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# Spatial and temporal trends in new case detection of leprosy in India

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*Summary*
*Background:* India achieved the goal of 'leprosy elimination' by reducing the burden of leprosy to less than one case per 10,000 inhabitants in 2005. Sustained and committed efforts by national programmes have led to a decline in the burden of leprosy to a great extent.
*Purpose:* To examine the spatial clustering of leprosy case detection and spatio-temporal trend using Bayesian space period model.
*Materials:* The National Leprosy Eradication Programme (NLEP) data of annual new case detection of leprosy in 34 districts of Maharashtra for eight data years 2007–08 to 2014–15.
*Methods:* The presence of spatial dependency was assessed using the case detection rate for each of the eight data years spanning from 2007–2015 using Moran's I statistic and the variation over space and time was modeled using the Bayesian Space Period model.
*Results:* The Moran's I value was found to be statistically significant for each of the time period. The period effect was significantly higher than the average in the year 2007(4%), 2009(5%), 2011(6%), 2013(18%) and significantly lower than the average in 2008(7%), 2010(4%), 2012(11%), 2014(9%). The spatial effects varied between 0·579 and 1·52. There was a higher risk of leprosy (50% or more) found in districts of Garhchiroli, Raigad and Warda. The lowest risk of 0·579 was observed in the Nagpur district.
*Conclusion:* The period effect of new case detection of leprosy using the SP model, measured in terms of relative risk shows a seesaw effect at work in districts of Maharashtra. The alternate jump in the risk of leprosy given by the model could be the actual scenario or due to expended activities in the study area. Further in depth investigation needed to ascertain the facts. Observing the spatial Bayesian effect districts Garhchiroli, Raigad and Warda are at greater risk and need priority care.

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## Background

India achieved the goal of 'leprosy elimination' by reducing the burden of leprosy to less than one case per 10,000 inhabitants in 2005.[1] There has been a dramatic fall in the prevalence rate (PR) of leprosy, but the new case-detection rate (NCDR) has not been reduced concurrently.[2] According to the World Health Organization (WHO), 65% of all new cases of leprosy globally are from India.[3] Sustained and committed efforts by national programmes have led to a decline in the burden of leprosy to a great extent. The National Leprosy Eradication Programme (NLEP) envisages a 'leprosy free India', and is striving to achieve the Neglected Tropical Diseases (NTD) goal of elimination of leprosy by 2020.[4] Also, the Bangkok Declaration emphasises the ambition to achieve the global target of reducing the occurrence of new cases with visible deformity (Grade 2 disabilities) to less than one case per million population by the year 2020.[5]

For many infectious diseases, cases are not spread uniformly in a geographical area, but occur in clusters. In fact, leprosy epidemiology shows a markedly uneven distribution in different geographic areas such as in China,[6] Indonesia,[7] in the state of São Paulo, Brazil,[8] and in India[9] where leprosy cases were extensively clustered. It has been observed that the distribution of leprosy is uneven even within the smallest community groups such as villages, right down to the household level.[10] In the literature, high rates of leprosy are generally observed in economically poorer strata, and situations of overcrowding and urbanisation.[9] In some cases, this could also relate to more efficient health services, enabling them to detect new cases of leprosy. Geographical or spatial analysis comes into play due to the existence of spatial dependence in the data. Therefore, data analyses and interpretation should not ignore spatial dependency.[11] The Bayesian method lends itself to representing spatial dependence during the estimation of model parameters.

The objectives of the study are

i) To examine spatial clustering of leprosy using Moran's I statistic in the data set.
ii) To assess spatio-temporal trends using the Bayesian space-period model.

## Materials

According to the annual reports of NLEP (which run from 1st April to 31st March every year), Maharashtra and Orissa are the two states which consistently showed an increasing new case

**Table 1.** Period effects and 95% credibility intervals, relative risk of Leprosy in Maharashtra Bayesian Space Period model.

| Period | Mid year | RR (95% CI) | Increase/Decrease in risk |
|---|---|---|---|
| 2007–08 | 2007 | 1·04 [1·03, 1·06] | 4% |
| 2008–09 | 2008 | 0·93 [0·91, 0·95] | −7% |
| 2009–10 | 2009 | 1·05 [1·03, 1·05] | 5% |
| 2010–11 | 2010 | 0·96 [0·95, 0·98] | −4% |
| 2011–12 | 2011 | 1·06 [1·04, 1·08] | 6% |
| **2012–13** | **2012** | **0·89 [0·87, 0·90]** | **−11%** |
| **2013–14** | **2013** | **1·18 [1·16, 1·20]** | **18%** |
| **2014–15** | **2014** | **0·91 [0·90, 0·93]** | **−9%** |

detection rate (NCDR) every year from 2007–2015.[12] Therefore, an attempt was made to explore the variations in leprosy incidence in Maharashtra which is an endemic state, comprising of 34 districts [Mumbai and Mumbai Suburban combined as one district, Mumbai, and Thane and Palghar combined as one district, Thane, in the analysis, due to missing data], as reported under NLEP within the defined timeframe.

