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Geostatistical patterns of co-morbidity of diarrhea, acute respiratory infection, and stunting among under-five children in Nigeria

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Abstract

Among children under five in Nigeria, in the year 2018, the prevalence of diarrhea was 13%, that of acute respiratory infections 3%, and that of stunting 37%. A shared-component model highlights geographic variations in the comorbidities of these diseases. The data are from the 2018 Nigeria Demographic and Health Survey. The majority of states in northern Nigeria presented clusters of higher risk for comorbidities of any pair of the three diseases. Compared with mothers with primary education or less, mothers with secondary education were 1.4 times less likely to have two or three of these diseases at the same time, and women with tertiary education 2.0 times less. Compared to childless women of the same age, mothers were 1.6 times less when aged 20-29, 1.9 times less when aged 30-39, and 2.0 times less when aged 40-49. Access to a protected water source reduced the risk by a factor of 1.3. Girls under age five were 1.2 times less likely than boys of that age to have two or three of these diseases at the same time. This factor was the same for breastfed children compared to those who were not breastfed.

Keywords: Shared component; Bayesian analysis; stunting; diarrhea; Nigeria

1 Introduction

Efforts to reduce child mortality from preventable diseases are paying off, as under-five mortality in 2019 had fallen by nearly 60% since 1990. However, sub-Saharan Africa still had an average mortality rate of 76 deaths per 1000 live births in 2019. In Nigeria in 2019, the prevalence of diarrhea was 13%, that of malaria 23%, and that of acute respiratory infections 3%. Malnutrition increased the mortality rate for these diseases by 50% among children (Black, Morris, and Bryce, 2003). Diarrhea and acute respiratory infections both impair growth and together are the leading cause of death in Nigeria (Stewart et al., 2013). The World Health Organization (2017) estimated that childhood diarrhea affected 1.7 billion children under the age of five worldwide in 2017, of which 525,000 died of this disease. In Nigeria, 10% of under-five deaths in 2017 were caused by diarrhea. Acute respiratory infections caused 4 of the 15 million under-five deaths that year. Schmidt et al. (2009) also showed that 26% of the episodes of diarrhea were associated with respiratory tract infections, which indicates that diarrhea and respiratory tract can occur simultaneously in the same individual.

Multivariate disease mapping is a technique that combines the prevalence values of several diseases to identify areas where diseases occur together. The information that this method provides on the locations of co-occurrence of multiple diseases suggests the presence of factors that enhance the joint occurrence of the diseases among the same individuals. Combining data from several diseases in a multiple disease mapping ensures more precise parameter estimates because the standard errors of the parameters are smaller when compared with single disease mapping, when the data are not abundant (Assunção and Castro, 2004; Manda, Feltbower, and Gilthorpe, 2012).

Kazembe and Namangale (2007) used a multinomial logistic model to estimate the odds ratios of comorbidity from diarrhea, fever, and pneumonia: Across the regions of Malawi, these odds ratios range from 0.55 to 2.45. Adebayo et al. (2017) used a geo-additive latent variable model to provide binary and ordinal indicators allowing the mapping of the prevalence distributions of malaria and anemia among children in Nigeria. They identified the areas of Sokoto, Kebbi, Zamfara, Yobe, Osun, Edo, Ebonyi, Abia, Akwa Ibom, and Rivers as the places of high prevalence of comorbidity for these diseases.

The authors we have cited have worked at regional scales. We address variations at the finer scale of 1400 areas, in order to identify possible clusters within Nigeria's administrative states.

The 2018 Nigeria Demographic and Health Survey allows us to link morbidity to maternal and child health indicators and demographics. It includes the latitude and longitude of the approximate geographical centers of the sampled locations. This offers us the opportunity to map the spatial distributions of the diseases, and identify comorbidities linking two diseases among acute respiratory infection, diarrhea, and stunting among children under five years of age, controlling for other risk factors related to mothers, children, and their households. A shared component model (Knorr-Held and Best, 2001) is the appropriate technique to do that, as it allows for breaking down the risk of being affected by several diseases at the same time into a component common to all diseases (”shared component”) and components specific (“not shared”) to each disease.

