Spatial Determinants of childhood Morbidity in Sub-saharan Africa: Implications for child Survival

Kandala Ngianga-Bakwin and Nyovani Madise

School of Social Sciences, University of Southampton SO17 1BJ UK

e-mail: nbk3@sosci.soton.ac.uk.

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Abstract

This paper applies a geo-additive generalized linear mixed model to describe the spatial variation in the prevalence of diarrhea, cough and fever among children under 5 years of age using the 1992 Demographic and Health surveys (DHS) of Malawi and Zambia. The model includes terms of the effects of child level covariates (age, birth interval and breastfeeding), household level covariates (crowding and socio-economic status), district level covariates (presence of primary health care system) and separate components for residual spatial and non-spatial variation. The residual spatial effects are modelled via Bayesian prior specifications reflecting spatial heterogeneity globally and relative homogeneity among neighboring districts. Metrical covariates (mother's age and child's age) are estimated nonparametrically using an appropriate prior. The results show that district-level socioeconomic characteristics are important determinants of child morbidity. Independent of other factors, a separate spatial process produces district clustering of childhood morbidity.

Keywords: Geo-additive models; childhood morbidity; breastfeeding; crowding; socio-economic status.

1. Introduction

The major diseases of children in Malawi and Zambia are malaria, diarrhea, and respiratory diseases, particularly pneumonia (Macro International, Inc., 1994). These three ailments are still a major cause of mortality among children in many developing countries, particularly in Sub-Saharan Africa. Yet, except for some descriptive reports by National Statistics offices of the these countries, few systematic studies of factors that influence the prevalence of malaria, cough and diarrhea morbidity among young children in these countries were carried out. The mapping of variation in risk of child morbidity can help improve the targeting of scarce resources for public health interventions. Bearing in mind that direct mapping of relevant environmental risk factors (which may vary considerably in both space and time) is difficult and this has led to investigations of environmental proxies (Thomson *et al., 1996*; Diggle *et al., 2002*). The

use of DHS data in the understanding of childhood morbidity has expanded rapidly in recent years (Woldemicael, 2001; Yenened et al., 1993; Ryland and Raggers, 1998; and Widarsa and Munijaya, 1994). However, few attempts have been made to address explicitly the problems of spatial auto-correlation and nonlinear effects of metrical covariates in the interpretation of results. Woldemicael, 2001 and Walter, 2001 reported a regression analysis of the prevalence of diarrhea among children in Erithrea and Kenya, including child and mother level covariates but they failed to control for the spatial autocorrelation in the data. This study show how the geo-additive model framework (Fahrmeir and Lang, 2001) can be adapted to extend the analysis of Woldemicael, 2001 and Walter, 2001 to provide an explanation of the residual spatial variation in the data and in particular to assess whether the variation is spatially structured. If this is true, it implies that adjusted prevalence are similar among neighboring districts, then the possibly explanation must be partly environmental. If not, a more likely explanation is that the residual spatial variation is induced by variation in unmeasured districts-specific factors. A 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. By estimating a structured and an unstructured effect we attempt to separate these effects. As a side effect we are able to assess to some extent the amount of spatial dependence in the data by observing which of the two effects is larger. If the unstructured effect exceeds the structured effect, the spatial dependence is smaller and vice versa. Such models are common in spatial epidemiology, see e.g. Besag et al. (1991).

The modelling framework implemented in BayesX (Brezger *et al.*, 2002) is the following. Consider regression situations, where observations (y_i, x_i, w_i), $i = 1, \ldots, n$, on a metrical response y, a vector $x = (x_1, \ldots, x_p)$ of metrical covariates, times scales or spatial covariates and a vector $w = (w_1, \ldots, w_r)$ of further covariates, in which categorical covariates, are often given. The generalized additive modelling framework (Hastie and Tibshirani, 1990) assumes that, given

x_i and w_i, the distribution of the response y_i belongs to an exponential family, with mean $\mu_i = E(y_i|x_i, w_i)$ linked to an additive semiparametric predictor $\mu_i = h(\eta_i), \eta_i = f_1(x_{i1}) + \cdots + f_p(x_{ip}) + w_i'\gamma$, where h is a known response function, and $f_1, \ldots, f_p$ are unknown nonlinear smooth functions of the covariates to be estimated. In this application, we have probit link function for the three ailments at each location (districts), enabling the inclusion of an additional, unstructured spatial effects between locations. We assume that y_i given the covariates and unknown parameters are independent.

2. Data and methods

The success of any policy or health care intervention depends on a correct understanding of the socioeconomic, environmental and cultural factors that determine the occurrence of diseases and deaths. Until recently, any morbidity information available was derived from clinics and hospitals. Information on the incidence of diarrhea, malaria and pneumonia obtained from hospitals represents only a small proportion of all illnesses, because many cases do not seek medical attention (Black, 1984). Thus, the hospital records may not be appropriate for estimating the incidence of diarrhea for programme developments (Woldemicael, 2001).

The Demographic and Health survey (DHS) programme of Malawi and Zambia conducted in 1992, is a first attempt to obtain population-based morbidity data. Bearing in mind that the DHS data only permit one to attribute child morbidity to specific causes for the last two weeks before the surveys.

Table 2.1 Distribution of the response variables.

Response	Malawi	No of cases	Percent	Zambia	No of cases	Percent
Diarrhea	0	2846	77.76	0	4069	77.11
	1	814	22.24	1	1208	22.89
Fever	0	2136	58.36	0	2902	54.99
	1	1524	41.64	1	2375	45.01
Cough	0	2000	54.70	0	2800	53.15
	1	1656	45.30	1	2468	46.85
Total		3660			5268	

Individual data record was constructed for 3660 children in Malawi and 5268

children in Zambia. Each record represents a child and consists of morbidity information and a list of covariates. Table 2.1 shows the distribution of diarrhea, fever and cough morbidity during the last two weeks before the interview (DHS, 1992).

We use a geo-additive logistic analyzes on the probability of a child being ill with malaria, cough and diarrhea during the reference period to determine the socio-economic, demographic variables that are associated with these three ailments while simultaneously controlling for spatial dependence in the data and possibly nonlinear effects of covariates. The model allows us to borrow streng from neighboring areas in order to obtain estimates for areas that may, on their own, have inadequate sample sizes. The findings are robust with respect to the specification of the prior distribution.

The response variable in this application is defined as

$$y_{it} = \begin{cases} 1: & \text{if child } i \text{ was ill during the reference period } t \\ 0: & \text{if child } i \text{ survives the illness,} \end{cases}$$

We analyzed and compared simpler parametric probit model and probit model with dynamic and spatial effects

$$pr(y_{it} = 1 | x^{\star}_{it}) = \phi(\eta_{it})$$

for the probability of falling ill at month t (i.e. we model the conditional probability of a child falling ill of diarrhea or cough or fever, given child's age in months, the district where the child live, and X, with the following predictors:

M1: $\eta_{it} = X'_{it}\beta$

M2: $\eta_{it} = f_1(age) + f_2(mab) + f_{unstr}(dist) + f_{str}(dist) + X'_{it}\beta$

The fixed effects in model $M1$ include all covariates with constant fixed effects. In comparing the results of models $M1$ and $M2$, it turned out that model $M2$ is superior in terms of the *Deviance Information Criteria*(DIC) [Spiegelhalter *et. al., 2002*] which may be used for model comparison (See table 8). Apart from the superiority of model $M2$ in the DIC, it accounts also for the unobserved heterogeneity that might exist in the data, all of which cannot be captured by

the covariates (see, Madise *et al.*, 1999). The effects of f_1 and f_2 are modeled by cubic penalized splines (P-splines) with second order random walk penalty.

For the spatial effect $f_{str}(s)$ we experimented with different prior assumptions. For both countries we 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 we found clear evidence for both countries of spatial correlation among neighboring districts. Hence, Markov random field priors was used for $f_{str}(s)$. The analysis was carried out using BayesX-version 0.9 (Brezger *et al.*, 2002), 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 effects (second random walk: RW2) and the choice of the hyper-parameter values a and b. We noticed that results for this application are not sensitive to the choice of the priors and hyper-parameter.

