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An investigation of district spatial variations of childhood diarrhoea and fever morbidity in Malawi

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Abstract

Although diarrhoea and malaria are among the leading causes of child mortality and morbidity in Sub-Saharan Africa, few detailed studies have examined the patterns and determinants of these ailments in the most affected communities. In this paper, we investigate the spatial distribution of observed diarrhoea and fever prevalence in Malawi using individual data for 10,185 children from the 2000 Malawi Demographic and Health survey. We highlight inequalities in child health by mapping the residual district spatial effects using a geo-additive probit model that simultaneously controls for spatial dependence in the data and potential nonlinear effects of covariates. The residual spatial effects were modelled via a Bayesian approach. For both ailments, we were able to identify a distinct district pattern of childhood morbidity. In particular, the results suggest that children living in the capital city are less affected by fever, although this is not true for diarrhoea, where some urban agglomerations are associated with a higher childhood morbidity risk. The spatial patterns emphasize the role of remoteness as well as climatic, environmental, and geographic factors on morbidity. The fixed effects show that for diarrhoea, the risk of child morbidity appears to be lower among infants who are exclusively breastfed than among those who are mixed-fed. However, exclusive breastfeeding was not found to have a protective effect on fever. An important socio-economic factor for both diarrhoea and fever morbidity was parental education, especially maternal educational attainment. Diarrhoea and fever were both observed to show an interesting association with child's age. We were able to discern the continuous worsening of the child morbidity up to 8–12 months of age. This deterioration set in right after birth and continues, more or less linearly until 8–12 months, before beginning to decline thereafter. Independent of other factors, a separate spatial process produces district inequalities in child's health.

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Keywords: Residual spatial effects; District inequalities; Clustering; Diarrhoea; Fever; Fixed effects; Bayesian approach; Malawi

Introduction

The success of any policy or health care intervention depends on a broader and accurate understanding of the socio-economic, environmental and cultural factors that determine the occurrence of disease and death. Until recently, available information on childhood morbidity

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was derived from clinics and hospital records. However, information obtained from hospitals represents only a small proportion of all cases, since many other cases do not seek medical attention (Black, 1984). Thus, the hospital records may not be appropriate for estimating the prevalence of diarrhoea for program developments (Woldermichael, 2001).

Policy-makers and researchers often want to know the distribution of a disease prevalence by geographical region, or association with environmental factors (Diggle, Moyeed, & Thomson, 2002; Thomson, Connor, Milligan, & Flasse, 1996). In this regard, mapping risk variations in child morbidity is an invaluable tool. Further, the mapping of variation in risk of childhood morbidity can help improve the targeting of scarce resources for public health interventions. Therefore, Geographic Information System (GIS) is a powerful tool for public health practitioners that can easily allow them to assess patterns, trends and relationships between health events and environmental, socio-economic and other geographic factors (see for instance the case of disease surveillance, preparedness and response coordination to combat health threats such as West Nile virus, anthrax, severe acute respiratory syndrome (SARS) and bioterrorism (Gardner & Harrington, 2003)). GIS further helps us to understand childhood disease prevalence at the community level (see for instance Garg, Omwomo, Witte, Lee, & Deming, 2001; Mbonye, 2003, 2004) and helps to identify underserved populations, and can help public health agencies to efficiently allocate scarce program resources to appropriate locations. For example, the Communicable Disease Control Division of the Boston Public Health Commission (BPHC) uses GIS to help identify at-risk populations and determine where to focus efforts to vaccinate residents against influenza. This paper is based on a study of the spatial distribution of childhood diarrhoea and fever in Malawi. The study applied Bayesian statistical and geo-statistical techniques to the 2000 Demographic and Health Survey (DHS) data of Malawi with location (district) attributes and other information to answer specific questions about geographic inequalities in childhood disease prevalence. The DHS in Malawi conducted in 2000 is a valuable resource for population-based morbidity data, although we recognize its limitation, like other DHSs elsewhere, in that it relates only to reported child morbidity during the last 2 weeks before the survey. Thus, our results might be influenced by the effects of seasonality in diseases prevalence.

To gain an understanding of the geographic variation or patterns based on the observed morbidity prevalence, a Bayesian hierarchical model was fitted, with the inclusion of spatial (district) and nonlinear metrical (mother's and child's age) covariates. Of particular interest in this study, was whether a significant

geographic variation in childhood diarrhoea and fever existed; and if so, what potential risk factors could explain such variation?

Background: characteristics of the study area

Malawi is an African country in the south-east region of the continent with a population of about 10 million and a population growth rate of about 2.5 percent/year (National Statistical Office [Malawi] and ORC Macro, 2001; WHO, 1998). With a gross national product (GNP) of US\$ 170/person/year, Malawi is among the 20 least economically developed countries in the world (National Statistical Office [Malawi] and ORC Macro, 2001; WHO, 1998). Agriculture accounts for over a third of the GNP, about 90 percent of export earnings and approximately three-quarters of total employment (UNICEF and Government of Malawi, 1993). Despite economic difficulties Malawi has invested a lot in health. According to UNICEF statistics there is a reasonably good network of health facilities in Malawi (the median distance from home to the nearest facility is 5 km). For 90 percent of births, mothers have received at least one antenatal care from a trained health worker, and 86 percent of children aged 12–23 months possess a health card indicating a high under-five clinic attendance and about 90 percent of children are reported to have been vaccinated against the most common illnesses. However, improvements in health indicators have been smaller than expected. Currently, the maternal mortality rate is estimated at 1120–1180/100,000 live births. Life expectancy at birth is only 44 years, largely because of high mortality amongst the children. For every 1000 live births, about 135 die before the age of 1 year and 200 before the age of 5 years (National Statistical Office [Malawi] and ORC Macro (2001). Findings of the 2000 MDHS point to important changes in Malawi's health and demographic profile. Mortality of children under age 5 has declined since the early 1990s. During the period 1988–1992, the under-five mortality rate was 234 deaths/1000 live births, compared with 189/1000 between 1996–2000 (National Statistical Office [Malawi] and ORC Macro (2001). Although this represents important progress, the rate of the downward trend is modest and childhood mortality remains at a very high level. A comparison of the 1992 and 2000 Malawi DHS shows that the prevalence of diarrhea decreased slightly from 20% to 17% between the two periods. However, the percentage of ill children who received treatment reduced. All these point to the fact that Malawian children are growing up in an environment of high morbidity, low utilization of health care, and consequently high mortality risks.