## Methods

The presence of spatial dependency was assessed using the case detection rate for each of the eight data years spanning from 2007–2008 to 2014–2015 using the Moran's I statistic.[13] The formula is described in Appendix 1.

To examine the variation in the detection of leprosy, Bayesian models described by Arbyn *et al.*[14] proposed earlier by Lagazio *et al.*[15] were used. The variation over space and time was modeled using the Bayesian Space Period model during the time periods 2007–2008 to 2014–2015 over 34 districts. The average of all periods was used as the reference.

**Table 2.** District effects and 95% credibility intervals, relative risk of NCDR of leprosy estimated from the SP model.

| District | Median RR | 95% CI | |
|---|---|---|---|
| AHMADNAGAR | 0·6950 | 0·6471 | 0·7496 |
| AKOLA | 1·4915 | 1·3907 | 1·6108 |
| AMRAVATI | 0·9040 | 0·8430 | 0·9755 |
| AURANGABAD | 1·1345 | 1·0590 | 1·2230 |
| BEED | 1·1507 | 1·0755 | 1·2389 |
| BHANDARA | 0·8701 | 0·8085 | 0·9416 |
| BOMBAY CITY | 0·9056 | 0·8443 | 0·9771 |
| BULDANA | 0·7638 | 0·7108 | 0·8251 |
| CHANDRAPUR | 1·1200 | 1·0472 | 1·2068 |
| DHULE | 1·2964 | 1·2122 | 1·3957 |
| **GARHCHIROLI** | **1·5176** | **1·1239** | **1·6218** |
| GONDIYA | 0·8170 | 0·7626 | 0·8812 |
| HINGOLI | 1·0904 | 1·0184 | 1·1741 |
| JALGAON | 1·0128 | 0·9461 | 1·0906 |
| JALNA | 1·0470 | 0·9755 | 1·1305 |
| KOLHAPUR | 0·9817 | 0·9159 | 1·0576 |
| LATUR | 1·1727 | 1·0963 | 1·2628 |
| NAGPUR | 0·5790 | 0·5397 | 0·6243 |
| NANDED | 1·4907 | 1·4309 | 1·6476 |
| NANDURBAR | 0·8584 | 0·8021 | 0·9244 |
| NASHIK | 1·2964 | 1·2141 | 1·3938 |
| OSMANABAD | 0·8620 | 0·8031 | 0·9305 |
| PARBHANI | 1·1943 | 1·1182 | 1·2845 |
| PUNE | 0·9634 | 0·9007 | 1·0362 |
| **RAIGAD** | **1·5106** | **1·2555** | **1·6535** |
| RATNAGIRI | 0·7147 | 0·6666 | 0·7714 |
| SANGLI | 1·1606 | 1·0845 | 1·2499 |
| SATARA | 1·0222 | 0·9545 | 1·1018 |
| SINDHUDURG | 0·8660 | 0·8085 | 0·9321 |
| SOLAPUR | 1·0745 | 1·0050 | 1·1558 |
| THANE | 0·9817 | 0·9174 | 1·0564 |
| **WARDHA** | **1·5039** | **1·4077** | **1·6933** |
| WASHIM | 0·9558 | 0·8927 | 1·0299 |
| YAVATMAL | 1·0446 | 0·9765 | 1·1243 |