3. Results

The presentation of the empirical results starts with residual spatial effects of the districts where the child live. It continues with results of nonparametric effects of the mother's age at child's birth and child's age. Finally results from various logistic regressions are presented that identify particular socio-economic and environmental characteristics as significantly associated with childhood morbidity. The results are robust with respect to the prior specifications and emerge from a unified model framework that enables thorough investigation into the associations of childhood morbidity incidence and areal-level risk factors, accounting for residual variation and spatial autocorrelation that likely arise from unmeasured confounders.

When we attempted to fit the standard model (1) with constant fixed effects for metrical covariates (child's age and mother's age at first birth of the child) and the spatial location (districts in dummy), we found that there was not enough information in the data to estimate the parameters X'_{it} correctly (confidence interval included zeros indicating no effects on the response variables). The posterior mean estimates for each model demonstrates that the district-level area

factor does not adequately explain the short-range spatial structure. Various models were tried, but these made no difference.

For both countries we 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 we found clear evidence for both countries of spatial correlation among neighboring districts. Hence, a spatially correlated effect f_{str} is included into the predictors of our final models. For the two countries, we additionally include an unstructured effect f_{unstr} because there is evidence of local extra variation in the highly urbanized areas of Malawi and Zambia.

We therefore considered including the spatial component $f_{unstr}(dist)+f_{str}(dist)$, thereby increasing model complexity. With such models, it is assumed that the random components at the contextual level (district) are mutually independent. Even though, in practical, this assumption is not actually implied by these approaches, so correlated random residuals can also be specified (see Langford et *et al.*, 1999). However, the estimates of the presumed spatial correlated district level random effects in fact showed strong evidence of spatial dependence. This is indicated in Fig. 1, which plots the posterior mean estimates of the spatial district effects. Though the spatial unstructured district effects for fever turns out to be insignificant, both maps show a strong spatial variation. Since prediction of spatial residual is our goals, the non-spatial model is clearly inadequate. We therefore focus on model (2), to give the results that were obtained during the fitting.

Figures 1 through 8 maps the estimates of the spatial effects (spatial residuals: the levels correspond to "high risk of morbidity (red coloured)" and "low risk (green coloured)")) with the significance maps, showing "probabilities maps". For a nominal level of 80% the levels correspond to "high risk of morbidity (black coloured)", "nonsignificant (grey coloured)", i.e. zero is within the credible interval around the estimate, and "lower risk of mobidity (white coloured)". Figure 9 through 14 give the result of the non-linear effect of child's age and the mother's age. Shown are the posterior means together with 80 % pointwise

credible intervals.

Table 1 through 7 shows the posterior mean and 80% credible interval for each of the fixed effects parameters for categorical covariates in model (2). There are sizeable fixed effects, which are highly significant (i.e. credible intervals are either strictly positive or strictly negative). The Bayesian spatial effects (Figures 1 and 5) suggest reasonable variation in the prevalence of diarrheal morbidity in Malawi and Zambia. The residuals posterior mean correspond to higher risk districts (red colored) and low risk districts (green colored).

3.1 Diarrheal morbidity

The data suggest considerable spatial autocorrelation in the underlying posterior means. The left panel of Figures 1 and 5 reveals high risk clusters mainly in the central districts of Malawi and in the north-east of Zambia.

The result of the non-linear effect of child's age (Figures 9 through 14) suggest that there are continuous worsening of the child morbidity up to about 6 months of age. This deterioration set in right after birth and continues, more or less linearly, until 10 months and decreases thereafter.

We find the influence of the mother's age (right panel of Figure 9) on diarrheal morbidity to be in the form of an inverse U-shape in Malawi, while in Zambia (Figure 12) we have a U-shape. While the U or inverse U looks nearly symmetric, the descending portion exhibits a much larger range in the credible region. Children from younger (less than 20 years) and older (more than 35 years) mothers are at higher risk of diarrheal morbidity compared to children from middle age group (20-35 years). Interpretation of results at the end of the observation (wide credible interval) is particularly unreliable in regions where there are few observations.

With regard to the fixed parameters, Table 2 shows that the prevalence of diarrhea in Malawi is lower among infants who are exclusively breastfed, whose mothers are well educated with a father having up to primary education, a long birth interval (24 months and more), a multiple birth and infants living in urban areas. Lower parental education and male children are associated with

higher risk of diarrheal morbidity. In Zambia (Table 5), higher risk of diarrheal morbidity is associated with lower and higher parental education (up to primary education for both parents and secondary education and higher for maternal education), male children, and mother's marital status (single mother). Children from large size household are associated with lower risk of diarrheal morbidity. Children from medium economic status households had lower risk of diarrheal morbidity if they lived in rural areas than if they lived in urban areas. This fact is only true for Zambian children. In the two countries, we didn't found a statistically significant association between diarrheal morbidity and prematurity of the child, vaccination status, the antenatal visit during pregnancy, child's place of delivery (whether hospital or home), the economic status of the household and child's size at birth.

3.2 Fever morbidity

The right panel of Figures 2 reveals a strong north-south gradient in the district spatial effects in Malawi with a fairly sharp dividing line that runs through the center (the capital city Lilongwe) of the country. Over and above the impact of the fixed effects, there appear to be negative influences on fever morbidity in the north that are spread and affect most of the districts there. The right panel of Figures 2 reveals also lower risk of fever morbidity in the capital Lilogwe in spite of being surrounded by some of the high risk districts. High risk clusters of fever morbidity in Zambia (Figure 6) are mainly located in the southern and north-east districts.

The result of the non-linear effect of child's age in the two countries (Figures 10 and 13) suggest that there are continuous worsening of the child morbidity up to about 10 months of age.

The right panel of figures 10 and 13 associate the influence of the mother's age on fever morbidity to be in the form of an inverse U shape in Malawi and a U shape in Zambia. Children from younger (less than 20 years) and older (more than 35 years) mothers are at higher risk of fever morbidity compared to children from middle age group (20-35 years).

The fixed parameters show that the prevalence of fever in Malawi (Table 4) is higher among infants from "poor" maternal education (up to primary education), vaccinated children and infants who are mixed feeding. Children born in hospital, breastfed exclusively and have a father with secondary education and higher are associated with lower risk of fever morbidity. In Zambia (Table 7), higher risk of fever morbidity is associated with lower and higher maternal education (up to primary education and secondary education and higher), premature birth, mother's marital status (single mothers) and low economic status households. Children from medium size households are associated with lower risk of fever morbidity. The data didn't show, in the two countries, a statistically significant association between fever morbidity and child's sex, family size, child's sex, child's place of delivery, the antenatal visit during pregnancy, the type of breastfeeding , child's size at birth, and child's place of residence.

3.3 Cough morbidity

There is a strong north-south (left panel of Figures 3) gradient in the district spatial effects in Malawi with a fairly sharp dividing line that runs through the capital (Lilongwe) of the country. There appear to be negative influences on cough morbidity in the north that are spread and affect most of the districts there.

The data suggest considerable spatial autocorrelation and local variation in the underlying posterior means for cough morbidity in Malawi and Zambia. The left panel of Figures 3 and 7 reveals high risk clusters mainly in the central and northern districts of Malawi and in the north-east of Zambia. Both maps show a strong spatial pattern. This becomes even more obvious with Figure 4 and 8 showing "probabilities maps". For a nominal level of 80% the levels correspond to "high risk of mortality (black coloured)", "nonsignificant (grey coloured)", i.e. zero is within the credible interval around the estimate, and "lower risk of mortality (white coloured)".

The result of the non-linear effect of child's age (Figures 11 and 14) suggest that there are continuous worsening of the cough morbidity up to about 6 months of

age and a decrease thereafter. We find the influence of the mother's age (right panel of Figure 11 and 14) on cough morbidity to be in the form of an inverse U shape in Malawi and a U shape in Zambia. Children from younger (less than 20 years) and older (more than 35 years) mothers are at higher risk of diarrheal morbidity compared to children from middle age group (20-35 years).

