Original Article

Examining spatial patterns in the distribution of Low Birth Weight babies in Southern India- the role of maternal, socio-economic and environmental factors

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A R T I C L E   I N F O

A B S T R A C T

While individual-level maternal risk factors continue to play a significant role in explaining low birth weight (LBW) outcomes, the need to better understand the contribution of other explanatory factors at both the individual and the neighbourhood level are vital to proposing future prevention strategies and interventions. Prevalence of LBW babies were calculated for all the villages in the Kaniyambadi block of Vellore district using the data from the Health Information System of the Department of Community Health, Christian Medical College, temporal trends in the distribution of LBW babies were mapped over a 20 year period (1991 to 2010). Spatial analysis was performed on a total of 7,058 births during 2006-2010 to identify statistically significant spatial clusters of high values of LBW deliveries using the Getis-Ord Gi* hotspot analysis tool in ArcGIS 10. At the village level, the LBW deliveries during the same period were modelled using global Ordinary Least Squares (OLS) linear regression and Geographically Weighted Regression (GWR) looking at various maternal risk factors, socio-economic indicators, and community-level environmental factors. The overall prevalence of LBW for the 20 year period was found to be 16.8%. Significantly high spatial clustering of LBW was observed in the region with hotspots being noted in 10 villages. The OLS regression for all term LBW births between 2006 and 2010 revealed that mothers with anaemia and under-educated members were significant predictors of LBW in the region (AICC = 442.4, adjusted R2 = 0.843). The GWR model provided a better fit, with an AICC = 436.4 and an adjusted R2 = 0.867. Spatial autocorrelation using the Global Morans I method revealed no statistically significant spatial clustering among the residuals of the GWR. After adjusting for spatial nonstationarity, the important risk factors predicting the burden of LBW babies in the region are maternal under-education and anaemic mothers. GIS tools provide a powerful way of exploring spatial phenomenon and trends, aiding a better understanding of public health concerns.

1. Introduction

Almost 30 million children worldwide are born every year with a birth-weight of less than 2,500 grams. Low Birth Weight (LBW) is a major determinant of mortality, morbidity and disability during infancy and childhood, also having a long-term impact on health outcomes once adulthood is attained [1]. Although the global prevalence of LBW births appears to be waning, the burden of LBW births in the developing countries still continues to be a cause for major concern. South Asia alone accounts for more than 50% of all LBW births worldwide, with 30% of all babies born LBW [2]. Estimates based on available data from institutional deliveries and smaller field-based studies suggest that one-third of all Indian babies are born with moderate to severe malnutrition and have less than optimal birth weight at a rate of 28 % [3, 4, 5]. Low birth weight is a significant contributor to infant mortality in India, with normal, small (1500-2500 grams) and very small (< 1500 grams) babies accounting for infant mortality rates of 49, 62, 129 per 1,000 live-births respectively [5].

Maternal factors such as socio-economic status, parity, weight gain during pregnancy, maternal height, anaemia and tobacco exposure are known to be significantly associated with LBW in developing countries such as India [6]. Economic, social and cultural factors further compound matters by making it difficult for prospective mothers and pregnant women to obtain the requisite nutrition and healthcare [7].

Interventions and programmes to control LBW have been difficult to formulate chiefly because of its multi-factorial nature [6, 8]. Traditional methods including dietary and micro-nutrient supplementation during pregnancy have focused more on

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preventing the occurrence of LBW. Given the complexity of handling and preventing LBW, an appropriate intervention is one that can include a public and individual health strategy with a prevention component to mitigate the detrimental effects of LBW [9].

Geographic Information Systems (GIS) provide a platform for both the powerful visualization of data and analysis which is spatially-driven. Mapping is often carried out to observe spatial phenomena such as clustering of events using GIS software, which may not be easily observable. Health data is often more useful if geo-referenced, i.e. linked to geographic locations; whether it be providing better delivery of health services, disease-tracking and surveillance or aiding effective public health intervention. Spatial analysis methods further bolster the understanding of health aspects that exhibit spatial patterns or phenomena, hence may be used to develop better research hypotheses or to afford better results after post-testing [10, 11].

GIS technology has been used for environmental health surveillance of LBW deliveries in Korea [12]. Automated zoning methods for the identification of high LBW and infant mortality zones have been performed in Michigan to better monitor and manage areas at a higher risk [13]. Hot spot analysis has been demonstrated to understand the spatial distribution of LBW in the Rasht villages of northern Iran to better inform health professionals for tailoring future interventions [14]. Recently, spatial statistical methods such as Geographically Weighted Regression (GWR) have been used to study spatially varying relationships between birth weight and its associated risk factors in the state of Georgia, USA. GIS analyses using GWR are known to provide models with better performance over a standard global regression analysis, and can identify local factors influencing the distribution of LBW more effectively [15].