2 Data and Method

2.1 Data

We use the Nigeria Demographic and Health Survey (2018) conducted from August to December 2018 by the National Population Commission of Nigeria in collaboration with the National Malaria Elimination Program of the Federal Ministry of Health of Nigeria.

The survey is based on stratified two-stage sampling conducted on 1400 enumeration areas drawn from 587 urban and 813 rural areas. The sampling frame was generated from the 2006 Nigerian Population and Housing Census. The survey team selected a representative sample of 41,668 households and interviewed 40,427 of them. This figure represents 41,821 women aged 15-49 from 11,699 urban and 22,225 rural households covering the 36 states and the Federal Capital Territory of Nigeria (Figure 1). The survey also contains information on all children under 5 years of age.

We considered all children with information on the three diseases whether or not they had it. We discarded all children for whom we could not know whether they had diarrhea, acute respiratory infection, or stunting. This selection led us to retain information on 23,634 children. We associated its latitude and longitude with each enumeration area.

The survey included a question to caregivers about whether the child had three or more loose or liquid stools during at least one day in the two weeks before the survey. For acute respiratory infection, a child was considered to have had an acute respiratory infection in the two weeks prior to the survey if he or she had short, fast, or difficult breathing. For stunting, which is a sign of chronic undernutrition, we used height and age measurements. "Z-scores" stipulated by the World Health Organization (2006) quantify the relationship of a given value to the average of these values over a given group: A child whose Z-score is less than minus two standard deviations from the reference population is said to be "stunted". We also have age, sex, breastfeeding status, birth order of children, type of residence, nature of drinking water source, presence of sanitation facilities, mother's education level, availability of electricity, whether or not the mother listens to the radio, watches television, or reads the newspaper at least once a week, whether or not the mother is in the labor force, and a household wealth index. Overall, 36% (8,541/23,634) of children had been stunted, 10% (2,492/23,634) had had diarrhea, and 4% (973/23,634) had had acute respiratory infection.

2.2 Method

A shared-component model contains a latent spatial field that may be shared by multiple diseases and other latent fields that are considered as non-shared random components (Held et al., 2005). We model the shared and non-shared spatial effects of diarrhea, acute respiratory infection, and stunting by using the stochastic partial differential Eq. (4) presented below, taken from Lindgren, Rue, and Lindström (2011), and which represents a continuous spatial process combined with a discretely indexed spatial random process. Bayesian inference is based on the integrated nested Laplace approximation, which is an algorithm providing posterior estimates (Rue, Martino, and Chopin, 2009). It is implemented in the R procedure “R-INLA” (Lindgren and Rue, 2015).

The response variable $y_{ijd} = 1, i \in \{1, ..., 23634\}$, if a child i living in cluster $j = 1, ..., 1400$ suffers from condition $d = 1, 2, 3$, $y_{ijd} = 0$ if otherwise. Therefore, $y_{ijd} \sim \mathrm{Bernoulli}(p_{ijd})$ such that

$$f(y_{ijd} \mid \eta_{ijd}) = p_{ijd}^{y_{ijd}}(1 - p_{ijd})^{1-y_{ijd}} = \exp(y_{ijd}\eta_{ijd} - \ln(1 + \exp(\eta_{ijd}))), \tag{1}$$

where $p_{ijd} = P(y_{ijd} = 1)$ and η_{ijd} is the predictor for child i living in cluster j. With a logit link function, it is $\eta_{ijd} = \mathrm{logit}(p_{ijd})$. The predictor for the shared component model is:

$$\mathrm{logit}(p_{ijd}) = \alpha + \omega\beta + g(\upsilon_j)\delta_d + g_d(s_j), \tag{2}$$

where α is the model intercept, which we take here common to the three diseases, β a vector of parameters for categorical variables, ω a vector of other available covariates, $g(\upsilon_j)$ the spatial field for all diseases, δ_d a weight used for each disease group to control how the disease d is affected by the shared field, and $g_d(s_j)$ are the non-shared spatial components.

