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Effects of varying temporal scale on spatial models of mortality patterns attributed to pediatric diarrhea

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ABSTRACT

Public health data is often highly aggregated in time and space. The consequences of temporal aggregation for modeling in support of policy decisions have largely been overlooked. We examine the effects of changing temporal scale on spatial regression models of pediatric diarrhea mortality patterns, mortality rates and mortality peak timing, in Mexico. We compare annual and decadal level univariate models that incorporate known risk factors. Based on normalized sums of squared differences we compare between annual and decadal coefficients for variables that were significant in decadal models. We observed that spurious relationships might be created through aggregating time scales; obscuring interannual variation and resulting in inflated model diagnostics. In fact, variable selection and coefficient values can vary with changing temporal aggregation. Some variables that were significant at the decadal level were not significant at the annual level. Implications of such aggregation should be part of risk communication to policy makers.

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1. Introduction

Research using exploratory analyses (Strina et al., 2003; Hamer et al., 1998), time series analyses (Kale et al., 2004) and spatial analyses (Balk et al., 2003; Pande et al., 2008) has greatly improved our understanding of the outbreak etiology of diarrheal disease. Spatial and spatio-temporal patterns, spatial dependence, clusters and hotspots of diarrheal disease have been investigated and observed (Jepsen et al., 2009; Chaikaew et al., 2009; Leyk et al., in press). Purely temporal variations in spatial disease patterns and their association with risk factors have also been described (Kelly-Hope et al., 2008; Anyamba et al., 2006; Alonso et al., 2006). However, when disease outcome (registry) data are compiled in the context of health policy, they are typically aggregated over time in order to derive measures at the same time interval as reported causal risk factors (Abellan et al., 2008). The period of aggregation can be on the order of every 5 or 10 years, for example when census data are released.

The integration of the time dimension into mapping models has been proposed to improve the interpretation of risk patterns (Waller et al., 1997; Abellan et al., 2008). In this paper we explore the effect of changing the temporal scale on spatial models of mortality patterns of pediatric diarrhea (age <5 years) in Mexico over the period 1979–1988. We define mortality patterns as the timing of peak mortality and the magnitude of annual mortality rates (cases per 100,000 population in this age group). We compare models fitted using data temporally aggregated over 10 years, "decadal model", with models using data on an annual basis. The aim is to assess differences in spatial distribution of mortality patterns and their associations with known or expected risk factors due to temporal aggregation of observed disease data. The implications of using

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results from such models in setting international and national global health policy are discussed.

2. Data and data preparation

2.1. Mortality data and mortality patterns

We obtained Mexican mortality data from 1979 to 1988 for each state ($N = 32$) in Mexico from the Instituto Nacional de Estadística Geografía e Informática (INEGI). The data were compiled from death certificates and cause classified using the International Classification of Diseases (ICD; http://www.who.int/classifications/icd). We used all deaths of children younger than 5 years of age and classified ICD-9 codes 001-009 (intestinal infectious disease) in our study. We calculated monthly mortality rates of diarrhea per 100,000 children in this age group based on state-specific age-classified population estimates, which were projected to each year using linear interpolation between census statistics from 1980 to 1990 (INEGI, 2009). We calculated the annual mortality rates MR_a for each state, and then averaged them over the ten year study period to produce an average annual decadal mortality rate MR_{dec}. We determined the month with the highest number of deaths from the raw data for each year (annual mortality peak timing; MPT_a) and averaged a scalar value ranging from 1.0 (May 1st) to 12.99 (April 30th) representing the peak timing over the study period (decadal mortality peak timing; MPT_{dec}). We selected May as starting point of this digital scale because it represented the earliest peak month observed during the study period.

2.2. Climate data

We obtained monthly climatic data for Mexico and the same period as our mortality data set from interpolated climate maps (Mitchell and Jones, 2005) with pixel size 0.5° (latitude) by 0.5° (longitude), or approximately 2500 km^2. The climatic variables used were: number of wet days, precipitation in mm, averages of daily mean, maximum, and minimum temperatures (°C), diurnal temperature range and vapor pressure in hectopascal. We derived climate variable values for each state using the average of the pixel intersecting the location of its capital city and the adjoining pixels which intersect the state area. In most cases this allowed us to link the averaged climate variable to the area of the most populated regions in each state. For each climate variable, we derived peak timing, the month when the value has its maximum, mean values and maximum (peak) values for each year, and used these values to create an average variable over the decadal modeling period (1979–1988).

2.3. Elevation

We obtained 1 km spatial resolution elevation data (*dem*) from the Shuttle Radar Topography Mission (SRTM) digital elevation model (http://www2.jpl.nasa.gov/srtm/), and calculated average elevation within the aforementioned climate grid cells used in our study.

2.4. Population and population density

As mentioned above, state population by age were obtained from the census statistics of 1980 and 1990 (INEGI, 2009). Based on the annual state-specific projections and decadal averages of total population we calculated population density ($popd_a$, $popd_{dec}$; people per km^2). We used spatial gridded databases from the Gridded Population of the World (GPW) and the Global-Rural Mapping Project (GRUMP) (http://sedac.ciesin.columbia.edu/gpw/index.jsp) (CIESIN, 2005) of the year 1990 and with a spatial resolution of 30" (approximately 1 km^2), to create demographic variables, including proportion of urban area (*propur*), or percentage of urban population (*popurb*) for each state. Because the data were only available for 1990, we assumed them to be constant over our study period. We also derived a variable (*popslp*) representing urban population growth rate for the largest Mexican localities within each state using decennial population counts (1930–1980) (INEGI, 2009), assuming the rate of growth prior to our study period could influence know risk factors for enteric disease.

2.5. Socio-economic variables

We obtained the proportion of population (households) in each state without residential access to drinking water (*nowater*), sewage treatment facilities (*nosew*) and electricity (*noelectr*) from the 1980 to 1990 census data (INEGI, 2009), and projected these statistics to each year of the study using a linear function. We also obtained and projected the proportion of the population older than 15 years that is illiterate (*illit15*), using the same method. We then calculated a decadal (averaged annual) value for each of these variables for each state.

3. Methods

We used a three-step approach to identify, develop and evaluate models for annual (MR_a) and decadal mortality rates (MR_{dec}), and corresponding mortality peak timing (MPT_a, MPT_{dec}) for the period 1979–1988: (i) a preliminary analysis to determine whether spatial or non-spatial model procedures should be used, (ii) development of spatial models (annual, decadal) for MR, and MPT, and (iii) an analysis of model coefficients; testing for consistency of relationships between mortality patterns and predictive risk factors in annual models, and for the deviation of these annual relationships from the corresponding ones in a decadal model.

3.1. Preliminary analysis: spatial autocorrelation, spatial clustering and non-spatial baseline models

We calculated standard deviation in annual mortality patterns, MPT_a and MR_a, in order to quantify their variability during the study period. We visually evaluated the spatio-temporal distribution of mortality patterns across Mexican states for the period of our decadal model (1979–1988) by creating maps of MPT_{dec} and MR_{dec} (Fig. 1). The mapped data suggest a spatio-temporal

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