The fixed parameters (Table 3) show that the prevalence of cough in Malawi is higher among children from low economic status households, infants who are mixed feeding and infants with poor maternal education. Children who are breastfed breast milk exclusively, with higher parental education and a large family size are associated with lower risk of diarrheal morbidity. For Zambia (Table 7), higher risk of cough morbidity is associated with lower maternal education (up to primary education). Children from medium size household (between 5 and 10 households members), have a long birth interval, were born with average size are associated with lower risk of cough morbidity. Children from medium economic status households had lower risk of diarrheal morbidity if they lived in rural areas than if they lived in urban areas. This fact is only true for Zambian children.

In the two countries, we didn't found a statistically significant association between cough morbidity and child's sex, vaccination status, child's place of delivery, mother's marital status and child's place of residence.

4. Discussion

To gain an understanding of the geographic variation or patterns based on the observed morbidity prevalence, we begin our analysis by first fitting the Bayesian hierarchical model without the inclusion of spatial (district) and non-linear metrical (mother's and child's age) covariates. The Bayesian estimation of this model alone is impractical given the fact that we have to consider 31 dummies for the 32 districts in Malawi and 53 dummies for the 54 districts in Zambia, from which the reduction in variation in childhood morbidity can be readily assessed. We note that the issues of particular interest in this study, and perhaps in health services research of similar kinds, are whether there is a

significant geographic variation in childhood morbidity; if the answer is yes, can such variation be explained by potential risk factors?

4.1 Spatial residual

Sub-Saharan Africa is geographically, demographically, socially, and culturally heterogeneous, and the extent and spread of child morbidity have accordingly been heterogeneous as well. Obviously this study has shown a sizeable district-specific geographical variation in the level of child morbidity in Malawi and Zambia.

Over and above the impact of the fixed effects in Malawi (Figure 1), there appear to be negative influences on child morbidity in the central districts that are spread and affect most of the districts there. 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 climate variation are among possible explanation for these negative effects. Furthermore the central districts are among high density population areas which affect the child's physical environment, which in turn influence exposure to disease.

At the district level, for Zambia, Figure 4, it appears that children living in provincial capital (Lusaka and Kabwe), Solwezi, Milenge, Chilengi, Kasama, Lundazi or Luangwa are significantly better-off than children in the rural areas. The negative spatial effects on child morbidity in Eastern districts (left panel of Figure 4) correspond to districts that are among density populated areas in the province, therefore their share of disease spread may be one of the major factor of this negative impact on child morbidity.

From the analysis, it also appears that living in the capital cities Lilongwe and Lusaka is associated with significantly better fever morbidity in Malawi and better diarrhea, fever and cough morbidity for Zambia despite being surrounded by areas with negative district effects on childhood morbidity. Living in the capital must thus provide access to mosquitos nets and health care that is superior in

ways that have not been captured adequately in the fixed effects.

Figure 4- show the structured and the unstructured random effects of the three ailments for Zambia. The structured effects show a sizeable difference between significantly worse undernutrition in the Northern parts of the country (in particular the districts in Luapula and Northern province), and significantly better nutrition in the Central and South-Western parts. These regional patterns are similar, but not identical to analyses of poverty and deprivation undertaken by the World Bank (World Bank, 1995). In terms of income poverty, the World Bank found poverty to be lowest in the Central parts of the country. In addition, poverty was also much lower along the main trunk road and railroad lines even outside the central part of the country. In terms of deprivation (based on a mean score of various service items), the World Bank also found Luapula province among the worst off, while it surprisingly included the Central province and the Northwestern Province among the worst-off regions. While we also find Luapula province to be among the worst off in the country, our analysis shows a clearer geographic pattern with the North-East being worst off and the Central and South-Western districts being best off.

The unstructured random effects are mostly not significant. But they nevertheless point in interesting directions. In particular, they suggest a fair amount of variation over and above the structured effects. Particularly noteworthy is the fact that for some urban centers, the unstructured effects point to lower child morbidity, once the fixed effects (which include a positive effect of urban areas) and the structured effects are controlled for. This is particularly noteworthy for Kitwe in the Copperbelt, but also visible for Lusaka and Kabwe in the Central Part of the country. In contrast to Malawi, it thus appears that some urban agglomerations are associated with better child morbidity. While major health interventions, an overhaul of the economic environment or environmental factors (drought shocks: indeed, drought was reported in the southern part of Malawi during the 1992 DHS survey) may cause such differentials from one district to another, differences in food prices may also be a possible reason. To explore dis-

tricts differences further we postulate also that districts differences in total cost of living may be indicative of the observed districts differences. Food prices in the two countries may fluctuate considerably from one district to another due to erratic rainfall patterns. It is also, in this respect, of immediate policy relevance to examine the direct effect of relative food prices on childhood morbidity.

This analysis has provided an explanation of the residual spatial variation in the data and in particular it has shown that the variation is spatially structured. If this is true, it implies that adjusted diarrhea, cough and fever prevalence are similar among neighboring districts, then the possibly explanation must be partly environmental. If not, a more likely explanation is that the residual spatial variation is induced by variation in unmeasured districts-specific factors.

4.2 Nonlinear effects

In Malawi and Zambia, childhood morbidity is associated with child's age and the mother's age at birth of the child for the three ailments. While the effect of the variable "mother's age" is almost linear for diarrheal morbidity in both countries, its effect and that of the variable "child's age" are clearly nonlinear. The curve has a bathtub shape, and indicates that not only children from younger mothers but also children from older mothers are at higher risk, compared to "middle" age mothers (20-35 years old). As suggested by the morbidity literature, we are able to discern the continuous worsening of the child morbidity up to about 6 months of age. This deterioration set in right after birth and continues, more or less linearly, until 10 months. Such an immediate deterioration in child morbidity is not quite as expected as the literature typically suggests that the worsening is associated with weaning at around 4-6 months. One reason for this unexpected finding could be that, according to the surveys, most parents give their children liquids other than breastmilk shortly after birth which might contribute to infections. We find the influence of the mother's age on child's morbidity to be in the form of an inverse U shape or U shape for the three ailments. While the inverse U or U looks nearly symmetric, the descending portion exhibits a much larger range in the credible region. Children

from younger (less than 20 years) and older (more than 35 years) mothers are at higher risk of being ill compared to children from middle age group (20-35 years). The relationship varies across socio-cultural settings depending on levels and age patterns of fertility. Part of the negative association of morbidity risk of children between a younger mother's age and child survival may be attributed to the tendency for young mothers to be socially and economically disadvantaged (World Bank, 1995) and the fact that younger mothers do not often use obstetric and antenatal services much as older mothers (Magadi *et.al., 2000*).

4.3 Fixed effects

After controlling for the spatial dependance in the data, the fixed effects show the importance of mother's education, household economic status, residence, the birth interval, the antenatal visit during pregnancy, the marital status of the mother, and child's sex on child morbidity. The finding are generally as expected and consistent with the literature. These findings point to the potential for child morbidity reduction that could result from successful efforts to improve and maintain adequate child physical environment in the two countries. We find that the risk of child morbidity through breastfeeding appears to be greatest in the first few months of life and is lower among infants who are fed breast milk exclusively than among those who are mixed feeding in Malawi. But this is not the case in Zambia, the data did not show any protective effects of exclusive breastfeeding for the three ailments.

4.4 Interaction terms

We tested several interactions. First, we ran separate models for males and females (results not reported here) but we found them to be very similar. Second, we interact the effect of economic status and the rural or urban location to account for the difference in the asset index as a measure of the household economic status in the two locations. This interaction only had a significant effect in Zambia. Bearing in mind that one limitation of this study is that measuring wealth (with the principal component analysis used) is problematic. 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 form machinery). The consequence of this misclassification would be to lower the morbidity risks 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 five years of the survey, this bias will not be substantial.

One issue of this study worth mentioning is that one cannot assume that the clusters selected in each district are fully representative of the districts in which they are located, as the surveys only attempted to generate a fully representative sample at the provincial level. Consequently, the spatial analysis will be affected by some random fluctuations. Some of this random variation can be reduced through the structured spatial effects as it includes neighboring observations in the analysis. It should, however, be pointed out that such a spatial analysis should preferably be applied to census data, the most important official demographic data source in most developing countries, where the precision of the spatial analysis would be much higher. Unfortunately, most censuses do not collect data on undernutrition and often the full dataset is not available for such analyses.

