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Estimation of malaria incidence in northern Namibia in 2009 using Bayesian conditional-autoregressive spatial–temporal models ☆

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ABSTRACT

As malaria transmission declines, it becomes increasingly important to monitor changes in malaria incidence rather than prevalence. Here, a spatio-temporal model was used to identify constituencies with high malaria incidence to guide malaria control. Malaria cases were assembled across all age groups along with several environmental covariates. A Bayesian conditional-autoregressive model was used to model the spatial and temporal variation of incidence after adjusting for test positivity rates and health facility utilisation. Of the 144,744 malaria cases recorded in Namibia in 2009, 134,851 were suspected and 9893 were parasitologically confirmed. The mean annual incidence based on the Bayesian model predictions was 13 cases per 1000 population with the highest incidence predicted for constituencies bordering Angola and Zambia. The smoothed maps of incidence highlight trends in disease incidence. For Namibia, the 2009 maps provide a baseline for monitoring the targets of pre-elimination.

1. Introduction

Maps of malaria transmission intensity are increasingly being used for planning, monitoring and evaluation, and resource allocation (Hay et al., 2009; Noor et al., 2010; Omumbo et al., 2013). In countries where malaria elimination is feasible, the World Health Organisation (WHO) proposes a transition from measuring risk by malaria

Abbreviations: ACD, active case detection; CAR, conditional auto-regressive; CPO, conditional predictive ordinate; DIC, deviance information criterion; ESRI, Environmental System Research Institute; EVI, enhanced vegetation index; GF, Gaussian field; GIS, geographic information system; GMRF, Gaussian markov random field; GPS, global positioning system; GRUMP, Global Rural and Urban Mapping Project; HMIS, Health Management Information System; INLA, Integrated Nested Laplace Approximation; JAXA, Japan Aerospace Exploration Agency; MAUP, Modifiable Areal Unit Problem; MCMC, Markov Chain Monte Carlo; MODIS, MODerate-resolution Imaging Spectro-radiometer; MoHSS, Ministry of Health and Social Services; NASA, National Aeronautics and Space Administration; NVBDCP, National Vector-Borne and Disease Control Programme; PCD, passive case detection; PHS, public health sector; RDT, Rapid Diagnostic Test; SPA, Service Provision Assessments; TRMM, Tropical Rainfall Measuring Mission; TSI, temperature suitability index; WHO, World Health Organisation; ZIP, Zero-Inflated Poisson.

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prevalence surveys to surveillance through a combination of routine health management information systems (HMIS) and active case detection (World Health Organizastion, 2007). The year 2009 has a special significance for the fight against malaria in Namibia. This is when the Elimination Eight (E8) initiative was launched, under which eight southern African countries decided to collaborate to eliminate malaria in Namibia, Botswana, South Africa and Swaziland. Under this initiative, Namibia formally declared the ambition to eliminate malaria by 2020 (Noor et al., 2013a,b; Southern Africa Roll Back Malaria Network (Sarn), 2010). These ambitions were motivated by reported substantial declines in malaria burden in the four eliminating countries and by the 2008 global call for malaria elimination (World health Organizastion, 2008). A Namibian malaria indicator survey (MIS) conducted in 2009 showed a mean community *Plasmodium falciparum* prevalence of approximately 3% nationally (Ministry of Health and Social Services, 2010b). This is a threshold at which countries are advised to use case incidence data for measuring malaria risk (Hay et al., 2008; Yekutiel, 1960). In 2010, Namibia launched a national malaria strategy for the period 2010–2016 (Ministry of Health and Social Services, 2010c). The aim was to reduce malaria case incidence to 10 persons per 1000 population by 2013 and to move the country to pre-elimination status by 2016 where case incidence will be less than 1 person per 1000 population (Ministry of Health and Social Services, 2010c, d).