We based the prior distribution for δ_d on a lognormal distribution with mean 0 and “precision,” defined as the inverse of the variance, of 0.1, to allow for vague prior information. The linear parameters and the constant term are assigned a weakly informative Gaussian prior $\beta \sim N(0, \tau_\beta I)$ with small precision, where τ_β is the precision multiplied by the identity matrix. We take τ_β small enough to allow for the weakly information Gaussian prior that we assumed for the vector β of parameters for categorical variables. We implement the shared and non-shared spatial random components with the stochastic partial differential Eq. (4), which links the continuous spatial Gaussian field to the discretely indexed Gaussian Markov random field. We implement this link in the R-INLA package (Lindgren, Rue, and Lindström, 2011) of the R software. The covariance function and the dense covariance matrix of the Gaussian field are defined by a neighborhood structure in the form of a triangulation mesh, whose edges form the neighborhood structure, and a sparse precision matrix, which constitutes the Gaussian Markov random field (Cameletti et al., 2013). Unlike for Gaussian fields, Gaussian Markov random fields are characterized by sparse precision matrices, which allow efficient numerical methods (Cameletti et al., 2013). The triangulation $(\omega_k)_{k=1,\cdots,n}$ of the spatial domain divides the spatial domain into a set of non-intersecting triangles:

$$x(v) = \sum_{k=1}^{n} \epsilon_k(v)\omega_k, \tag{3}$$

where ω_k for vertex k of the triangulation represents the weight chosen to approximate the solution $x(v)$ of the stochastic partial differential Eq. (4) below in the n nodes of the mesh and ϵ_k is the basis function defined on the kth triangulation mesh, taking the value 1 at vertex k and 0 at the other vertices (Cameletti et al., 2013). In Eq. (3), the basis functions transform the approximation of the Gaussian random field $x(.)$ from the nodes of the mesh to the location of interest. The Gaussian Markov random field representation for the Gaussian field $x(.)$ is

$$(\kappa^2 - \Delta)^{\frac{\varrho}{2}} \tau(v) x(v) = \Psi(v), \tag{4}$$

where $\kappa > 0$ is a scaling parameter, Δ the Laplacian, $v \in \mathbb{R}^d$ and ϱ smoothing parameters, $\Psi(v)$ a Gaussian white noise, τ controls the variance, and the stationary Gaussian field $x(v)$ has a Matérn (Blangiardo and Cameletti, 2015) covariance function defined as

$$\mathrm{Cov}(x(v_i), x(v_j)) = \frac{2^{1-\lambda}}{\Gamma(\lambda)} \sigma^2 (\kappa \parallel v_i - v_j \parallel)^{\lambda} K_{\lambda}(\kappa \parallel v_i - v_j \parallel), \tag{5}$$

where $\parallel v_i - v_j \parallel$ is the Euclidean distance between locations v_i and $v_j \in \mathbb{R}^d$ and σ^2 is the marginal variance. The term K_λ is a modified Bessel function of the second kind and $\lambda > 0$ measures the degree of smoothness of the function (Blangiardo and Cameletti, 2015). $x(v)$ is the exact stationary solution of the stochastic partial differential Eq. (4). Hyperpriors for the precision parameters are based on penalized priors, which represent a unified prioritization for complex Bayesian models used to penalize the nested structure of model components. Nesting indeed improves Laplace approximations applying to latent Gaussian models (Rue et al., 2009). The prior is based on a two-parameter type-2 Gumbel distribution (Simpson et al., 2017):

$$\pi(\tau) = \frac{\mu}{2} \tau^{-\frac{3}{2}} \exp(-\mu \tau^{-\frac{1}{2}}) \qquad \tau > 0, \lambda > 0. \tag{6}$$

Unlike the Gamma prior, this penalized prior prevents over-fitting especially when the model is over-parameterized. Figure 2 shows the triangulation of the study area with vertices forming the base of the triangulation. The triangulation discretizes the continuous random field. The locations where the sample was collected are shown with points.