These findings are not only relevant for analytical purposes but have considerable policy significance. In particular, the age effect points to considerable morbidity problems immediately after birth, possibly related to the use of unclean liquids and the type of breastfeeding. This is a subject that should be investigated further. Second, the nonlinear influence of mother's age indicates that not only younger parents, but also older parents might also have negative effects on the morbidity status of children. Third, the districts influences on child morbidity also are of high policy significance. In particular, they suggest that in Zambia children living provincial capital are much less affected by mor-

bidity, even if they suffer similar risk factors (as captured by the fixed effects). The same is, however, not true in Malawi, where some urban agglomerations are associated with higher risk of child morbidity. Also, more emphasis must be placed upon the role of remoteness as well as climatic and geographic factors on undernutrition. The North-South divide in Malawi and the regional effects in Zambia bear out the importance of such considerations.

Conclusion

This analysis suggests that if interest focuses on the regression parameters β there is little to be gained from an elaborate spatial modelling exercise for these data. However, in many spatial epidemiology applications including this, the practical interest extends to constructing predictive maps for the risk of diarrhea, cough and fever throughout the country, as an aid to the targeting of scarce public health resources. Our results suggests that this requires smooth spatial interpolation of estimated districts effects in addition to smooth point estimates at any given location (district). A failure to take into account the posterior uncertainty in the spatial location (district) would overestimate the precision of the diarrhea, fever and cough prevalence prediction in unsampled districts. The general interpretation of the inclusion of the spatial effect is that the spatial effect $f_{spat} = f_{unstr}(dist) + f_{str}(dist)$ represents the cumulative effect of unidentified covariates which, if they had been available, would have been included in the estimation. These possible unidentified additional covariates could be environmental, social and even cultural.

Maps could be used for targeting development efforts at a glance, or for exploring relationships between welfare indicators and others variables.The visual nature of the maps may highlight unexpected relationships that would be overlooked in a standard regression analysis.

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Table 1 Factors analyzed in child morbidity study in Malawi and Zambia

Factor	Malawi (%)	Zambia (%)	coding
Individual characteristics			
Sex of child: Male	50.7	50.1	1: male
Female	49.3	49.9	-1 reference category
Preceding birth interval: Less than 24 month	19.38	17.8	-1 reference category
Greater than 24	80.62	82.2	1
Type of breastfeeding: Exclusive breastfeeding	5.65	7.22	category 1
Mixed feeding	57.2	52.04	category 2
No breastfeeding	37.15	40.74	-1 reference category
Premature child: Yes	4	4.80	1
No	96	95.20	-1 reference category
Receive vaccination: Yes	77.83	72.82	1
No	22.17	27.18	-1 reference category
Child a twin: Singleton birth	95.93	96.05	-1 reference category
Multiple birth	4.07	3.95	1
Child's size at birth: Small size	17.73	11.84	-1 reference category
Average size	61.95	67.96	1
Large size	20.33	20.20	2
Family characteristics			
Mother's age: Less than 21	29.79	33.78	-1 reference category
22-35	56.93	55.93	category 1
Greater than 35	13.28	10.29	category 2
Mother's Educational attainment:			
No education and incomplete primary educ.	84.45	48.21	1
Up to primary educ.	10.14	32.83	2
Secondary educ. and higher	5.41	18.96	-1 reference category
Partner's Educational attainment:			
No education and incomplete primary educ.	60.08	28.11	1
Up to primary educ.	22.95	30.63	2
Secondary educ. and higher	16.96	41.26	-1 reference category
Marital status: Single mothers	11.48	15.24	1
Married	88.52	84.76	-1 reference category
Antenatal visit: Yes	93.59	93.24	1
No	6.41	6.76	-1 reference category
Asset index: Low-income household	38.93	36.75	1
Middle-income household	40.02	40.45	2
high-income household	20.4%	21.66	-1 reference category
Parity: Small family (less than 5 members)	56.06	58.77	-1 reference category
Medium size (between 5 and 10 members)	40.98	37.83	1
Large size (more than 10 members)	2.96	3.40	2
Community characteristics			
Place of residence: Urban	25.5	42.7	1
Rural	74.5	57.3	-1 reference category
Household size: Small size (less than 6 members)	46.72	33.45	-1 reference category
Medium size (between 5 and 9 members)	43.16	42.74	1
Large size (more than 9 members)	10.12	23.81	2
Child's place of delivery: Hospital	62.51	49.56	1
Home and others	37.49	50.44	-1 reference category
District:	32	62	spatial covariate

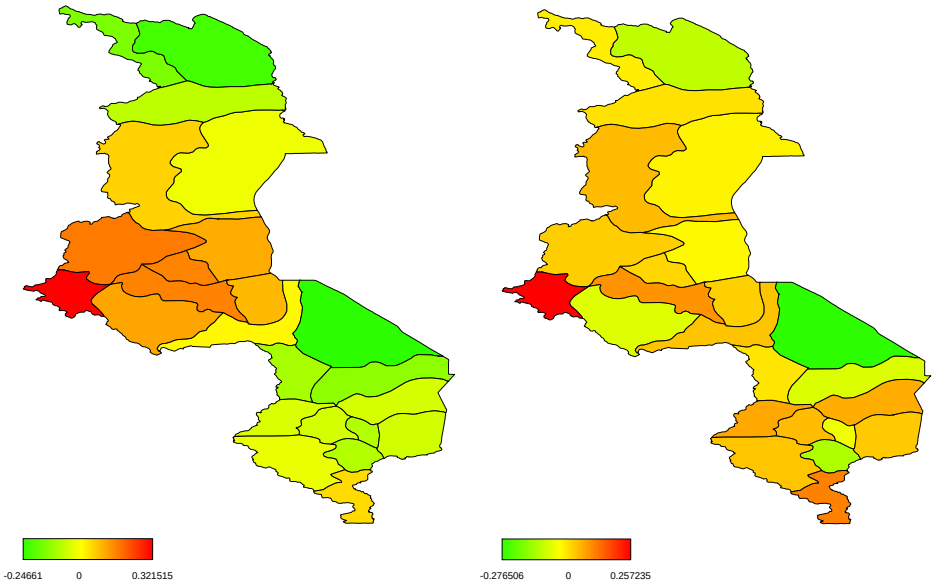

Figure 1 Structured (left) and unstructured (right) spatial effects for diarrhea in Malawi (Model M2).

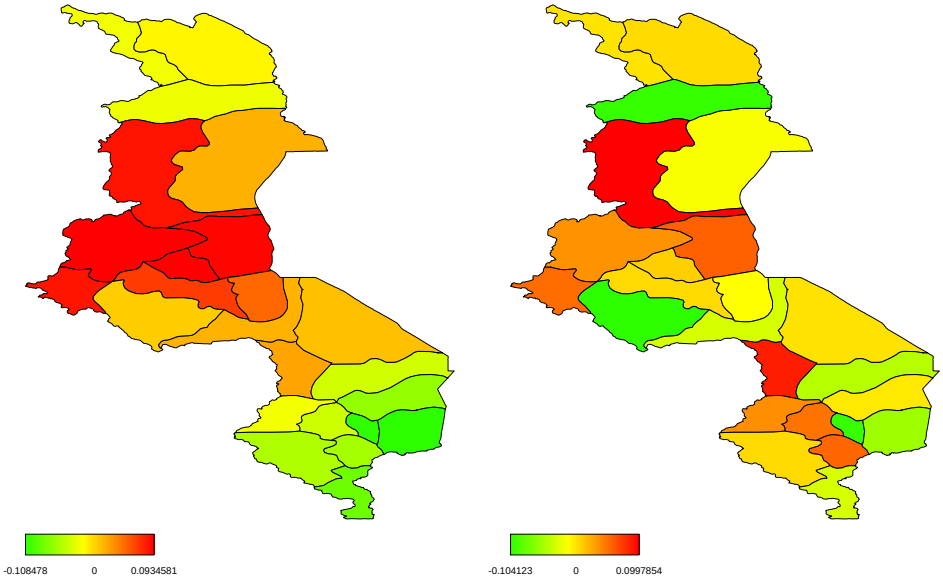

Figure 2 Structured (left) and unstructured (right) spatial effects for fever in Malawi (Model M2).

