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Assessing seasonal variations and age patterns in mortality during the first year of life in Tanzania

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ABSTRACT

Lack of birth and death registries in most of developing countries, particularly those in sub-Saharan Africa led to the establishment of Demographic Surveillance Systems (DSS) sites which monitor large population cohorts within defined geographical areas. DSS collects longitudinal data on migration, births, deaths and their causes via verbal autopsies. DSS data provide an opportunity to monitor many health indicators including mortality trends. Mortality rates in Sub-Sahara Africa show seasonal patterns due to high infant and child malaria-related mortality which is influenced by seasonal features present in environmental and climatic factors. However, it is unclear whether seasonal patterns differ by age in the first few months of life. This study provides an overview of approaches to assess, capture and detect seasonality peaks and patterns in mortality using the infant mortality data from the Rufiji DSS, Tanzania. Seasonality was best captured using Bayesian negative binomial models with time and cycle dependent seasonal parameters and autoregressive temporal error terms. Seasonal patterns are similar among different age groups during infancy and timing of their mortality peaks do not differ. Seasonality in mortality rates with two peaks per year is pronounced which corresponds to rainy seasons. Understanding of these trends is important for public health preparedness.

1. Introduction

Demographic Surveillance Systems (DSS) sites established within the INDEPTH network in many Sub Saharan African countries continuously collect large amount of data on trends of disease morbidity, mortality, in- and out-migration (INDEPTH Network, 2002; Sankoh and Binka, 2005). Due to lack of efficient and reliable national vital registration systems to collect data on population and health in developing countries, these surveillance data are invaluable for evidence-based health planning and guide policy decisions (Snow et al., 1998a; INDEPTH Network, 2002; Kynast-Wolf et al., 2002; Hammer et al., 2006; Lutambi et al., 2010). DSS data have been used to study number of health indicators such as mortality rates, produce life tables and estimating burden of diseases (Tollman and Zwi, 2000; Korenromp et al., 2004).

Most DSS sites are located in rural areas and in countries which are endemic for malaria (http://www.indepth-network.org) where environmental factors such as rain and temperature influence highly the patterns and seasonality of transmission (Snow et al., 1998b). In these sites, just like in many parts of Sub-Saharan Africa, one-fifth of all deaths that occurred, including those of neonates, infants and children between 1 and 5 years is attributed to malaria alone (WHO, 2010). That is due to indirect effect of malaria including low birth weights (Steketee et al., 2001), high prevalence at early stage of life (Greenwood, 2006) and lack of proper determination of specific cause of death (Masanja et al., 2008; Ramroth et al., 2009; Adjuik et al., 2010; Shabani et al., 2010). Nevertheless, factors related to child immune development and passively transferred antibodies from mother to child, are believed to cause a relatively protection of neonates and infants under age of 3–6 months from severe consequences of malaria illness (Riley et al., 2000, 2001; Mutabingwa et al., 2005) hence malaria-related mortality would be expected to be low (Amaratunga et al., 2011; Kitua et al., 1996; Le Hesran et al., 2006; Snow et al., 1998a,b). However, other differential factors such as age, quality of health services and genetics influences ultimately modify the mortality pattern, especially in young children (Riley et al., 2000; Poespoprodjo et al., 2010).

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The complexity of the factors associated with mortality trends, especially in infants, pose a difficulty to predict the timing that mortality peaks and to assess whether these peaks are age-dependent. Utilizing the richness of DSS databases, vigorous quantitative methodologies can be formulated to study and quantify association with risk factors and at the same time estimate seasonal peaks and temporal trends. Clarity in these variations is crucial to timely interventions (Lawn et al., 2005a,b), prepare health system demand and for guiding proper allocation of resources (Fisman, 2007; Medina et al., 2007; Naumova et al., 2007; UNICEF, 2005).

Most epidemiological and longitudinal studies employ summary statistics, graphical presentation (Becker and Weng, 1998; Pascual et al., 2008) and statistical tests (Bailey et al., 1992; Yip and Yang, 2004; Singh et al., 2007; Vitali et al., 2009) while assessing seasonality. Selected applications extended the seasonality assessment with application of time series methodologies such as Seasonal Auto-Regression Integrated Moving Average (SARIMA) models (Tong et al., 2005; Hu et al., 2007; Zhang et al., 2007; Briët et al., 2008). However SARIMA models are mainly appropriate for Gaussian data (Zeger et al., 2006; Huang et al., 2011). Statistical techniques which incorporate harmonic functions with varying coefficients in traditional models have also been used to efficiently model seasonality, though claimed to introduce a large number of parameters and sometimes over fit the data (Stolwijk et al., 1999; Rau, 2006; Eilers et al., 2008). However, there are limited applications, which involved assessing seasonality in tropical diseases or utilizing various DSS data specifically on mortality (Becher et al., 2008; Becker and Weng, 1998; Byass et al., 2002; Kynast-Wolf et al., 2006; Ramroth et al., 2009). The referred studies utilized Poisson regression models with trigonometric functions to capture seasonality proficiently (Kynast-Wolf et al., 2006; Becher et al., 2008). It is an observation that most of the modeling attempts ignore accounting for temporal correlation and overdispersion which are vital in longitudinal data analysis (Cameron and Trivedi, 1998).