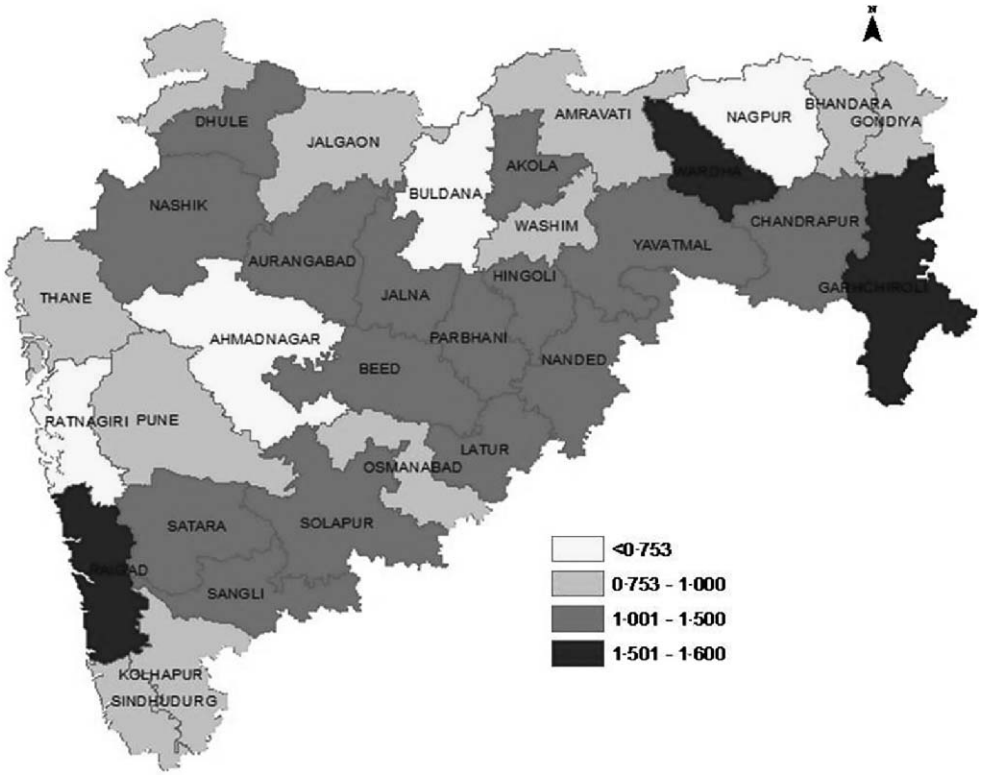


**Figure 1.** The median relative risk of detection of leprosy across 34 districts of Maharashtra estimated from the Space Period model [2007–08 to 2014–15].

Posterior distributions of the parameters of interest were obtained using Gibbs sampling in WinBUGS.[16] The description of the model is given in Appendix 2.

The spatial effects of the relative risk of leprosy given by the SP model were used to portray geographical variations within the districts.

## Results

The spatial pattern of clustering of the case detection rate was confirmed using Moran's I value, a measure of spatial autocorrelation. It was found to be statistically significant over all the time periods (Moran's $I > 0{\cdot}58$; $P < 0{\cdot}05$).

### PERIOD EFFECT USING THE SPACE PERIOD (SP) MODEL

The period effect of case detection of leprosy using the SP model is shown in Table 1.

The period effect measured in terms of relative risk, significantly declined from a higher than average of 4% during the (mid) year 2007, to a reduction in risk of 9% during 2014. The trend pattern was not uniform. There is a leap up and down alternately. The period effect was

significantly higher than the average in the years 2007, 2009, 2011 and, 2013 and significantly lower than the average during 2008, 2010, 2012 and 2014.

### SPATIAL EFFECT USING THE SP MODEL

The spatial effects of different districts are listed in Table 2 and can be further visualised in the Choropleth map (Figure 1).

The spatial effects of relative risk varied between 0·579 and 1·52. The Bayesian model identified 15 districts that had a significantly higher risk of detection of leprosy. There was a higher risk of leprosy (50% or more) found in 3 districts of Maharashtra namely Garhchiroli, Raigad and Wardha. The lowest risk (relative risk 0·579) was observed in the Nagpur district.

## Discussion

Leprosy case detection rates in Maharashtra show a strong spatial dependency. The period effect of detection of leprosy using the SP model, measured in terms of relative risk shows a seesaw effect at work in districts of Maharashtra. It might be a true oscillation in the incidence rate or, as seems more likely, it could be due to the effect of the application of special programme case-finding efforts, such as: selective special drives, leprosy detection drives in endemic blocks, house to house surveys for new case detection, mass awareness campaigns, etc., which identify larger numbers of new cases during certain time periods.[17–19] The reduction in risk of leprosy detection at other times may be due to reduced active case-finding activities, operational shifts in leprosy control activities, or, over a longer time-frame, changes in urbanistion, better hygiene or an improved standard of living.[9,20]

Similar patterns were previously observed in the NCDR of rural Satara district of Maharashtra.[21] The authors state that the effect may be due to training and retraining of peripheral health care workers, adequate and proper placement of workers, periodic evaluation of their work, Modified Leprosy Elimination Campaigns (MLEC), or intensified IEC (Information, Education, and Communication) activities.

The marginal increased risk of 4% in 2007 may be due to the 'Block Leprosy Awareness Campaign' (BLAC-IV) focused on high priority districts, the Situational Activity Plan (SAP 2007) and the 'Urban Leprosy Sensitisation and Awareness Campaign' (ULSAC) in urban areas.[22] Special efforts for leprosy case detection by the DPMR (Disability Prevention and Medical Rehabilitation) programme in 2009 could be a reason for the 5% increased risk in the corresponding period.

The increased risk of 6% in 2011 may be due to focused special drives in the endemic regions of Maharashtra.