The census results also indicate that there is geographic variation in the rates of infant and under-five

mortality with highest mortality rates in the Southern regions followed by the Central regions and the least in the Northern regions. Household socio-economic status is associated with child survival because it determines the amount of resources (such as food, good sanitation and health care) that are available to infants (Millard, 1994). Measures of socio-economic status that are thought to be associated with infant health include: maternal and paternal education; household wealth; household size; parental occupation; and rural or urban residence. Kandala and Madise (2004), who used the 1992 DHS data from Malawi and Zambia, in their study of childhood morbidity, found that the level of maternal education was highly significant in the two countries. They also found that childhood morbidity was lower among educated women, and that although this effect attenuated with the inclusion of other socio-economic factors in the models, maternal education remained significant.

Lower morbidity was also reported in households with large number of adult members (Kandala, 2002; Kandala & Madise, 2004). The impact of the household's size should, however, not be over-interpreted, since to some extent it directly mirrors infant mortality. For instance, a household with high mortality risk will remain small. In contrast, a household's size might also reflect its wealth, as a rich household will attract occupants. Again, in a large household, a child might benefit from the help of several adults. Large households may benefit from scale economies in time for childcare as well as in expenditures. Alternatively, they may have become better at raising children through accumulated experience (Christianensen & Alderman, 2001).

Child-level demographic factors such as birth order, the length of preceding birth interval, and the survival status of the preceding child have been shown to be strongly associated with infant mortality and health in Africa as well as Asia (Cleland & Sathar, 1984; Kandala, 2002; Kandala & Madise, 2004; Koenig, Phillips, Campbell, & D'Souza, 1990; Madise & Diamond, 1995; Whitworth & Stephenson, 2002). First and higher order births, those born after birth intervals of less than 2 years, and those whose previous sibling have died appear to have high risks of morbidity and of dying in infancy. Some researchers have documented evidence of a U-shape pattern in the association between maternal age and infant mortality and morbidity, with teenage and older mothers having elevated risk of child loss (Bicego & Ahmad, 1996; Geronimus & Korenman, 1993; Kandala, 2002; Kandala & Madise, 2004; Manda, 1998).

Sex differentials in infant health and mortality have been observed universally. In the majority of the world regions, girls have lower mortality, at least for the first few months of life (Curtis & Steele, 1996; Kandala, 2002; Sastry, 1997). Exceptions have been noted in some Asian

countries. In India, girls are more than 30 percent likely to die before their fifth birthday than boys and this is thought to be the result of son preference, which is manifest in lower spending on health for girls and higher prevalence of immunization among boys (Claeson, Bos, Mawji, & Pathmanthan, 2000; Timaeus, Harris, & Fairbarn, 1998).

Historically, variations in incidence and prevalence of diarrhoea and fever have been related to family socio-economic factors and neglected temporal and geographical gradients and other variations in risk, in order to generate hypotheses towards the causation of disease. In this paper, we take advantage of advances in GISs and how the technology provides opportunities to study associations between environmental exposure and the spatial distribution of diseases. Jacquez (2000) discusses how GIS can be used to monitor disease outcomes, identify health risks, and design and implement intervention plans. The epidemiological approach has not yielded all the answers, but it holds great merit and much potential to further contribute to the knowledge of disease etiology. This study enhances our understanding of diarrhoea and fever prevalence in a dimension that could not have been possible prior to the availability of GIS. The results will help us making further decisions in planning for diarrhoea and fever research.

Data and methods

Individual data record was constructed for 10,185 children for diarrhoea and 10,180 children for fever. Each record consisted of morbidity information and a list of covariates as shown in Appendix A. Geo-additive logistic models were used (on the probability of a child having diarrhoea and fever during the reference period) to determine the socio-economic and demographic variables that are associated with the ailments while simultaneously controlling for spatial dependence in the data and possible nonlinear effects of covariates. The DHS data have been collected hierarchically at the family and community levels which are inter-related. Standard analysis of the fixed effects covariates for child morbidity neglects this correlation structure and dependence in the data. This neglect leads to underestimation of standard errors of the fixed effects that inflates the apparent significance of the estimates (Bolstad & Manda, 2001). Our analysis includes this correlation structure and account for the dependence of community in the model. The model also permitted borrowing strength from neighbouring areas to obtain estimates for areas that may, on their own, have inadequate sample sizes. This gives more reliable estimates of the fixed effect standard error.

Statistical methods

The response variable in this application is defined as $Y_i = 1$ if child i had diarrhoea or fever during the reference period t , and $Y_i = 0$ otherwise. The commonly adopted model for the analysis of this data is the probit or logistic model, and the standard measure of effects is the odds ratio (OR) (Mbonye, 2003, 2004; Woldermichael, 2001; Yoannes, Streat-eld, & Bost, 1992). Because of the geographical nature of our data and the presence of nonlinear effects for some covariates, the assumption of a strictly linear predictor may not be appropriate, however.

We use semi-parametric models to flexibly model the effects of selected socio-economic factors, continuous (metrical) and spatial covariates. Our analysis is based on a flexible geo-additive model using the district as the geographic unit of analysis, which allows separating smooth structured spatial effects from random effect and estimate the effect of continuous covariates nonlinearly without assuming a linear functional form. A probit model with dynamic and spatial effects $\Pr(y_i = 1|x_{it}^*) = \Phi(\eta_{it})$ with an additive semi-parametric predictor $\mu_i = h(\eta_i)$,

$$\eta_i = f_1(x_{i1}) + \dots + f_p(x_{ip}) + f_{\text{spat}}(s_i) + w_i'\gamma \quad (1)$$

was used instead; where h is a known response function with a probit link function, and f_1, \dots, f_p are nonlinear smooth effects of the nonlinear covariates and f_{spat} is the effect of district $s_i \in \{1, \dots, S\}$ where child i lives. In a further step, we split up the spatial effect f_{spat} into a spatially correlated (structured) and an uncorrelated (unstructured) effect: $f_{\text{spat}}(s_i) = f_{\text{str}}(s_i) + f_{\text{unstr}}(s_i)$. The rationale is that a spatial effect is usually a surrogate of many unobserved influences, some of them may obey a strong spatial structure and others may be present only locally.