Most malaria eliminating countries in Africa, including Namibia, are yet to adopt active case-detection (ACD) systems (World Health Organization, 2012) and the main source of data for measuring disease incidence is from passive case detection (PCD), assembled through the public health sector (PHS). Such data, however, have deficiencies that limit their use for estimating overall case incidence accurately. A substantial proportion of malaria cases are treated outside of the PHS (Cibulskis et al., 2011; Cibulskis et al., 2007), while only a proportion of health facilities in the PHS submit returns and even fewer report every month of the year, making the data incomplete spatially and temporally (Gething et al., 2008; Gething et al., 2006; Murray et al., 2004; Stansfield, 2005). Third, only a subset of reported cases is diagnosed parasitologically and most of these cases are fevers that have been diagnosed presumptively as malaria (Cibulskis et al., 2011; Cibulskis et al., 2007). The use of such data therefore requires approaches that adjust for the non-utilisation of the PHS, incomplete data reporting which underestimate burden and the presumptive diagnosis which inflate incidence (Alegana et al., 2012; Cibulskis et al., 2011). In addition, these approaches must harness the spatial and temporal autocorrelation of the available data to predict at locations and periods where data are missing as well as estimate robustly the uncertainties of these predictions (Loha and Lindtjorn, 2010; Reid et al., 2012).

Bayesian hierarchical conditional auto-regressive (CAR) models can improve the quality of HMIS data at a national level, where routine surveillance is inefficient, by representing risk via a set of environmental or ecological factors and random effects using CAR priors (Barnerjee et al., 2004; Gelfand and Vounatsou, 2003; Gething et al., 2006). Examples of such approaches have been used previously in modelling spatial–temporal variation of disease risk in Yunnan province in China (Clements et al., 2009) and in identifying social and ecological factors driving malaria risk in Vietnam (Manh et al., 2011). These methods handle uncertainty in a coherent manner, are able to predict risk in areas where data are not recorded while at the same time smoothing variability where the denominator (population) is small (Gelfand and Vounatsou, 2003; Reid et al., 2012). These approaches are used in this study with the primary aim of predicting malaria incidence at second administrative unit level (constituencies) in northern Namibia where malaria is considered endemic (Ministry of Health and Social Services, 2010c). In addition, a novel approach is used to adjust PHS utilisation rates to estimate catchment population. Secondary aims of this study were to calculate populations at risk to determine areas where interventions can be targeted to provide universal coverage and to evaluate the use of environmental factors such as rainfall and vegetation indices in predicting incidence.

2. Methods

2.1. Study area

Namibia is divided into 13 regions (administrative level 1) and 108 constituencies (Ministry of Health and Social Services, 2010c; Zere et al., 2006) (Fig. 1). The country is largely dry and sparsely populated with an estimated 2.1 million people in 2009 living in an area of approximately 0.83 million km^2 (National Planning Commission, 2012). The risk of malaria is constrained by aridity (Ministry of Health and Social Services, 2010c; Snow et al., 2010) with the larger and sparsely populated south made up of four regions, Karas, Hardap, Khomas and Erongo, considered either malaria-free or supporting high focal very low transmission intensity (Ministry of Health and Social Services, 1995, 2010c). The majority of the population resides in the other nine northern regions of the country that are also considered to contribute almost the entire malaria burden in Namibia (Ministry of Health and Social Services, 2010b, c, e). In this study, analysis of malaria incidence was restricted to the 78 constituencies in the nine northern regions (Fig. 1).

2.2. Assembly of malaria case data

Monthly data (January to December) for 2009 on confirmed and suspected (clinically diagnosed) cases of malaria among patients of all ages were obtained from the Ministry of Health and Social Services (MoHSS) after a national Service Provision Assessment (SPA) survey was conducted (Ministry of Health and Social Services (MoHSS) and Icf Macro, 2010). The health facility survey covered 273 facilities in the north comprising of hospitals, health centres, clinics and sick bays that are managed by the Ministry of Health and Social Services (MoHSS), missions, Non-Governmental Organisations (NGOs), the private sector and Ministry of Defence (MoD) and police. Of these, only