The prominent increased risk of 18% in new cases detected during 2013 may be attributable to the NLEP strategy of carrying out extensive house to house surveys for new case detection in 2012–13, capacity building of staff, awareness drives, enhanced monitoring and supervision, and treatment of identified new cases with Multidrug Therapy (MDT) to cut down the transmission potential in 2013–2014,[18] obviously the outcome being a reduction in risk of 9% in 2014.

The *spatial effect* using the SP model shows the variation in the geographical distribution of leprosy detection in the state of Maharashtra. Observing the spatial Bayesian effect, districts Garhchiroli, Raigad and Wardha are at greater risk and need priority care. These

districts have been already labeled as high endemic districts by NLEP. Moreover the NLEP conducts extensive leprosy drives twice every year in endemic blocks and cases are treated with MDT.[22] The alternating jump in the detection of leprosy should be further explored by removing the effects expended by various programmes in the study area. This would help us to ascertain whether the pattern is an artefact.

## Limitation

If the data had been readily available at micro level (block or village) then the centroid points would have been much finer and the leprosy high-risk pockets would have been pinpointed more precisely for remedial measures. The results are dependent on the data reported under NLEP, which could have missed some new cases in the study area. Since the analysis was done using only NLEP data the outcome was related to NLEP activities and there could be other organisations that might also have contributed to the impact.

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## Appendix-1

### Moran's I statistic

The Moran's I statistic provides a test of spatial dependence. Data with a spatial independence give an expected value of I close to zero, spatial aggregation or clustering leads to positive values, with an upper limit of Moran's I statistic near to one but its precise value of the upper limit depends on the neighborhood structure.

The Moran's I statistic is given by

$$I = \frac{n\sum_i\sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i\sum_j w_{ij}\sum_i (x_i - \bar{x})^2}$$

Under the null hypothesis of spatial random data, mean and variance of I is $E(I) = -1/(n-1)$; $\text{var}\,(I) = \left(n^2 S_1 - nS_2 + 3S_0^2\right)/S_0^2(n^2-1) - E^2(I)$

$$S_0 = \sum_i\sum_j w_{ij}, \quad S_1 = 1/2\sum_i\sum_j (w_{ij} + w_{ji})^2, \quad S_2 = \sum_i \left(\sum_j (w_{ij} + w_{ji})\right)^2$$

## Appendix-2

### Bayesian Space period model

Let *Yit* denote the observed count of leprosy incidence cases in district i (i = 1, 2, . . . , 34) and during the time period t (t = 1, 2, . . . , 8). The expected value is based on the overall incidence value.

*Yit* be the observed number of leprosy cases in the $i^{th}$ district at time period t.
*Eit* be the expected number of leprosy cases in the $i^{th}$ district at time period t.
$Y_{it} \sim$ Poisson ($\mu_{it}$)
With $\mu_{it} = R_{it}E_{it}$, where i = 1, 2, . . ., 34 districts
t = 1, 2 . . ., 8 time period

$$\left(\log\left(\frac{\mu_{it}}{E_{it}}\right)\right) = \log\left(RR_{it}\right) = \eta_{it}$$

where $\eta_{it}$ is a linear predictor, and $RR_{it}$ is the relative risk of the $i^{th}$ district and the time t. The linear predictor $\eta_{it}$ is specified as.

For the model $\eta_{it} = \alpha + b_i^{struct} + b_i^{unstruct} + b_t^{period}$
Where $\alpha$ is the intercept term
Where $b_i^{struct}$ represents structured spatial variability
$b_i^{unstruct}$ represents unstructured spatial variability
$b_t^{period}$ represents the effect of the $t^{th}$ time period

The prior distribution of all effects are multivariate normals

$$b^{struct} \sim N\left(0, \left(\tau_{struct}K_{struct}\right)^{-1}\right)$$

$$b^{unstruct} \sim N\left(0, \left(\tau_{unstruct}I_{34}\right)^{-1}\right)$$

$$b^{period} \sim N\left(0, \left(\tau_{period}K_{period}\right)^{-1}\right)$$

The structured spatial term is assigned the Gaussian Conditional Autoregression (CAR) prior distribution and period effect is assigned the Gaussian prior. The prior values were assigned to the precision terms $\tau_{struct}, \tau_{unstruct}$ *and* $\tau_{period}$; for detailed specification of matrices $K_{struct}$ and $K_{period}$ and the algorithmic steps for the model using WINBUGS are discussed in detail elsewhere.[14]

In the model the spatial effect (autocorrelation) depends on

(i) whether any two districts share a common boundary and
(ii) number of shared neighbors (districts).

For fitting the models without interactions with a burn-in of 5 000 iterations and an additional 10 000 iterations and Convergence was checked using standard procedures.[23,24]