Models with a predictor that contains a spatial effect are also called geo-additive models (see Kammann & Wand, 2003). More detailed description of these models is available elsewhere (for example, Fahrmeir & Lang, 2001; Kandala, Lang, Klasen, & Fahrmeir, 2001; Kandala & Madise, 2004).

This model is an extension of the probit or logistic model with a strictly linear predictor $\eta_i = \alpha + w_i'\gamma$, the two main differences are the use of a flexible predictor to model the effects of covariates that clearly have nonlinear effects on diarrhoea and fever and the use flexible methods to introduce the spatial dimension on determinants of diarrhoea or fever and allocate these spatial effects to structured and unstructured (random) components. This is done jointly in one estimation procedure that simultaneously identifies socio-economic determinants, and the spatial effects that are not explained by these socio-economic determinants. In this way, we are able to identify district patterns of

prevalence of diarrhoea and fever that are either related to socio-economic variables that are not in the model and that have a clear spatial pattern, or point to spatial (possibly epidemiological or environmental) processes that account for these spatial patterns. Identifying spatial patterns of disease prevalence beyond the known family socio-economic determinants should also assist in poverty mapping and associated district targeting of resources (Elbers et al., 2001).

The standard measure of effect is still the OR for logistic model and mean for probit model (but because of the use of a fully Bayesian approach that relies on prior assumption to make posterior inference, instead of 'OR' or mean, we have 'posterior OR' or posterior mean), and tests for significance, linear trends and interactions are not carried out as usual using likelihood ratio tests but the Deviance Information Criteria (DIC) (Spiegelhalter, Best, Carlin, & Van der Linde, 2002) is used instead for model fit and comparison. To account for possible departures from the assumed distribution, 95% confidence intervals (CIs) for the posterior ORs and probability maps (the equivalent of CIs for the spatial effects) are calculated using robust standard errors estimated via Markov Chain Monte Carlo simulation techniques.

The estimated coefficients follow the same interpretation as those of ordinary logistic regression: $y_1 = 0$, $y_2 = 1$, and $\exp(\beta_i)$ is the OR that $y = 1$ when X_i increases by 1. Note that the probit model corresponds to a logistic model with the cumulative distribution function replaced by the standard normal distribution. The coefficient of covariates (say, child's place of delivery: hospital, Antenatal visit, marital status, etc.) represent the difference in posterior log odds between the various categories and they are not easy to interpret apart from the sign. Taking the exponential of the coefficients gives the posterior OR and exponentiating the 95% confidence limits gives the confidence interval for the OR. Although the estimation process is complex,¹ the estimated posterior coefficients (posterior mean) should be interpreted as those of ordinary probit models.

¹We estimated models where either a structured or an unstructured effect was included as well as a model where both effects were included. Based on these results, Markov random field (MRF) priors were assumed for the structured effect ($f_{\text{str}}(s)$) and Penalized spline (P-spline) prior for the nonlinear effects of metrical covariates f_1, \dots, f_p . The analysis was carried out using BayesX-version 0.9 (Brezger, Kneib, & Lang, 2003), a software for Bayesian inference based on Markov Chain Monte Carlo simulation techniques. We investigated the sensibility to the choice of different priors for the nonlinear and spatial and we noticed that results for this application are not sensitive to the choice of different priors.

Results

Preliminary results

Visual inspection of the maps of the observed diarrhoea and fever prevalence by regions and districts (Figs. 1 and 2) suggest that regional classification conceal district variations. Table 1 shows that overall, the highest prevalence of both diarrhoea and fever were observed in the Central region, followed by the Southern region. Although the Northern region reported the lowest overall prevalence of both fever and diarrhoea, it had the district with the highest fever incidence of 63 percent (Nkhata Bay), further confirming that regional classifications do mask important district variations.

The geographical variation was apparent for the district maps for the two morbidity conditions, but from the region maps it was not apparent. The hypothesis that regional classifications conceal district variations was investigated for both levels separately using Geo-additive probit models. Prevalence of disease for each household were related to the distance of the household from the nearest next district and region. The region variables were categorized into dummies. There was a clear spatial pattern as observed in the distribution of diarrhoea and fever prevalence at the district level

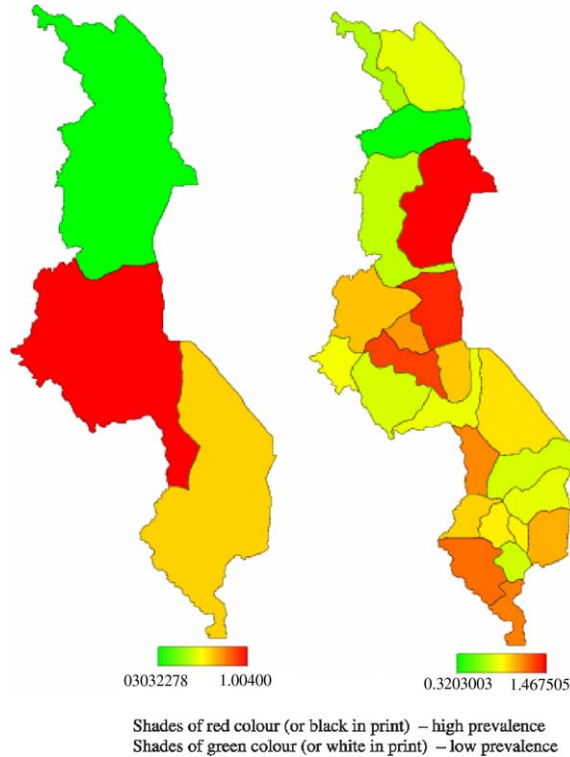


Fig. 1. Spatial distribution of observed diarrhoea by regions (left) and districts (rights) in Malawi.