We attempted to use GIS tools to spatially map and study the magnitude and trend of LBW deliveries at the village level, and to demonstrate spatially varying relationships in the distribution of LBW deliveries in Kaniyambadi block, a rural development block in southern India using the GWR technique Temporal and spatial patterns for LBW distribution were assessed using population-based data for two decades (1991-2010).

2. Materials and Methods

Kaniyambadi block is a third-level administrative sub-division with 82 villages belonging to the state of Tamil Nadu in Southern India. It is composed of a population of 104, 792 (2008 census) and the centroid of the block lies at 79°7'39''E Longitude and 12°48'16''N Latitude.

The Community Health and Development (CHAD) program run by the Department of Community Health, Christian Medical College, Vellore provides primary and secondary health care services to the villages of the block. A health information system has also existed as part of the CHAD program since 1986. Regular surveillance of antenatal and perinatal outcomes is carried out as part of the health delivery system. Information on pregnancies, deliveries, births, deaths, morbidity and immunization status among mothers is recorded onto a computerized database on a weekly basis after validation by the community health workers from each village [16]. The study included information on all births for the period 1991 to 2010.

Gestational age (GA) at delivery was estimated using the date of last menstrual period available from the Health Information System. Analyses were restricted to live births and stillbirths with gestational age of ≥ 28 weeks (period of viability) and a birth weight ≥ 1000 g when the GA was not available [17]. Rates of LBW, moderately low birth weight (MLBW)(birth weight between 1500 to 2500g) and very low birth weight (VLBW) (birth weight <1500g) (per 1000 live-births) were calculated. A master database comprising 25,752 births was finally prepared by merging spatial data for each of the households of the block and non-spatial data with information on maternal, socio-economic and environmental risk-factors of LBW for spatial analysis.

Spatial and temporal trends were observed for 5-year periods by creating GIS maps for each birth weight category aggregated at the village-level. Spatial analysis was performed to identify statistically significant spatial clusters of high rates of LBW deliveries using the hotspot analysis tool (Getis-Ord Gi*) with Cluster and Outlier analysis (Anselin Local Morans I) using ArcGIS 10 software (ESRI, California, USA) [18]. At the village level, LBW deliveries from 2006-2010 were modelled using the global Ordinary Least Squares (OLS) linear regression [18] looking at maternal risk factors such as proportions of short statured mothers, anaemia during antenatal period, primi-gravidas, and pre-term deliveries. Socio-economic indicators such as type of house of the family and mothers educational status, and community-level environmental factors such as proximity to a health facility, population-density of the village and type of natural resources in the village (thematic and risk-zonation mapping with soil, slope, drainage, landuse, water quality layers) were included in the model. Spatial autocorrelation (Global Morans I) was performed on the regression residuals of each significant variable to ensure a randomised distribution of the observations in space [18].

Spatial nonstationarity for each of the significant predictors of LBW in the block was explored using GWR to provide a model with a better fit for explaining the possibile influence of local spatial effects on the pattern of LBW distribution in the block.
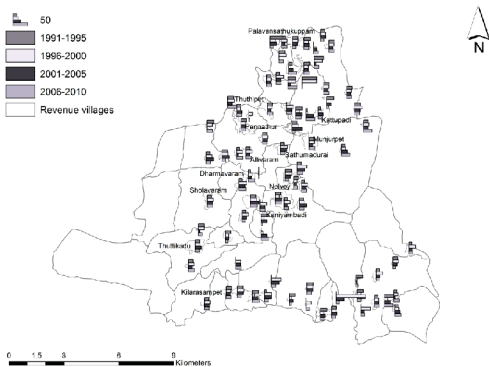
3. Results

There were a total of 25,752 births in Kaniyambadi between 1991 and 2010 with a crude birth rate of 13.3/1000 population for the last five years of study (Table 1). The overall low birth weight rate was found to be 16.8% and the rate of preterm births was 10.7%. Careful visual examination of the five-yearly trends for LBW at the village-level revealed a slight decline in the magnitude of LBW from 1991-1995 to 2006-2010, with 30 (38%) villages exhibiting a decreasing trend and 30 (38%) villages with an increasing trend (Figure 1). Rates of LBW had declined by 2.95% during the last five years of study (p for linear trend = 0.115), with the rate of VLBW births found to be 1.5%.