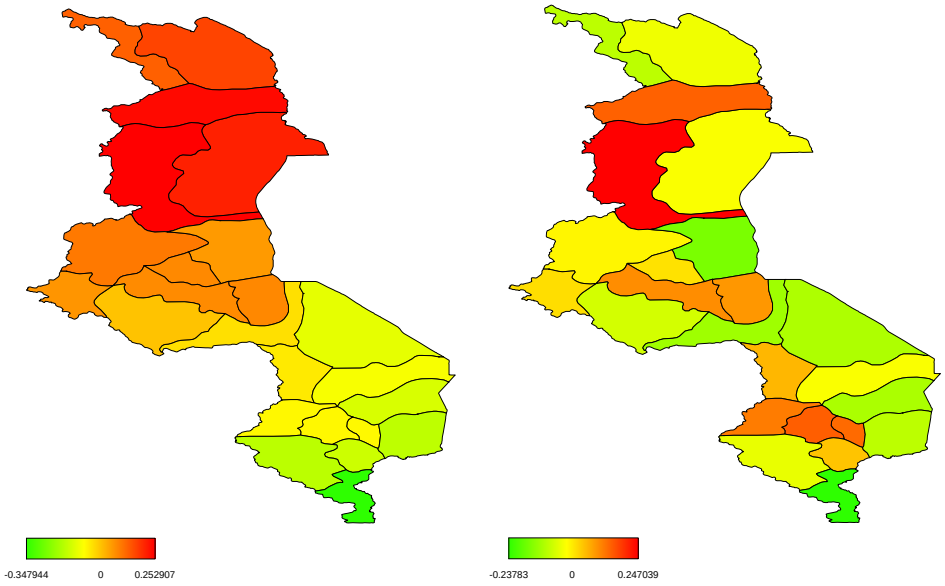

Figure 3 Structured (left) and unstructured (right) spatial effects for cough in Malawi (Model M2).

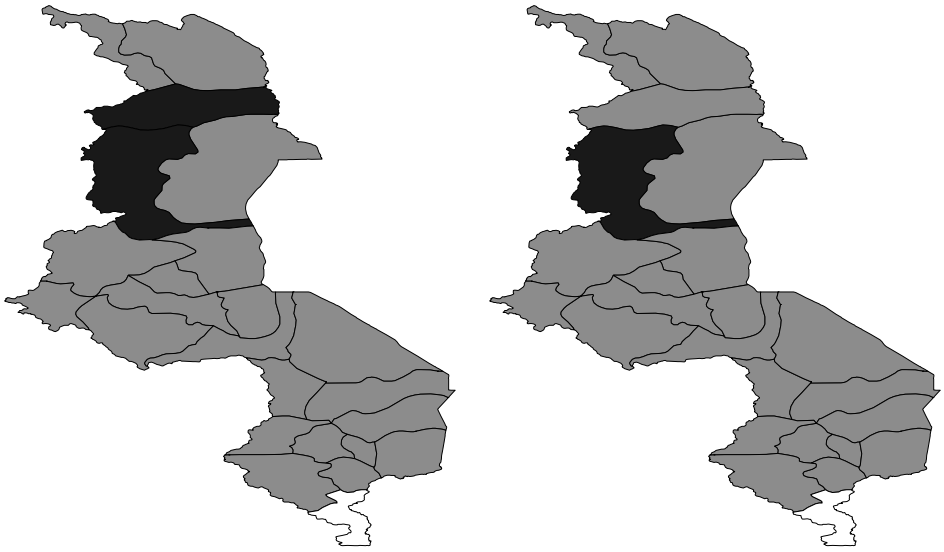

Figure 4 Maps of 80% posterior probabilities for the structured (left) and unstructured (right) spatial effects for cough in Malawi (Models M2).

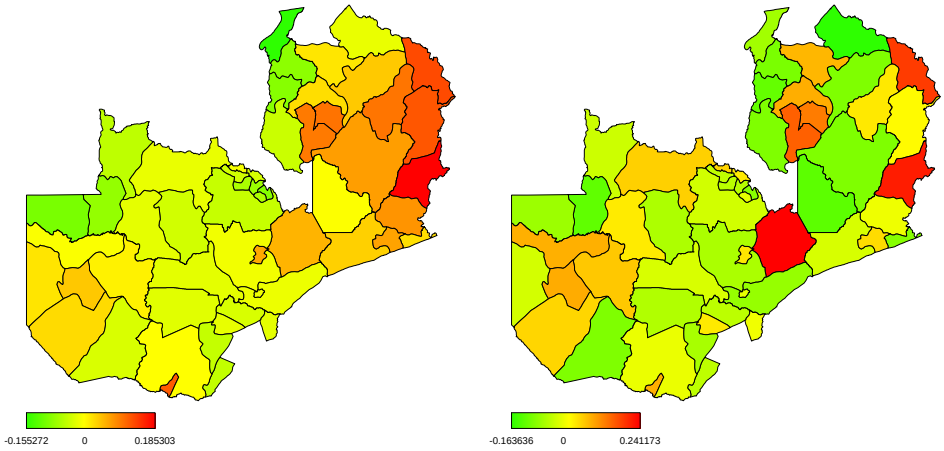

Figure 5 Structured (left) and unstructured (right) spatial effects for diarrhea in (Model M2).

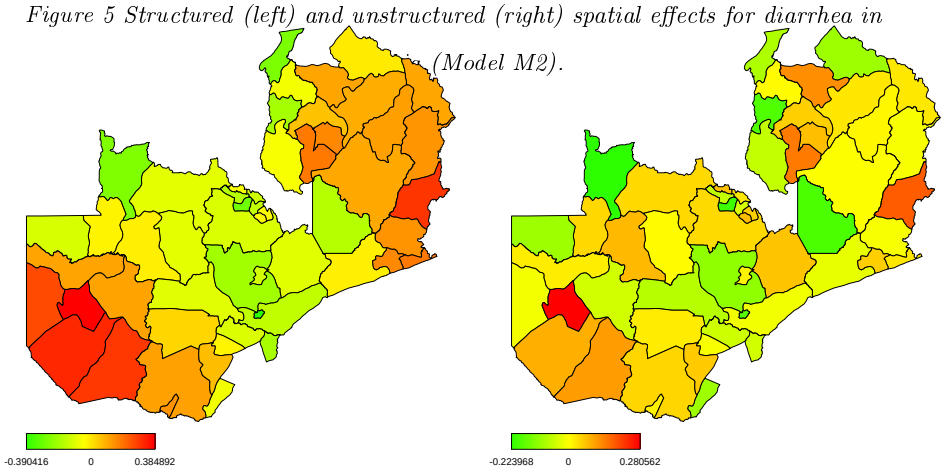

Figure 6 Structured (left) and unstructured (right) spatial effects for fever in Zambia (Model M2).

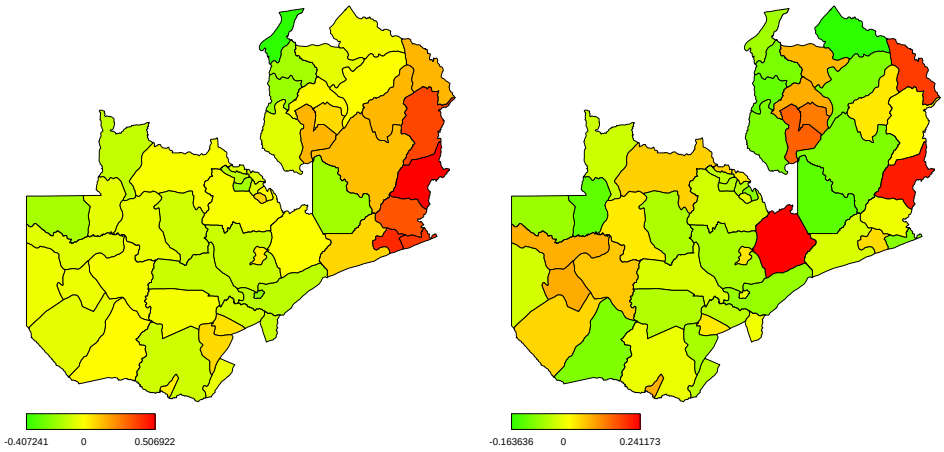

Figure 7 Structured (left) and unstructured (right) spatial effects for cough in Zambia (Model M2).