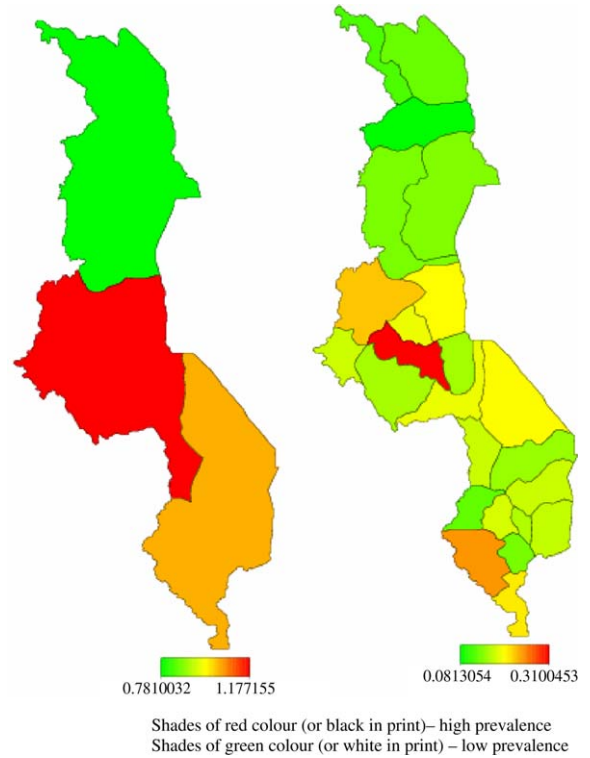


Fig. 2. Spatial distribution of observed fever by regions (left) and districts (rights) in Malawi.

(Table 1). For example, the aggregate regional levels of diarrhoea (Table 1 or left panel of Fig. 1) in the central and northern regions of Malawi mask large district variability. The geographical information given in Table 1 (or right panel of Fig. 1) is highly aggregated and conceals local and district specific effects. On the other hand, diarrhoea prevalence by districts in Table 1 (or Fig. 2) strongly depended on the sample size and may be rather unstable. Smoothing techniques were used to stabilize the observed prevalence in the sample as shown in Figs. 1 and 2.

The bivariate distributions of fixed effects included in the analysis by the outcome variables are given in Appendix A, also showing significance based on Chi-square (χ^2) tests. In the bivariate analysis based on the χ^2 tests, factors that were significantly associated with diarrhoea are type of breastfeeding, child's age, parental education (both mother's and father's education), number of under-five children in the household, household size, place of residence (rural-urban), antenatal visit during pregnancy, child's place of delivery and the ethnicity. For fever, these factors are type of breastfeeding, child's size at birth, child's age, parental education (both mother's and father's education), number of under-five children in the household, household size,

Table 1
Observed fever and diarrhoea prevalence by districts of Malawi (DHS, 2000)

Region	District	Fever: % (N)	Diarrhoea: % (N)	P-values	
North		36.4 (1662)	12.9 (1666)	0.000	
	Chitipa (CHIT)	32.6 (138)	11.6 (138)		
	Karonga (KARO)	37.2 (732)	12.8 (734)		
	Nkhata Bay (NKH-B)	62.8 (121)	14.1(121)		
	Rumphi (RUMP)	16.3 (86)	8.1 (86)		
	Mzimba (MZIM)	33.9 (585)	13.6 (587)		
Central		44.6 (3767)	19.3 (3770)	0.000	
	Kasungu (KASU)	45.0 (611)	22.2 (613)		
	Nkhota Kota (NKH-K)	59.0 (200)	19.7 (203)		
	Ntchisi (NTCH)	48.7 (154)	18.8 (154)		
	Dowa (DOWA)	57.0 (402)	31.1 (402)		
	Salima (SALI)	44.5 (620)	15.5 (620)		
	Lilongwe (LILON)	36.1 (718)	15.7 (718)		
	Mchinji (MCHI)	38.8 (271)	17.3 (271)		
	Dedza (DEDZ)	38.0 (438)	18.8 (436)		
South		41.7 (4751)	17.1(4749)	0.000	
	Ntcheu (NTCHE)	50.4 (353)	17.3 (353)		
	Mangochi (MANG)	42.2 (512)	19.8 (511)		
	Machinga (MACHI)	35.8 (835)	15.0 (834)		
	Zomba (ZOMB)	37.4 (645)	17.2 (645)		
	Chiradzulu (CHIR)	40.7 (162)	16.1 (162)		
	Blantyre (BLAN)	41.0 (591)	17.8 (591)		
	Mwanza (MWAN)	43.7 (103)	12.6 (103)		
	Thyolo (THYO)	35.2 (590)	13.6 (589)		
	Mulanje (MULA)	47.0 (845)	16.9 (846)		
	Chikwawa (CHIK)	52.9 (312)	24.4 (312)		
		Nsanje (NSAN)	51.3 (156)		20.5 (156)
	All		41.7 (10180)		17.2 (10185)

Pearson χ^2 significance at 0.05.

place of residence, antenatal visit during pregnancy, child's place of delivery and ethnicity.

Multivariate results

Diarrhoea

The results for diarrhoea presented in Figs. 1 and 3 suggest considerable spatial auto-correlation in the underlying posterior means. The left panel of Fig. 3 reveals high-risk clusters mainly in the central districts of Malawi.

The result of the nonlinear effect of child's age (Figs. 2 and 4) suggests that there is continuous worsening of the diarrhoea morbidity up to about 12 months of age. Shown are the estimated posterior means together with the 95% CIs. For comparison a regression line obtained by assuming a linear fit is added to the plot. This deterioration set in right after birth and continues, more or less linearly, until 12 months and decreases thereafter.

We find the influence of the mother's age (Fig. 5) on diarrhoea to be nonlinear. There is a general tendency for diarrhoea morbidity to decline with increasing maternal age, but the patterns for older age are inconclusive. In particular, the interpretation of results at the end of the observation (wide confidence interval) is less reliable due to few observations.

With regard to the fixed parameters, Table 2 shows that the prevalence of diarrhoea in Malawi is lower among infants who are exclusively breastfed (but higher for those who are mixed fed), whose mothers are well educated, with a father having up to primary education (posterior mean either strictly negative or positive indicating, respectively, low risk and higher risk of diarrhoea). In general, lower parental education is associated with higher risk of diarrhoea.