Significantly high spatial clustering of LBW was observed in the region with hotspots being noted in 10 villages using the hotspot analyst tool (Figure 2). Cluster and outlier analysis revealed 2 villages with significant High-high clustering of LBWs and 2 villages with significant High-low clustering possibly indicating the later group had a much higher LBW burden as compared to the villages in their vicinity.

Table 1- Low birth weight, births and birth rates (2006-2010)

| Year	Total population	Total births	Crude birth rate (per 1000)	LBW births	LBW birth rate (%)
2006	103,883	1289	12.40	200	15.51
2007	104,832	1442	13.75	244	16.92
2008	105,885	1385	13.08	228	16.46
2009	106,994	1507	14.09	256	16.98
2010	108,332	1435	13.24	245	17.07

Figure 1

Legend: Five-yearly distribution of LBW in the Kaniyambadi block (1991-2010)

Table 2- OLS regression results for deliveries (excluding pre-term) for 2006-2010

Variables	Coefficient	Std. Error	t-statistic	Probability
Intercept	1.3980	1.3864	1.0083	0.316
No. of Kutcha [a] houses	-0.0363	0.0405	-0.8983	0.371
Anaemic mothers	0.1674	0.0280	5.9713	0.000[b]
Short-statured mothers	0.2001	0.1565	1.2789	0.204
Low maternal education	0.4862	0.1069	4.5456	0.000[b]
Population density	-0.0010	0.0008	-1.2499	0.215
Distance to health centre	0.4911	0.3534	1.3894	0.168
Natural resources	-0.2511	0.6006	-0.4182	0.677

a) Statistically significant at the 0.05 level
b) Kutcha houses have walls and/or roofs made of material such as mud, grass, reeds, thatch or loosely packed stones.
c) Number of Observations: 82
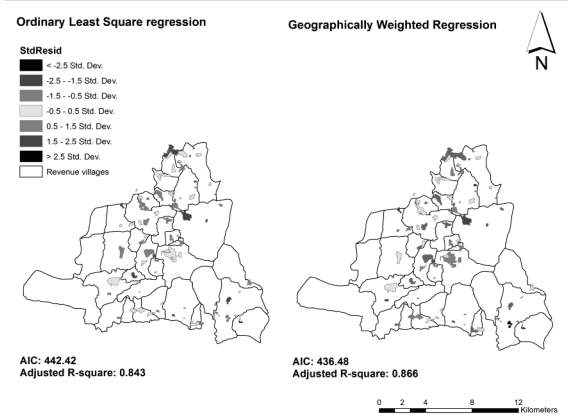d)Adjusted R-Squared: 0.843393

Figure 2
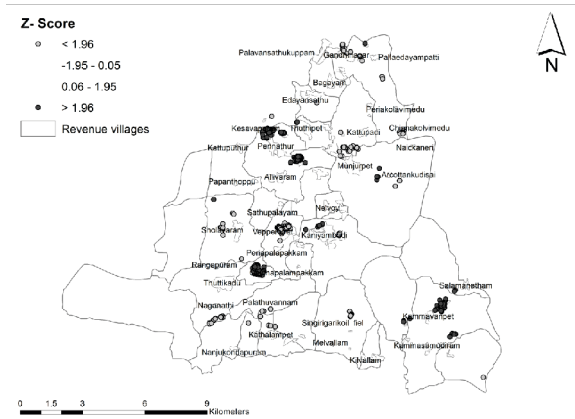
* Z score interpretation: < -1.96 = Cold Spots, > 1.96 = Hot Spots at p < 0.50

Legend: Hot Spot Analysis of LBW in the Kaniyambadi block (1991-2010)

Figure 3

*Standard Residual is the difference between observed and predicted values of LBW.
**AIC: Akaike Information Criteria

Legend: Results of the Ordinary Least Square and Geographically Weighted Regression analysis

Predicting the burden of LBW using the OLS regression method with data on all births for the period 2006-2010 revealed that the proportions of under- educated mothers (up to 5th grade), mothers with anaemia, pre-term delivery and distance from a health centre were statistically significant predictors at the village-level (AIC = 444.1, adjusted R2 = 0.937). Since pre-term delivery is known to have well established association with LBW, the OLS regression was repeated after removing pre-term deliveries with the following results: anaemic mothers and under-educated mothers remained significant predictors for LBW in the Kaniyambadi block for the 5 year period of analysis (AIC = 442.1, adjusted R2 = 0.843) (Table 2).Spatial autocorrelation analysis of the regression residuals (Global Morans I) revealed a random distribution with a p value of 0.271.