This study aims to provide an overview of different approaches to assess seasonality in mortality data. Further extensions of existing measures are given to allow statistical inference and in contrary to previous application, negative binomial (NB) regression models with temporal random effects are used instead, to provide a rigorous but simplified approach for modeling seasonal patterns and detection of mortality peaks at different age groups in infancy. Models are formulated in a Bayesian framework and accounted for excess zeros, temporal correlation and used various components to capture seasonal patterns. The methods are illustrated using the infant mortality data from the Rufiji DSS (RDSS) database and outputs are discussed to suggest best approaches that can be used to assess mortality peaks. The analysis was carried out for different age-groups during infancy and on pooled data (combining all age groups). This paper is organized as follows; Section 1 defines the data used, Section 2 describes methods considered in measuring seasonality with formulation of models. Results and discussion are presented in Sections 3 and 4 respectively.

1.1. Data

1.1.1. Infant mortality

Mortality data were extracted from the Rufiji DSS database covering a period of October 2001–September 2004. The RDSS, located in Rufiji District, Tanzania commenced in 1998. It extends from 7.470 to 8.030 south latitude and 38.620 to 39.170 east longitude. The DSS monitors 85,000 people, which is about 47% of the total population of the District (Source: INDEPTH Monograph). From the database we extracted dates of birth, entry and exit from a survey (given by day, month and year) and death status (Source: Rufiji DSS). The outcome of interest is a binary variable indicating a death status of an infant at exit of a specific calendar month during the study period. Infants were grouped in age intervals of thirty days (i.e. 0–30days, 31–60days . . ., 331–360days) and referred to age in month 0 to month 11. It is worth noting that, person-time (period) methods were used for data analysis, rather than cohort analysis based on number of live births, hence rates calculated on the basis of person-times are expected to be higher than those based on number of live-births. However, the approach facilitated analyses of multiple age groups.

Total death counts and *time at risk* were calculated by calendar month and by age group. An individual's "*time at risk*" is defined as number of days an infant was alive during a specific age group and/or a calendar month. Age-specific mortality rates (rate at ith month of life, i=0,...,11) were calculated by taking a ratio between total deaths counts and total *time at risk* (multiplied by 1000) and expressed as deaths per 1000 person-years. For this study, years are defined as Year 1 (October 2001–September 2002), Year 2 (October 2002–September 2003) and Year 3 (October 2003–September 2004).

1.2. Seasonality

Rufiji district is characterized by two main rainy seasons; short rains (October–December) and long/heavy rains (February–May) with the remaining months (January, June, July, August and September) remain relatively dry. In this study two seasons were considered, a dry season which comprised of the dry months and wet season which included both, the short and heavy rain months (season). This categorization was used in the calculation of the mortality indices and included in the regression models (described in the next section).

2. Methodology

In this section methods to assess seasonality patterns considered in this paper are described. These include mortality indices, statistical testing and modeling.

2.1. Seasonality index

The ratio of wet season mortality rate (MR) to dry season MR is the most commonly index used to measure the strength of seasonality (Rau, 2006). Mathematically, a point estimate for this index (denoted as θ) is calculated as: $\theta = \sum_{i \in s_1} MR_i / \sum_{k \in s_2} MR_k$, where S_1 is a set of wet months and S_2 a set of dry months. The value $\theta = 1$ indicates no difference between the two seasons, $\theta > 1$ indicates higher mortality rate in wet season while $\theta < 1$ indicates higher rates during the dry season. However, a measure uncertainty for the parameter θ is not always considered hence limit making statistical inference for the index. To address this, a model based approach was used to estimate θ with its associated confidence intervals. Details of model formulation are described in the modeling section. In this study, point estimate values for θ denoted as θ_P were calculated for each age group on annual basis and for pooled data and while model based index denoted as θ_m were calculated only for pooled data. Results are presented and discussed.

2.2. Goodness-of-fit test

This is a form of a chi-square test which has been commonly applied to measure seasonality in time series data (Sogoba et al., 2007; Zhang et al., 2007; Mohorovic et al., 2010). Thinking of a time series as a process, the test determines whether the process systematically deviates from pre-defined expectation (Zeger et al., 2006). In this study the test was used to indicate whether it is reasonable to assume that mortality rates (of specific age group or