We did not find a statistically significant association between the risk of diarrhoea and child's sex, preceding birth interval, multiple birth (twin or singleton birth), the antenatal visits during pregnancy, birth order of the child,

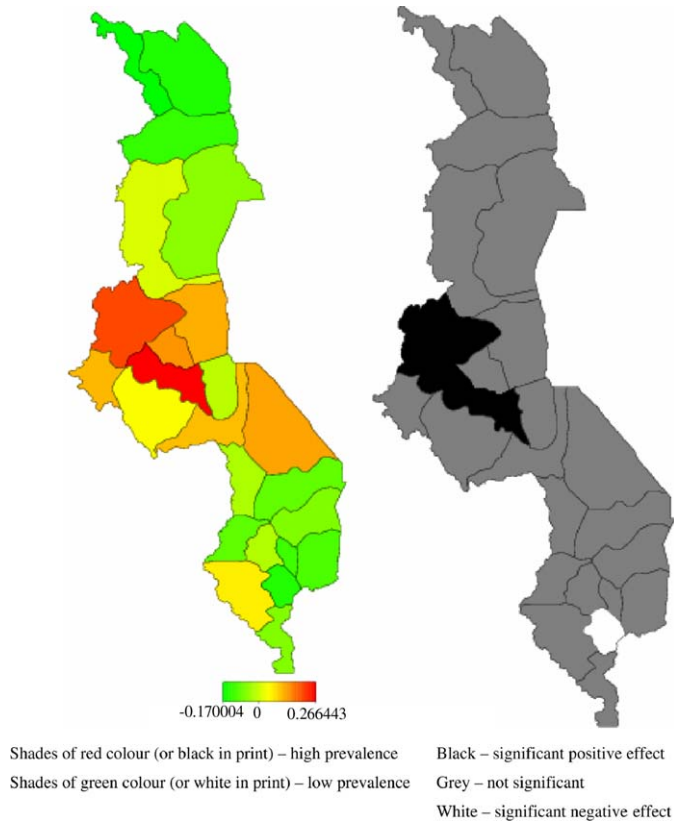


Fig. 3. Residual spatial districts effects (left) and 95% posterior probability map (right) of diarrhoea in Malawi.

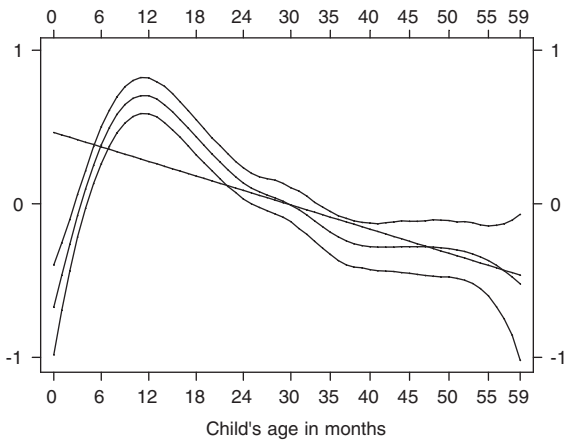


Fig. 4. Nonlinear effects of child's age on diarrhoea in Malawi. Shown are the posterior means together with 95% confidence intervals.

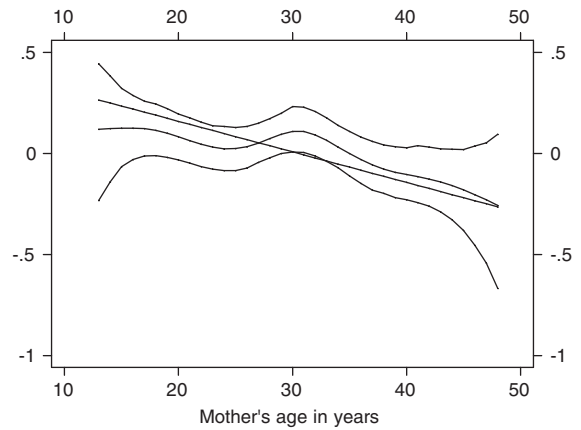


Fig. 5. Nonlinear effects of mother's age on diarrhoea in Malawi. Shown are the posterior means together with 95% confidence intervals.

father's education, vaccination status, child's place of delivery (whether hospital or home), mother's marital status, child's place of residence, household size, the economic status of the household and child's size at birth.

Fever

The right panel of Fig. 6 reveals a strong north-south gradient in the district spatial effects in Malawi with a fairly sharp dividing line that runs through the centre

Table 2
District posterior mean estimates of the fixed effect parameters for diarrhoea in Malawi

Variable	Mean	Std. error	2.5% quantile	97.5% quantile
Constant	-1.37	0.16	-1.70	-1.04
Type of feeding				
No breastfeeding ^a	0			
Exclusive breastfeeding	-0.46	0.12	-0.69	-0.22*
Mixed feeding	0.15	0.07	0.02	0.27*
Mother's education				
No education ^a	0			
Incomplete primary education	0.01	0.06	-0.10	0.12
Complete primary education	-0.04	0.08	-0.20	0.12
Secondary and higher education	-0.18	0.09	-0.35	-0.01*
Ethnicity				
Chewa	0.15	0.13	-0.10	0.42
Tumbuka	-0.03	0.13	-0.27	0.23
Lomwe	0.22	0.14	-0.05	0.50
Tonga	0.12	0.18	-0.25	0.46
Yao	0.16	0.14	-0.12	0.44
Sena	0.34	0.17	0.03	0.68*
Nkonde	0.16	0.15	-0.13	0.45
Ngoni	0.14	0.14	-0.14	0.42
Amanganja/Anyanja	0.30	0.15	0.02	0.62*
Other ^a	0			

*Significant at 0.05%.

^aReference category.

(the capital city Lilongwe) of the country. Over and above the impact of the fixed effects, there appear to be negative influences on fever in the north and central-west that are spread and affect most of the districts there. The right panel of Fig. 6 reveals also lower risk of fever in the capital Lilongwe in spite of being surrounded by some of the high-risk districts.

The result of the nonlinear effect of child's age (Fig. 7) suggests that there is continuous worsening of the child morbidity rate up to about 8 months of age. Fig. 8 shows the influence of the mother's age on fever to be nonlinear, but with a general tendency to decline with age. The results for the youngest and oldest maternal ages are less reliable as shown by the wide CIs.

The fixed parameters show that the prevalence of fever (Table 3) is higher among infants of small size at birth and low parental education (incomplete primary education). Children living in urban areas are associated with lower risk of fever. The variables child's sex, family size, mother's marital status, the number of antenatal visits during pregnancy, the type of feeding, preceding birth interval, multiple birth (twin or singleton birth), birth order of the child, vaccination status, child's place of delivery (whether hospital or home), the economic status of the household and child's size at birth were not statistically significant.