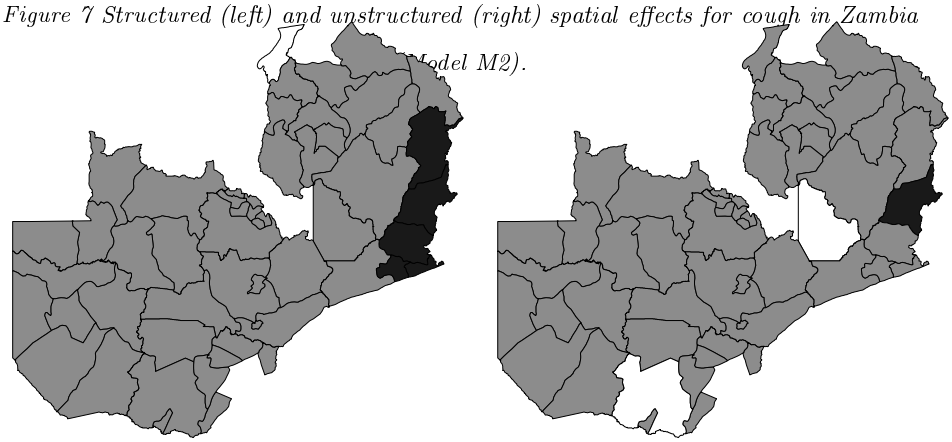

Figure 8 Maps of 80% posterior probabilities for the structured (left) and unstructured (right) spatial effects for cough in Zambia (Models M2).

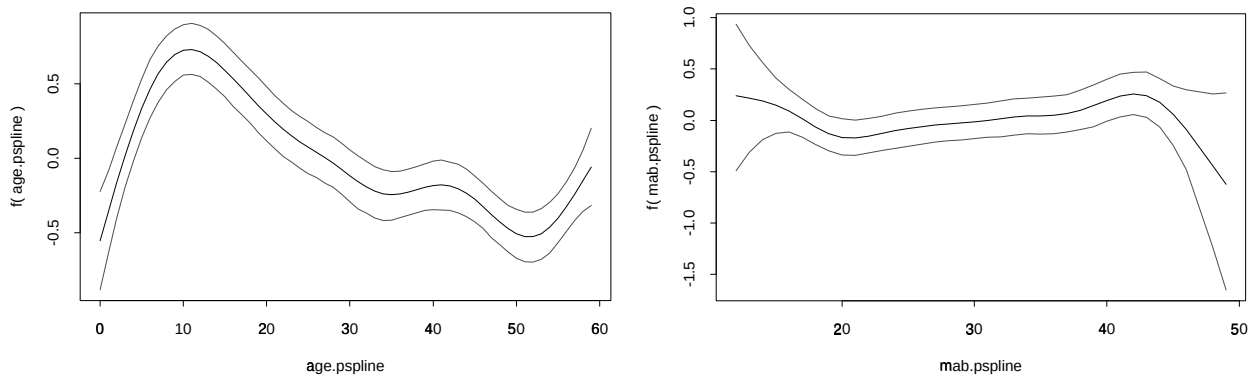

Figure 9 Estimated nonparametric effect of child's age and mother's age for diarrhea in Malawi. Shown is the posterior mean within 80% credible regions.

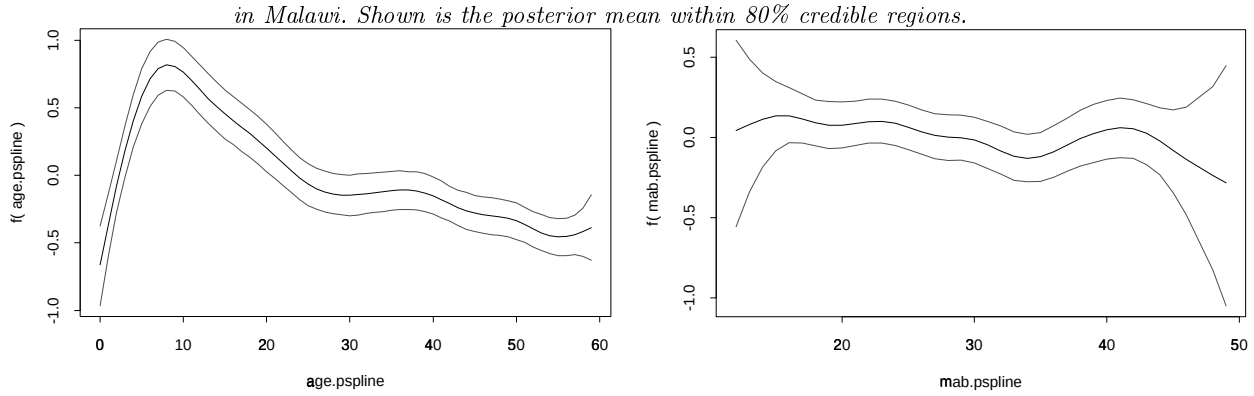

Figure 10 Estimated nonparametric effect of child's age and mother's age for fever in Malawi.

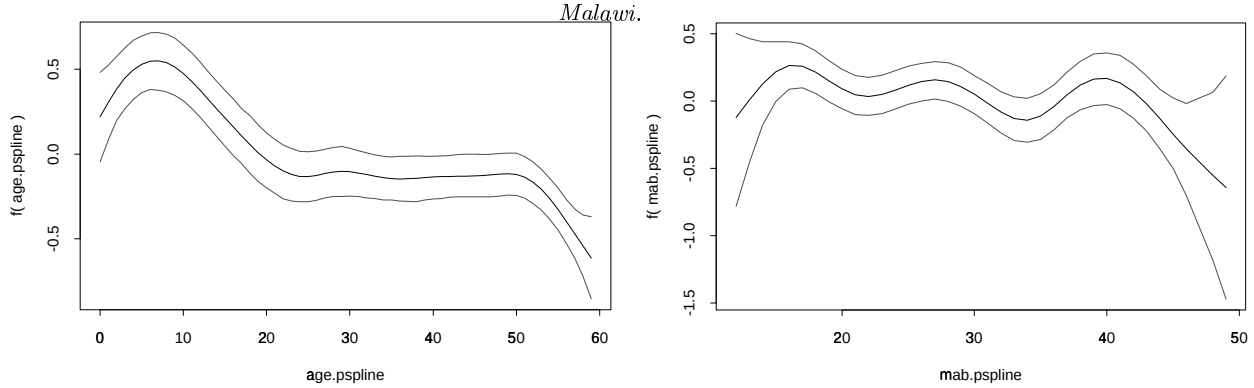

Figure 11 Estimated nonparametric effect of child's age and mother's age for cough in Malawi.

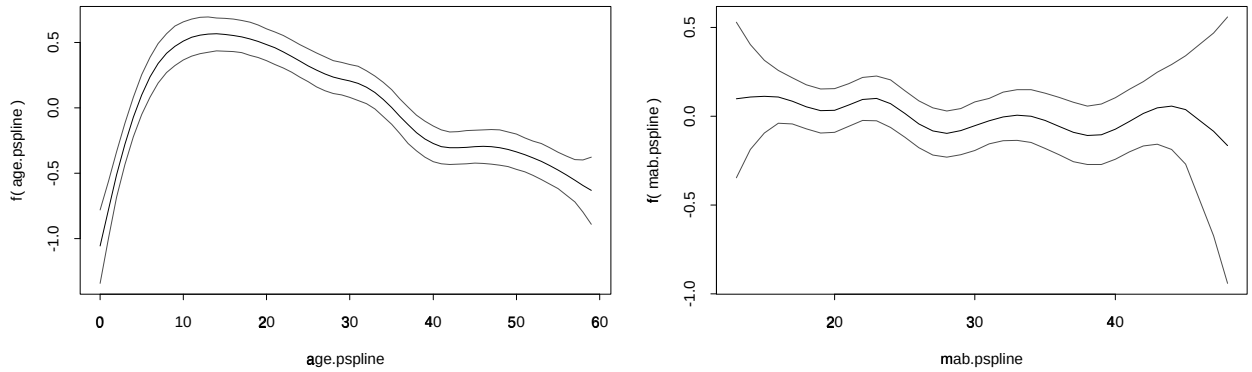

Figure 12 Estimated nonparametric effect of child's age and mother's age for diarrhea in Zambia.

