Spatial Modeling of Risk Factors for Gender-Specific Child Mortality

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INTRODUCTION AND BACKGROUND

The global reduction of child mortality has been a priority of international and national organizations for the last few decades. Despite widespread global efforts to improve child survival, the latest UNICEF report on the *State of the World's Children 2000* (UNICEF, 2000) indicates that child mortality rates continue to remain higher in lesser developed countries (LDCs), and in some areas, girls continue to die at a greater rate than boys.

Matlab, a rural area of Bangladesh, shows child mortality has declined greatly in the last two decades (Figure 1). The rates have also declined in other rural areas across the country, though a lesser extent than in Matlab. The gender mortality differential that was notoriously high in Matlab in the 1980s virtually disappeared by the mid-1990s. Despite the large decline and elimination of gender disparity in child mortality, spatial variations in mortality continue to exist in Matlab (Ali et al., 2001). This variation most likely exists in the rest of Bangladesh, as well as in other less developed countries.

A multitude of social, demographic, economic, and environmental factors has been identified as global factors for contributing to the gender differential of child mortality in Bangladesh (Bairagi et al., 1999; Basu, 1989; Bhuiya & Streatfield, 1991; Chen et al., 1980; Fauveau et al., 1991; Islam & Ataharul, 1989; Koenig & D'Souza, 1986; Muhuri, 1995; Muhuri & Menken, 1997; Salway & Nasim, 1994). Measuring these social environments at a local geographic scale is important for identifying the environments that have a link with higher child mortality. The knowledge would eventually help in directing our effort towards the areas where it is essentially needed for child survival. Using a geographic information system (GIS), we attempted to define local level social environments, and to identify the environments that are influencing local level geographic variation of gender specific mortality in Matlab.

DATA AND METHODS

Child (one to four years) mortality for the periods 1984-86 and 1994-96 were chosen from Matlab demographic surveillance systems to examine the changes in local level spatial variation of mortality over a decade. The three-year periods were chosen to avoid temporal bias in the data.

The Matlab GIS (Figure 2) provided 7691 geographically referenced points of *baris* (a group of patrilineally households living in a geographic space). The mortality rates were smoothed at the point of *baris* by a spatially adaptive filtering that counted population (child) size close to 35. The choice of the specific population size is a trade- off between very low and very high smoothed data. Then, by using *kriging* (a method that is used to extrapolate the data at a regular spaced interval (Oliver &Webstar, 1990)) and contour mapping, gender specific surface maps of higher mortality were created for the two time periods. The temporal surface maps of each gender group were cross-classified, and an output map of each gender group was created (Figures 3 and 4) with the changes shown in: risk area remains risk area (R-R), risk

Table 1. Thresholds (deaths/1,000 children) for defining high-risk areas of child mortality

Gender	1984-86	1994-1996
Male	30.4	9.0
Female	41.4	10.5

Table 2. Results of the multiple logistic regression (spatial) of the male child mortality

Variables	Model: Non-risk to Risk (N-R)		Model: Non-risk to Non-risk (N-N)	
	Regression coefficient	t-test	Regression coefficient	t-test
Intercept	-3.817858	-250.14736	2.690645	166.0446
multiple groups of professionals	0.000090	39.580791	-0.000058	-26.80997
high educational status	0.000362	18.031919	-0.000044	-2.516286
high fertility	0.000106	10.347898	0.000123	13.851040
comparison area	0.170880	17.679539	-0.058213	-6.269722
outside embankment	0.469618	51.742344	-0.306266	-35.09447
cost distance to TC	0.001229	21.177443	-0.000528	-9.392699
high density of population	0.009980	1.036064	0.054325	5.873418
Hindu dominance	0.001021	17.087276	-0.000358	-6.205904
Adjusted R^2	**0.114470**		**0.034517**	

Models: Non-risk area changed to risk area (N-R) and non-risk remains risk area (N-N).

area changed to non-risk area (R-N), non-risk area changed to risk area (N-R), and non-risk area remains non-risk area (N-N). These maps were used as the dependant variable in a spatial regression model.

The data on social environment were smoothed using a fixed filtering of size 210 square meters. Here, our notion is that social environment beyond that distance has little influence on an individual's health outcome. The filtered data were used to create surface maps of the environment using the same kriging and contour mapping techniques. The social environment maps include educational status, population density, fertility rate, major occupations such as agriculture, fishing, and business, and Hindu (minority religious group) predominant areas. All of these maps were described in binary category: the dominant surface got the value "1"; else get the value "0". Finally, distance surfaces were created from the dominant surface of each of these maps; the closer a point to the dominated surface, the smaller the value of the point.

A distance map was created for embankment as an input variable of the model. The study site consists of two programmatic areas: non-intervention and intervention. The attribute of the former one was denoted by "1" and the latter one was denoted by "0". The map of accessibility to nearest health care was determined by cost (in time) distance. In computing the cost distance, rivers and canals were treated as barriers, and assigned their cost five times higher than that of the ground, which is based on waiting time and speed of movement through bodies of water.

Analytical Methods

Logistic regression was employed to determine predictive risk factors for gender-specific child mortality. The regression model takes the form:

$$\mathrm{logit}(p)=\ln(p/1-p)=a+b_1x_1+b_2x_2+\ldots\ldots+b_nx_n$$

where p is the dependent variable expressing the probability of the outcomes.

RESULTS

The thresholds to define higher mortality areas for boys and girls are given in Table 1. The results of the multiple logistic regression show that the combined effects of the factors explain 11% of the total variations in predicting N-R for male children (Table 2). Being in an area outside an embankment is the most important factor in predicting risk for male child mortality, followed by areas of multiple groups of professionals. A high fertility rate also predicts spatial risk for male child mortality. Areas of higher population density show the lowest spatial risk among the factors. On the other hand, the same factors do not predict much (only 3% of total variations) in explaining N-N.

The results of the analysis for predicting R-R and R-N of male children are presented in Table 3. In the table, the model R-R shows that the comparison area predicts higher spatial risk for male child mortality. The effect of an