Discussion

This study has shown significant district-specific geographical variation in childhood diarrhoea and fever in Malawi. The posterior mean estimates of the residual smooth spatial district effects (shades of white coloured = low risk morbidity, shades of black coloured = high risk morbidity, and shades of grey coloured = not significant risk) are shown in the left panel of maps of Figs. 3 and 6. In addition, posterior probability maps (right panel of Figs. 3 and 6) indicate significance of the spatial effects (negative/positive effect on diarrhoea, grey coloured = non-significant). Note that the residual spatial effects are centered about zero, i.e. the average over all districts is zero, while the overall level is estimated through the intercept term in Eq. (1).

Over and above the impact of the fixed effects, there appear to be widespread negative influences on child morbidity in the central districts. The central districts are at a lower altitude than other parts of the country. It is likely that climatic factors and associated diseases are responsible for this pronounced district pattern. Food insecurity associated with drought and flooding in the shire valley, which is a result of hazardous effect of climatic variation are among possible explanations for these negative effects. Furthermore, the central districts

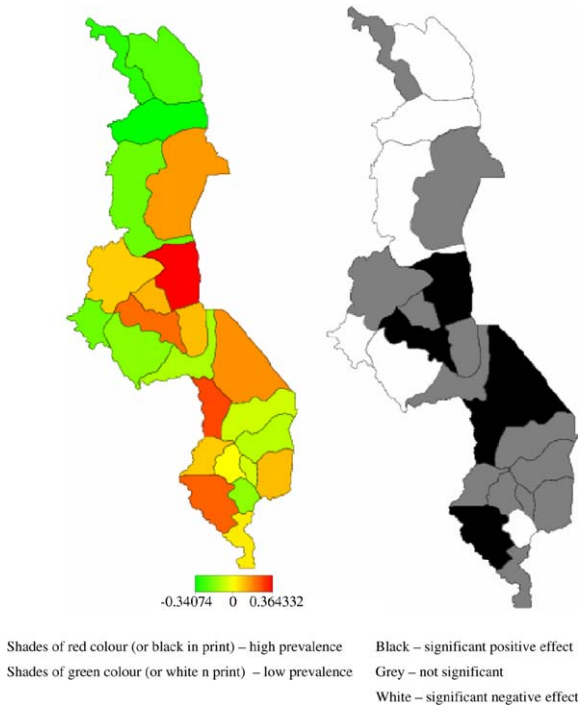


Fig. 6. Residual spatial districts effects (left) and 95% posterior probability map (right) of fever in Malawi.

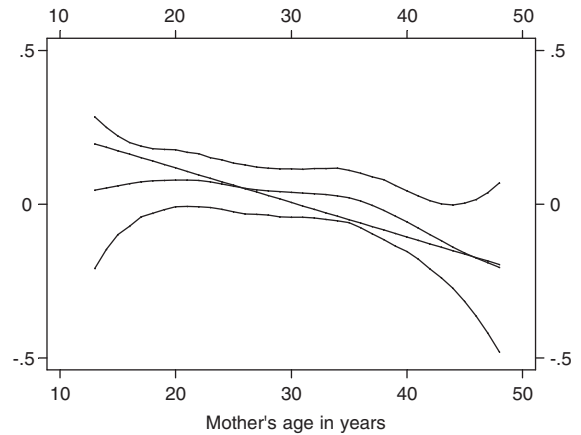


Fig. 8. Nonlinear effects of mother's age on fever in Malawi. Shown are the posterior means together with 95% confidence intervals.

general, children living in provincial capitals are at significantly lower risk compared with children in the rural areas. The negative spatial effects on child morbidity in southern districts correspond to districts that are among densely populated areas in the province; therefore, their share of disease spread may be one of the major factors of this negative impact on child morbidity.

From the analysis, it also appears that living in the capital cities such as Lilongwe is associated with significantly lower prevalence of fever, despite being surrounded by areas with negative district effects. Living in the capital is likely to provide access to health care that is superior in ways that have not been captured adequately in the fixed effects. The same is, however, not true for diarrhoea, where some urban agglomerations, such as Lilongwe, are associated with higher risk of diarrhoea. Possibly because of the high density of population associated with the phenomenon of slums in urban areas.

Nonlinear effects of mother's age and child's age

In Malawi, childhood diarrhoea and fever are associated with child's age and mother's age at birth of the child. Figs. 4 and 7 show the effect of child's age on diarrhoea and fever in Malawi and Figs. 5 and 8 show the effect of mother's age on the two ailments. Shown are the posterior means together with 95% CIs. For comparison a regression line obtained by a linear fit is added to the plot. While the effect of the variable "mother's age" is almost linear for both ailments, its effects on the variable "child's age" are clearly non-linear. The linear model assumes a negative relationship between mother's age at child's birth and risk of diarrhoea or fever, and between child's age and risk of diarrhoea and fever. As we show in Figs. 4, 5, 7 and 8,

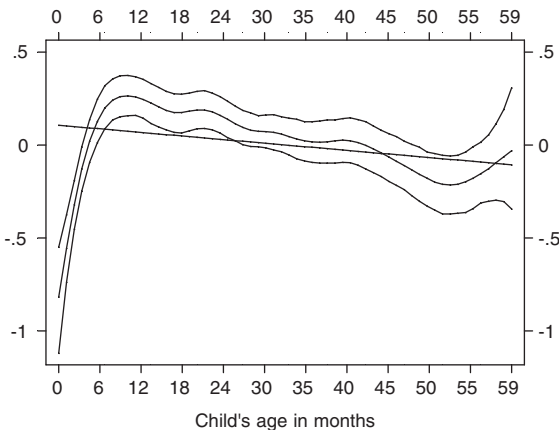


Fig. 7. Nonlinear effects of child's age for fever in Malawi. Shown are the posterior means together with 95% confidence intervals.

are among the high-density population areas and this environment tends to increase the child's exposure to disease.