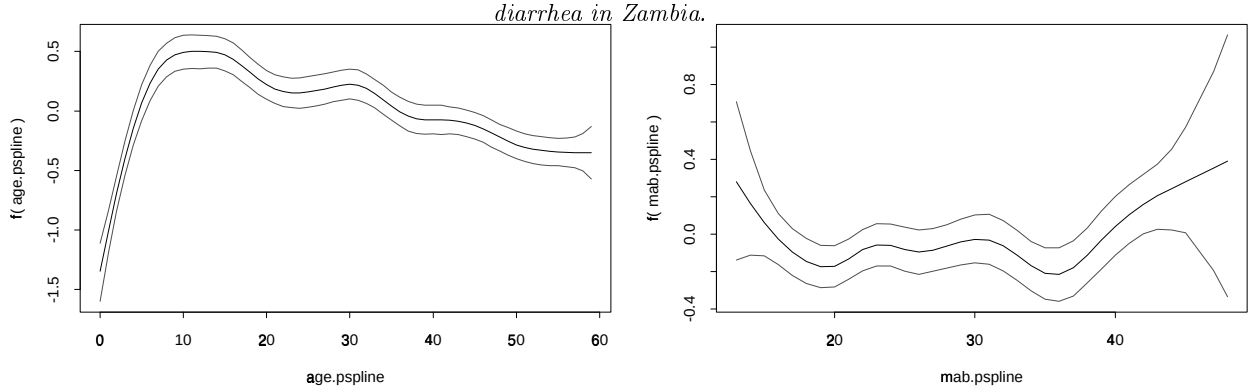

Figure 13 Estimated nonparametric effect of child's age and mother's age for fever in Zambia.

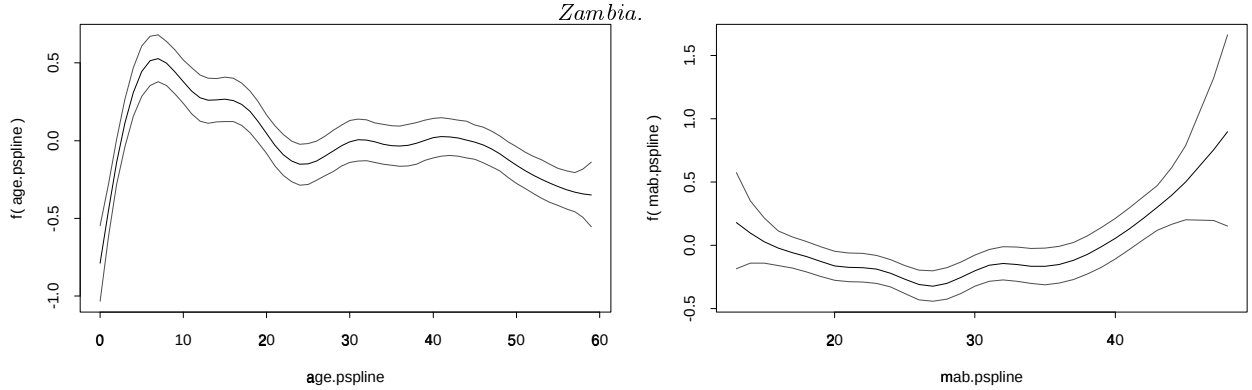

Figure 14 Estimated nonparametric effect of child's age and mother's age for cough in Zambia.

Table 2 Posterior estimates of the fixed effect parameters for diarrhea in Malawi

Variable	mean	std. error	10% quantile	90% quantile
Constant	-1.24	0.16	-1.24	-1.05
Maternal education: Up to primary educ.	0.23	0.07	0.14	0.31
Secondary educ. and higher	-0.17	0.07	-0.27	-0.08
Patner education: Up to primary educ.	-0.08	0.04	-0.14	-0.02
Secondary educ. and higher	-0.06	0.04	-0.11	0.001
Sex of child: Male	0.06	0.03	0.02	0.09
Premature birth	-0.06	0.10	-0.18	0.07
Child received vaccination	0.08	0.10	-0.04	0.21
Marital status: Single mothers	-0.001	0.05	-0.06	0.06
Children from "low-income" hous.	0.04	0.07	-0.05	0.13
Children from "medium-income" hous.	0.004	0.05	-0.06	0.06
Medium size household	-0.002	0.04	-0.05	0.05
Large size household	0.01	0.06	-0.06	0.08
Parity (between 5 and 9 members)	-0.07	0.06	-0.15	0.004
parity (more than 9 members)	0.13	0.11	-0.005	0.28
Child's size at birth: small	0.03	0.05	-0.04	0.09
Child's size at birth: average	0.004	0.04	-0.04	0.05
Long birth interval	-0.08	0.03	-0.13	-0.04
Antenatal visit during pregnancy	-0.02	0.11	-0.15	0.12
Child's place of delivery (hospital)	-0.01	0.03	-0.04	0.03
Multiple birth	-0.13	0.08	-0.24	-0.02
Exclusive breastfeeding	-0.13	0.10	-0.27	-0.005
Mixed feeding	0.06	0.06	-0.01	0.13
Child's place of residence:Urban	-0.07	0.05	-0.13	-0.01
Interaction terms:				
Low-income hous.* rural areas	0.03	0.07	-0.06	0.12
Medium-income hous. rural areas	-0.01	0.05	-0.08	0.05

Table 3 Posterior estimates of the fixed effect parameters for fever in Malawi

Variable	mean	std. error	10% quantile	90% quantile
Constant	-0.36	0.14	-0.53	-0.18
Maternal education: Up to primary educ.	0.22	0.06	0.14	0.29
Secondary educ. and higher	-0.03	0.06	-0.11	0.05
Partner education: Up to primary educ.	-0.03	0.04	-0.08	0.02
Secondary educ. and higher	-0.07	0.04	-0.12	-0.02
Sex of child: Male	-0.005	0.02	-0.03	0.02
Premature birth	0.08	0.08	-0.02	0.18
Child received vaccination	0.27	0.08	0.17	0.38
Marital status: Single mothers	0.03	0.04	-0.02	0.09
Children from "low-income" hous.	0.04	0.06	-0.04	0.12
Children from "medium-income" hous.	-0.01	0.04	-0.07	0.04
Medium size household	-0.01	0.04	-0.06	0.04
Large size household	0.02	0.05	-0.05	0.09
Parity (between 5 and 9 members)	0.04	0.05	-0.03	0.10
parity (more than 9 members)	-0.11	0.10	-0.24	0.03
Child's size at birth: small	-0.04	0.04	-0.10	0.02
Child's size at birth: average	-0.02	0.03	-0.06	0.03
Long birth interval	-0.02	0.03	-0.05	0.02
Antenatal visit during pregnancy	-0.11	0.10	-0.23	0.01
Child's place of delivery (hospital)	-0.05	0.03	-0.08	-0.01
Multiple birth	0.07	0.07	-0.02	0.16
Exclusive breastfeeding	-0.23	0.09	-0.35	-0.12
Mixed feeding	0.11	0.05	0.05	0.17
Child's place of residence:Urban	-0.04	0.04	-0.09	0.005
Interaction terms:				
Low-income hous.* rural areas	-0.03	0.06	-0.10	0.05
Medium-income hous. rural areas	0.02	0.04	-0.04	0.07