The GWR analysis, incorporating significant factors from the OLS model provided a model with a better fit (AIC= 436.4, adjusted R-square= 0.867) (Figure 3) with the over and under predictions being randomly distributed across the block. After adjusting for spatial nonstationarity, the important risk factors predict ting the burden of LBW babies in this block were the numbers of under educated and anaemic mothers were maternal education and positively associated with the burden of LBW in the study region (Table 2).

4. Discussion

Of the factors incorporated into the OLS regression analysis, maternal anaemia and under-educated mothers were the most significant predictors for LBW in the region. Adding a spatial context to the predictors using GWR analysis provided a model with better fit and performance.

Maternal Anaemia is known to increase the risk of pre-term delivery and low birth weight in developed and developing countries alike [19]. In a study from Sudan, mothers with anaemia were found to have a 9 times greater risk of having a low birth weight child than mothers with normal haemoglobin levels [20]. Maternal anaemia was a significant predictor of LBW in the Kaniyambadi block, and merits special focus, even as more substantial links emerge between maternal anaemia and the risk of an LBW birth outcome. Iron supplementation is widely accepted to increase maternal iron status, and must be administered especially during the period between early childhood and adulthood [19]. Vitamin A and Iron Folic Acid supplementation is being carried out in India under the National Nutritional Anaemia Prophylaxis Programme (NNAPP) by the Government of India (GOI), which targets pre-school children (6 months- 5 years), school children (6-10 years), adolescents (11-18 years), pregnant and lactating women [21]. Alternative methods of iron supplementation such as Double Fortified Salt (DFS) is provided to government school children as part of the Mid-day meal scheme in Tamil Nadu; fortified wheat flour is also distributed as part of a state food based programme in Tamil Nadu, among other states [22]. There is a need to bolster such services by facilitating more public-private partnerships, and also to increase awareness on the nutrition requirements of both children and adults, especially among young girls and prospective mothers.

Education is known to have a significant impact on behaviour, especially health-enhancing behaviour. Education to women is all the more vital, as it has a consequent effect on child health and survival [23]. Mothers with up to a primary education (≤ 5 years of schooling) have been documented to be at a greater risk of having a LBW baby by a study from Tanzania, with the risk increasing substantially where no formal education at all was undertaken [24]. Maternal under-education appeared as a significant predictor of LBW in the region, thus highlighting its gravity especially in developing countries. Free primary education is being provided by the GOI's Sarva Siksha Abhiyan since 2001, which aims to construct more schools and strengthen

existing education infrastructure. Education to girls is being bolstered by the Mahila Samakhya Programme, but needs to be encouraged at both the household and community level along with support for the provision of higher education if required [25]. Female education is vital to reduce child mortality and morbidity and may even influence maternal health and survival, which directly influences the risk for low birth weight delivery [23].

The study served to demonstrate the use of spatial methods; namely hot spot, OLS and GWR techniques in exploring a matter of growing public health concern. Spatial analysis was restricted to the last 5 years, as data for the predictors was most complete for that period.

More predictors serve to improve the OLS and GWR analysis, and maybe used for future studies. Spatial methods such as GWR are not "first-choice" regression methods and should not be used to generate a priori hypothesis for testing, it can serve to generate hypothesis for the further testing of research topics or hypotheses. Further, GWR results greatly depend on the variables incorporated into the model and the locality of the study, the results thus cannot be generalised outside the study area [11].

Spatial exploration methods are fast gaining importance and credibility in the better understanding of public health and global health concerns such as attributing disease association and risks, combating emerging infectious diseases, environmental health monitoring and analysis, community health assessments and outreach and life-style intervention programmes [26-31]. Provided the availability of information and GIS infrastructure, the same spatial methods could be used to aid the better understanding and management of other public health concerns.

5.Conclusion

Spatial methods were used to model the important maternal, socio-economic and environmental predictors of LBW in the Kaniyambadi block. Of the predictors chosen; maternal anaemia and maternal under- education proved significant for explaining the burden of LBW during the period of analysis. Hotspot analysis revealed locations with high and low clustering of events; and could help in prioritising locations for intervention. A Global regression method (OLS) was used to identify generalised significant predictors for LBW in the region, and to further account for local variations of the predictors; a GWR modelling was undertaken. GWR methods are useful in complementing understanding of phenomenon that have important spatially varying relationships or explanations. Given the availability of the data and infrastructure, GIS based approaches add a new component to the traditional ways of studying causality and major public health issues could be visualised in a new light.

Acknowledgements

1. Mr. Diwakar PG, Mr. Elango from the Regional Remote Sensing Service Centre, Bangalore, ISRO for providing the natural resource layers and the risk-zonation of Kaniyambadi block.
2. Primary health care team, CHAD, CMC, Vellore.
3. Data management team, CHAD, CMC, Vellore.

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