For fever, it appears that children living in northern and central-west districts are at lower risk compared with children living in the central-east and south. In

Table 3
District posterior mean estimates of the fixed effect parameters for fever in Malawi

Variable	Mean	Std. error	2.5% quantile	97.5% quantile
Constant	−0.43	0.14	−0.70	−0.16
Child's size at birth				
Small size	0.12	0.05	0.01	0.21*
Average size	−0.01	0.04	−0.08	0.06
Large size ^a	0			
Mother's education				
No education ^a	0			
Incomplete primary education	0.09	0.04	0.01	0.16*
Complete primary education	0.05	0.07	−0.08	0.18
Secondary and higher education	−0.12	0.07	−0.27	0.02
Partner's education				
No education ^a	0			
Incomplete primary education	0.10	0.05	0.00	0.20*
Complete primary education	0.04	0.06	−0.08	0.16
Secondary and higher education	−0.03	0.07	−0.16	0.10
No partner	0.04	0.10	−0.16	0.23
Place of residence				
Urban	−0.15	0.05	−0.24	−0.06*
Rural ^a	0			
Ethnicity				
Chewa	0.22	0.12	−0.00	0.46
Tumbuka	0.08	0.12	−0.13	0.30
Lomwe	0.08	0.12	−0.16	0.31
Tonga	0.24	0.16	−0.07	0.56
Yao	−0.00	0.12	−0.24	0.26
Sena	0.40	0.15	0.10	0.67*
Nkonde	0.38	0.12	0.13	0.63*
Ngoni	0.07	0.12	−0.19	0.30
Amanganja/Anyanja	0.11	0.13	−0.14	0.37
Other ^a	0			

*Significant at 0.05%.

^aReference category.

this glosses over important nonlinearity in the effects. The data suggest deterioration in child diarrhoea that sets in right after birth and continues, more or less linearly, until 12 months of age. This immediate deterioration in child morbidity was not expected, as the literature commonly associates such deterioration with weaning at around 4–6 months. In a Kenyan study, children aged 1–2 years were the most vulnerable (Magadi, 1997). One reason for this unexpected finding could be that, according to the DHS surveys, most parents gave their children liquids other than breast milk shortly after birth, a factor which might contribute to infections. This is due to the influence of poor-quality nutrition that is replacing breast milk as well as the onset of infectious diseases. These diseases are often related to unclean water and food which is replacing the breast milk, and the child no longer benefits from the mother's antibodies that are transmitted through the breast milk

(Stephenson, 1999). Initially, the worsening health status shows up as acute under-nutrition. But then childhood morbidity develops and worsens until about age 1. At that time, the body has developed its immune system to fight the impact of infectious diseases more effectively (Moradi & Klasen, 2000; WHO, 1995).

The influence of mother's age on child diarrhoea and fever show a general tendency for child morbidity to decline with increasing maternal age. Part of the explanation for the observed association of morbidity risk and younger mother's age may be attributed to the tendency for young mothers to be socially and economically disadvantaged (World Bank, 2000), and the fact that younger mothers do not often use health services as much as older mothers (Magadi, Madise, & Rodrigues, 2000). These results are indicative of general trends and may be of use to planners for targeting policy.

Fixed effects (results shown in Tables 2 and 3)

After we controlled for the spatial dependence in the data, the fixed effects show the importance of parental education, breastfeeding, ethnicity, size of child, and rural–urban residence on child morbidity. The findings are generally as expected and consistent with the literature. Children of highly educated mothers or living in urban areas are at lower risk of fever than other children (Cleland & Sathar, 1984; Curtis & Steele, 1996; Hobcraft, McDonald, & Rutsein, 1985; Kandala, 2002; Madise, Banda, & Benaya, 2003). The higher rural fever risk is possibly due to the fact that rural areas in Sub-Saharan Africa are under-developed and have less public service per capita compared with urban areas (Brockhoff, 1993; Kuate Defo, 1996). As a result, living in rural areas provides no access to beds with mosquito nets or better health care and increases the risk of malaria and fever. After we controlled for child, household, and districts characteristics the residential location (rural versus urban) does not affect child diarrhoea. The urban–rural effect may be captured by the district effects. Furthermore, the lack of corresponding urban advantage with respect to diarrhoea may be partly attributed to growing urban poverty in many parts of sub-Saharan Africa, which has been associated with poor sanitation in the densely populated slum settlements leading to increased incidence of diarrhoea among children of the urban poor (Magadi, 2003).

We have established in this analysis that diarrhoea and fever especially during the early months of life is sensitive to low levels of parental education. Similarly, in a study of the variation in African mortality, Blacker (1991), cites the much lower levels of female education in each country. Studies using WFS and DHS data have shown that about half of the education–mortality association is accounted for by the economic condition of the household (Bicego & Boerma, 1993; Cleland & van Ginneken, 1988).

We find that, maternal education rather than paternal education matters a lot in reducing diarrhoea risk, whereas both low maternal and paternal education influence fever risk.

There are also some ethnic differences in terms of diarrhoea and fever risk where, for example children from the Sena ethnic group are more likely to have both diarrhoea and fever compared to other children. This suggests the need for in-depth studies in these communities to understand cultural child rearing practices that may put children at an increased risk of diarrhoea and fever.

It should be noted that in the DHS data set, questions regarding fever control apply also to malaria control although there is a net clinical difference between the two diseases. Malaria-relevant indicators include the reported treatment and care (whether antimalarials were

given and facilities attended) to under-5s who had fever in the 2 weeks preceding the interview. The interpretation of fever in this report should take into account the fact that the DHS surveys are (for logistical reasons) mostly conducted in the dry, least malarious season (Africa Malaria Report, WHO, 2003). In addition, the observed prevalence of diarrhoea can be considered as incidence rate of diarrhea. Because of the short follow-up period of 2 weeks before the interview, we have ignored the role of competing risk, although diarrhoea may be present in different forms: persistent diarrhoea (more than 14 days), acute watery diarrhoea, or dysentery (blood in stool). Other diseases that can occur concurrently with diarrhoea include measles and malaria. Malnutrition also often accompanies diarrhoea.

It is important to point out that some of the factors observed to be significantly associated with prevalence of both fever and diarrhoea in the bivariate analysis, such as antenatal care and delivery care, turned out not to be significant in the multivariate analysis that simultaneously controlled for spatial effects as well as the effects of other covariates. It is possible that health care utilization is a reflection of accessibility of health care services and has been captured by the spatial effects in the multivariate analysis. Also vaccination status turns out to be statistically insignificant, although other studies in rural sub-Saharan Africa have reported immunization status of a child as an important factor associated with diarrhoea (see for instance Mbonye, 2003, 2004). It should be noted that in the DHS, the reliability of parental recall of vaccination status for vaccines given to infants has not been studied and it is therefore unknown and may affect these results.

