methods because the model can evaluate spatial effects and those of other explanatory variables.

With Fully Bayesian modeling, it is possible to project more accurate estimates of the leprosy detection coefficient and evaluate the possible influences of socioeconomic indicators. Studies that used the Fully Bayesian model were also able to incorporate spatial effects in evaluations of the AIDS epidemic in the state of São Paulo and infant mortality in Rio Grande do Sul. In these studies, municipal estimates were analysed with greater

---

**Figure 2.** Maps: (A) Map of spatial random effects ($B_i$); (B) Map of detection coefficient of cases of leprosy based on the Fully Bayesian model estimates. Vitória, State of Espírito Santo (ES), Brazil, from 2005 to 2009. Source: the Authors.
confidence due to greater stability, and the models performed better when spatial structures were incorporated with the covariates.

Because it is based on the assumption that poverty is a factor in the health situation of people affected by leprosy, the present study presents a number of aspects for discussion, taking into account the results obtained. The random effects show that the geographic pattern also exists above and beyond the pattern of poverty.

Studies conducted in endemic countries have shown that leprosy distribution is associated with poverty. In these studies, the differences in prevalence between regions, states and municipalities showed higher disease concentrations in the poorest regions. An important issue in the evaluation of regional health status is the development of indicators that can detect health risk conditions that arise from poor socioeconomic status and thus provide information for public health policy planning.

In Brazil, recent studies have demonstrated the influence of socioeconomic variables on health conditions. The association between areas with low socioeconomic indicators and high leprosy incidence rates that was found in the present study corroborates the results of Cury et al. (2012). Moreover, the results from the present study and the study by Cury et al. agree with regard to the identification of clusters of leprosy cases and heterogeneous disease occurrence rates.

This finding is clearly apparent when analysing the thematic map of the Vitória Municipality (Figure 1), wherein the leprosy rate is greater in areas with lower IQU, or those with lower socioeconomic status. These results are consistent with a study by Maciel (2010), in which spatial analysis was used to examine the significance of the relationship between the socioeconomic status of the state and the incidence of tuberculosis, another infectious disease, in the same municipality that was examined in the present study.

Although the municipality under study has indicators of a good socioeconomic level, it presents contrasts between the socioeconomic indicators (IQU) and the leprosy rate in nearly all areas. This uneven disease distribution pattern, observed on the thematic maps, indicates that there is a greater risk of contracting leprosy in areas with lower IQU, compared to those with higher IQU. Areas with worse socioeconomic indicators thus have populations that are more exposed to illness.

This methodology has proven to be of great importance to the identification of critical disease areas and to evaluations of the impact of strategic actions intended to combat leprosy that are implemented in the municipality, including the risk factors related to socioeconomic indicators.

Conclusions

The study revealed that the distribution of new leprosy cases in Vitória, ES, Brazil occurs unevenly among the neighbourhoods. The findings confirm the previously held assumption that the pattern of new leprosy cases in the municipality is related to socioeconomic indicators.

The use of the Fully Bayesian model permitted verification of the influences of spatial structure and the covariates related to the social determinants of health. The results suggest that leprosy control in certain neighbourhoods requires improvements in socioeconomic indicators and also indicate the need for the implementation of health policies geared toward populations that reside in areas in which there is a higher risk of contracting the disease.
The results also show that geographic patterns remain, even after accounting for the impact of poverty as measured by the IQU.

An awareness of the life and health conditions of a population is essential when planning health service provisions and evaluating the effects of health actions. These results contribute to the body of knowledge regarding the spatial distribution of leprosy in Vitória and emphasise the importance of space as a methodological alternative for the planning, monitoring and evaluation of health actions and the direction of interventions intended to reduce the inequalities between neighbourhoods.

Financial Support

This study was financially supported by the Ministry of Health (MS), the Ministry of Science and Technology (MCT), and the National Council for Science and Technological Development (CNPq) through Edict MCT/CNPq/CT – Saúde/MS/SCTIE DECIT No. 034/2008, along with additional studies to assist in interventions for leprosy control in cluster No. 4 municipalities (States of Espírito Santo, Bahia and Minas Gerais).

References

Leprosy and socioeconomic indicators