Table 4 Posterior estimates of the fixed effect parameters for cough in Malawi

Variable	mean	std. error	10% quantile	90% quantile
Constant	-0.45	0.13	-0.62	-0.28
Maternal education: Up to primary educ.	0.15	0.06	0.08	0.23
Secondary educ. and higher	-0.01	0.06	-0.09	0.07
Partner education: Up to primary educ.	-0.10	0.04	-0.15	-0.05
Secondary educ. and higher	-0.06	0.04	-0.11	-0.01
Sex of child: Male	-0.003	0.02	-0.03	0.03
Premature birth	0.07	0.08	-0.03	0.17
Child received vaccination	0.09	0.08	-0.01	0.20
Marital status: Single mothers	0.03	0.04	-0.03	0.08
Children from "low-income" hous.	0.08	0.06	0.01	0.16
Children from "medium-income" hous.	0.05	0.04	-0.004	0.11
Medium size household	0.03	0.04	-0.01	0.07
Large size household	-0.003	0.05	-0.07	0.06
Parity (between 5 and 9 members)	0.12	0.06	0.05	0.20
parity (more than 9 members)	-0.23	0.10	-0.37	-0.09
Child's size at birth: small	-0.003	0.04	-0.06	0.05
Child's size at birth: average	-0.02	0.03	-0.06	0.02
Long birth interval	0.03	0.03	-0.01	0.06
Antenatal visit during pregnancy	-0.10	0.10	-0.22	0.03
Child's place of delivery (hospital)	-0.02	0.03	-0.06	0.01
Multiple birth	-0.01	0.07	-0.10	0.08
Exclusive breastfeeding	-0.36	0.08	-0.47	-0.25
Mixed feeding	0.15	0.05	0.09	0.22
Child's place of residence:Urban	0.001	0.04	-0.05	0.05
Interaction terms:				
Low-income hous.* rural areas	-0.03	0.06	-0.11	0.05
Medium-income hous. rural areas	-0.01	0.04	-0.06	0.05

Table 5 Posterior estimates of the fixed effect parameters for diarrhea in Zambia

Variable	mean	std. error	10% quantile	90% quantile
Constant	-0.85	0.11	-0.99	-0.71
Maternal education: Up to primary educ.	0.09	0.04	0.04	0.13
Secondary educ. and higher	0.08	0.03	0.03	0.12
Patner education: Up to primary educ.	0.06	0.04	0.01	0.10
Secondary educ. and higher	-0.02	0.03	-0.06	0.02
Sex of child: Male	0.06	0.02	0.03	0.08
Premature birth	-0.06	0.07	-0.15	0.02
Child received vaccination	-0.05	0.06	-0.13	0.03
Marital status: Single mothers	0.07	0.04	0.02	0.12
Children from "low-income" hous.	0.06	0.09	-0.05	0.16
Children from "medium-income" hous.	0.06	0.06	-0.02	0.13
Medium size household	0.01	0.03	-0.02	0.05
Large size household	-0.08	0.04	-0.12	-0.03
Parity (between 5 and 9 members)	-0.06	0.05	-0.12	0.01
parity (more than 9 members)	0.01	0.09	-0.10	0.13
Child's size at birth: small	0.04	0.05	-0.02	0.11
Child's size at birth: average	-0.02	0.03	-0.06	0.02
Long birth interval	-0.02	0.03	-0.06	0.02
Antenatal visit during pregnancy	0.04	0.09	-0.07	0.15
Child's place of delivery (hospital)	0.001	0.03	-0.03	0.04
Multiple birth	0.01	0.06	-0.06	0.09
Exclusive breastfeeding	-0.04	0.07	-0.14	0.05
Mixed feeding	-0.01	0.04	-0.06	0.04
Child's place of residence:Urban	0.005	0.04	-0.05	0.06
Interaction terms:				
Low-income hous.* rural areas	-0.05	0.10	-0.18	0.08
Medium-income hous. rural areas	-0.13	0.08	-0.24	-0.03

Table 6 Posterior estimates of the fixed effect parameters for fever in Zambia

Variable	mean	std. error	10% quantile	90% quantile
Constant	0.062	0.10	-0.07	0.19
Maternal education: Up to primary educ.	0.13	0.03	0.08	0.17
Secondary educ. and higher	0.05	0.03	0.01	0.09
Patner education: Up to primary educ.	-0.04	0.03	-0.08	0.01
Secondary educ. and higher	0.02	0.03	-0.01	0.06
Sex of child: Male	0.01	0.02	-0.02	0.03
Premature birth	0.13	0.06	0.05	0.21
Child received vaccination	0.03	0.06	-0.04	0.11
Marital status: Single mothers	0.06	0.03	0.02	0.10
Children from "low-income" hous.	0.12	0.08	0.01	0.22
Children from "medium-income" hous.	-0.04	0.05	-0.10	0.02
Medium size household	-0.07	0.03	-0.10	-0.03
Large size household	-0.003	0.03	-0.04	0.04
Parity (between 5 and 9 members)	-0.004	0.04	-0.06	0.05
parity (more than 9 members)	-0.01	0.08	-0.11	0.09
Child's size at birth: small	-0.04	0.05	-0.10	0.02
Child's size at birth: average	-0.02	0.03	-0.06	0.02
Long birth interval	-0.03	0.02	-0.06	0.004
Antenatal visit during pregnancy	0.01	0.09	-0.10	0.12
Child's place of delivery (hospital)	-0.02	0.02	-0.05	0.01
Multiple birth	-0.03	0.06	-0.10	0.04
Exclusive breastfeeding	-0.04	0.07	-0.12	0.05
Mixed feeding	0.02	0.04	-0.02	0.07
Child's place of residence:Urban	-0.05	0.04	-0.10	0.0001
Interaction terms:				
Low-income hous.* rural areas	-0.07	0.10	-0.19	0.05
Medium-income hous. rural areas	0.09	0.07	-0.005	0.18

Table 7 Posterior estimates of the fixed effect parameters for cough in Zambia

Variable	mean	std. error	10% quantile	90% quantile
Constant	0.01	0.10	-0.12	0.14
Maternal education: Up to primary educ.	0.05	0.03	0.01	0.09
Secondary educ. and higher	0.02	0.03	-0.01	0.06
Partner education: Up to primary educ.	-0.01	0.03	-0.05	0.04
Secondary educ. and higher	0.02	0.03	-0.02	0.06
Sex of child: Male	-0.02	0.02	-0.04	0.005
Premature birth	0.06	0.06	-0.01	0.14
Child received vaccination	-0.01	0.06	-0.08	0.07
Marital status: Single mothers	-0.003	0.03	-0.04	0.04
Children from "low-income" hous.	-0.09	0.08	-0.20	0.02
Children from "medium-income" hous.	0.05	0.05	-0.02	0.12
Medium size household	-0.06	0.03	-0.09	-0.02
Large size household	-0.02	0.03	-0.06	0.03
Parity (between 5 and 9 members)	0.0004	0.04	-0.06	0.06
parity (more than 9 members)	-0.005	0.08	-0.11	0.09
Child's size at birth: small	0.02	0.05	-0.04	0.08
Child's size at birth: average	-0.04	0.03	-0.08	-0.002
Long birth interval	-0.04	0.02	-0.07	-0.01
Antenatal visit during pregnancy	0.10	0.08	-0.01	0.20
Child's place of delivery (hospital)	-0.02	0.02	-0.05	0.01
Multiple birth	0.01	0.05	-0.06	0.08
Exclusive breastfeeding	-0.02	0.07	-0.11	0.06
Mixed feeding	0.01	0.04	-0.04	0.06
Child's place of residence:Urban	-0.02	0.04	-0.07	0.03
Interaction terms:				
Low-income hous.* rural areas	0.09	0.10	-0.03	0.23
Medium-income hous. rural areas	-0.15	0.07	-0.24	-0.05

Table 8 Summary of the DIC for models M1 and M2 (Malawi: left and Zambia: right)

Model	Deviance	pD	DIC	Deviance	pD	DIC
M1 (Diarrhea)	904.962	20.10	925.96	1643.28	27.11	1670.39
M2(Diarrhea)	868.32	46.45	914.77	520.95	57.94	578.90
M1 (Cough)	1402.19	21.36	1423.55	2248.63	26.97	2275.6
M2(Cough)	1359.88	53.44	1413.3	753.28	67.17	820.45
M1 (Fever)	1341.37	21.27	1362.64	2166	26.26	2192.27
M2(Fever)	1305.35	50.47	1355.83	721.46	67.69	789.15