Possible reasons for the lack of association between childhood disease and the economic status may be because, many of the household wealth indices use assets that are more likely to be found in urban areas than in rural areas. Thus, most of the rural households will be in the lowest wealth category even if they have other indicators of wealth (e.g. livestock or farm machinery). The consequence of this misclassification would be to lower the risk of childhood diseases of rural households. Another limitation with household wealth indices derived from DHS is that they are based on current status data so that they might not capture the true level of household wealth during the infancy of children born several years before the survey. However, since these analyses are restricted to births within 5 years of the survey, this bias will not be substantial.

To explain further these inequalities in childhood diseases prevalence at district level in Malawi, further research is needed to scrutinize the spatial pattern of occurrence of water-borne illnesses to specific locations. This will enable us to draw a picture of where and whether events are concentrated, which will help in turn to guide local public health response or investigation to

help identify at-risk populations and determine where to focus efforts to vaccinate residents against malaria. Moreover, the measure of disease prevalence used here, recall of whether a child had been ill with diarrhoea or fever in the past 2 weeks is less perfect as it is quite subjective, based on a short-term recall. Future work needs to address the question of disease environment more closely.

Conclusions

In conclusion, the study findings carry some important general pointers to policy directions. For instance, the age effect suggests the need to pay attention to child

feeding practices, particularly during the first 6 months after birth. Second, the nonlinear influence of mother's age indicates that childcare promotion messages should be targeted particularly to younger parents. Of high significance are the district influences on child morbidity. In particular, they suggest that in Malawi, some urban agglomerations are associated with higher risk of diarrhoea. Also, more emphasis must be placed upon the role of remoteness as well as climatic and geographic factors on childhood morbidity. It would be of value to investigate district-level factors not included in our models, such as environmental, socio-economic, cultural and human behavioural factors involved in the etiology of the disease. The North-Central divide in Malawi highlights the importance of such considerations.

Appendix A. Distribution of factors analyzed in child morbidity study in Malawi (DHS, 2000)

Factor	Diarrhoea (% and <i>N</i>)	Fever (% and <i>N</i>)
<i>Individual characteristics</i>		
Sex of child:		
Male	17.7 (5051)	42 (5050)
Female	16.7 (5134)	41.4 (5130)
Preceding birth interval		
1st birth	17.1 (2337)	40.3 (2335)
< 24 month	17.2 (1494)	41.9 (6353)
24+	17.3 (6354)	43.2 (1492)
Type of feeding	*	*
No breastfeeding	10.5 (3001)	40.6 (2994)
Exclusive breastfeeding	6.1 (918)	26.3 (918)
Mixed feeding	22.1 (6266)	44.5 (6268)
Child a twin		
Singleton birth	17.3 (9850)	41.7 (9846)
Multiple birth	16.4 (335)	42.5 (334)
Child's size at birth		
Small size	17.4 (2598)	42.1 (2590)
Average size	18.5 (1543)	46.1 (1542)
Large size	16.9 (6001)	40.4 (6005)
Birth Order		
1st birth	17.1 (2337)	40.3 (2335)
2nd and 3rd order	17.4 (3597)	40.7 (3596)
4th and 5th order	17.1 (2123)	42.1 (2121)
6+ order	17.3 (2128)	44.6 (2128)
Child's age in months		
<6	12.2 (1259)	28.8 (821)
6–11	34.2 (1203)	50.7 (657)
12–23	30.8 (2188)	56.4 (1212)
24–35	13.6 (1960)	52.6 (2139)
36+	7.0 (3575)	34.9(5351)
<i>Family characteristics</i>		
Mother's age		
<20	18 (2107)	41.4 (2103)
20–24	16.5 (3294)	41 (3299)

25–29	17.1 (2185)	41.4 (2180)
30–34	19.2 (1340)	42.2 (1340)
35+	16.1 (1259)	44.2 (1258)
Mother's education	*	*
No education	17.8 (3043)	41.6 (3044)
Incomplete primary education	18.2 (5516)	44 (5513)
Primary education	14.0 (850)	36.6 (850)
Secondary education and higher	11.7 (776)	31.6 (773)
Partner's education	*	*
No education	18.1 (1422)	42.2 (1424)
Incomplete primary education	18.2 (4419)	44.4 (4416)
Primary education	17.1 (1696)	40.6 (1698)
Secondary education and higher	14.0 (1881)	35.3 (1878)
No partner	18.4 (767)	43.5 (764)
Marital status		
Single mothers	18.5 (1124)	41.4 (9059)
Married	17.1 (9061)	44.3 (1121)
Asset index		
1st quantile	17.6 (2543)	412.1 (2544)
2nd quantile	17.0 (2537)	41.9 (2540)
3rd quantile	17.2 (2562)	41.3 (2554)
4th quantile	17.1 (2543)	41.5 (2542)
Under 5 children	*	*
0 child	14.5 (152)	35.1 (148)
1 child	18.4 (3676)	45.6 (3671)
2 children	16.5 (4789)	40.2 (4792)
3+ children	17.1 (1568)	38.0 (1569)
Household size	*	*
2 members	18.7 (3174)	42.5 (3172)
Between 3 and 5 members	16.8 (4892)	40.6 (4890)
5+ members	16.0 (2119)	43.2 (2118)
<i>Community characteristics</i>		
Place of residence	*	*
Urban	14.1 (1855)	34.7 (1852)
Rural	17.9 (8330)	43.3 (8328)
Antenatal visit	*	*
No	24.7 (255)	56.5 (255)
< 3 visits	22 (2806)	47.5 (2804)
3+ visits	15.1 (7124)	38.9 (7121)
Child's place of delivery	*	*
Hospital	15.8 (5803)	39.6 (5798)
Home and others	19.2 (4374)	44.6 (4374)
Ethnicity in Malawi	*	*
Chewa	19.4 (2884)	46 (2881)
Tumbuka	13 (970)	35.2 (971)
Lomwe	16.6 (1834)	40.9 (1835)
Tonga	13.4 (1482)	45.6 (193)
Yao	17.3 (1482)	37.1 (1484)
Sena	22.8 (391)	53.7 (389)
Nkonde	14.9 (348)	42.8 (346)
Ngoni	16.8 (1107)	40.8 (1107)
Amanganja/Anyanja	18.14 (601)	43.2 (602)
Other	12.5 (369)	31.9 (367)
Total	17.2 (10185)	41.7 (10180)

* $\chi^2 p < 0.05$.

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