3 Results

We analyzed the three diseases in pairs and all three together. Table 1 shows odds ratios and 95% credible intervals for the linear covariates. Children with a protected water supply are less likely to have any of the three diseases. Children whose mothers watch television at least once a week are significantly less likely to suffer from stunting coupled with either acute respiratory infection, diarrhea, or both. The other coefficients are not significant.

Compared with children of mothers with no education, those of mothers with primary education are less likely to have diarrhea and stunting; those with secondary education are less likely to have either acute respiratory infection and stunting, diarrhea and stunting, or all three diseases; and children whose mothers have higher education are less likely to have a comorbidity, likely because they are more knowledgeable about accessing healthcare facilities. Children of working mothers are more likely to have diarrhea with either an acute respiratory infection or stunting. Compared with adolescent women (15-19 years), children of women aged 20 years or older are less likely to have a comorbidity and the coefficients are all significant. This is consistent with Wemakor et al. (2018), who showed that teenage mothers are less likely to nurse babies after delivery and guarantee adequate dietary intake, access to safer water, and sanitary conditions for their children. Children of second or higher birth order are more likely to have either an acute respiratory infection with stunting, diarrhea with stunting, or all three diseases at the same time. Girls are significantly less likely to have all three diseases at the same time, but they can have diarrhea and acute respiratory infection at the same time. Thanks to maternal immunity, breastfed children have a lower probability for all comorbidities (Kazembe and Namangale, 2007).

Children aged 24 months or older are significantly less likely to have an acute respiratory infection with diarrhea. Stunting promotes comorbidity in children aged 12 months or older. Place of residence, type of toilet, and access to newspaper or radio have no significant effect.

Figure 3 shows the maps of the non-shared spatial fields. It reveals the existence of disparities in disease morbidity even in the smallest spatial units.

Figure 3a shows that children are more likely to suffer from acute respiratory infection when they live in northeastern Nigeria, parts of northern Niger (the Nigerian state) extending to the southern region of Kebbi, and parts of the states of Edo, Delta, Bayelsa, Imo, Anambra, and Abia. The estimates of the parameters (Figure 3b) of the risk of diarrhea show that children living in the northeastern states of Yobe, Bauchi, Gombe, Taraba, Adamawa, Borno, and Plateau in the North Central are the most affected. The estimates of the parameters of the risk of stunting (Figure 3c) show a north-south contrast, reflecting the fact that children in the northern Nigerian states of Kebbi, Sokoto, Zamfara, Kaduna, Niger, Katsina, Kano, Jigawa, Yobe, Bauchi, Plateau, Gombe, Borno, Adamawa, and Taraba are more stunted than those living in the southern states of Enugu, Ebonyi, and Anambra. People under five years of age are less likely to suffer from stunting in areas located in the southern states of Oyo, Ondo, Edo, Delta, and Bayelsa, where, according to Amare et al. (2018), mothers have better nutrition and better access to healthcare facilities, compared to women living in northern Nigeria.

Figure 4 presents the estimates for the shared spatial fields. Figure 4a shows that children in the northeastern part of the country and in the states of Kebbi, Sokoto, and Edo of Niger (the Nigerian state) have more comorbidity with acute respiratory infection and diarrhea. Figures 4b, 4c, and 4d map acute respiratory infection or diarrhea with stunting. They show that children in the north of the country were more affected. These results are consistent with Akinyemi and Morakinyo (2018a), who attributed this higher risk of acute respiratory infection to religious and cultural practices that are against vaccination.

4 Conclusion

We used a shared-component model to highlight comorbidities between diarrhea, stunting, and acute respiratory infection. We started from point observations to estimate patterns of comorbidities of these three diseases at a continuous spatial scale. We deduced spatial fields that highlight comorbidities in areas where the Demographic Health Survey did not go. Mapping based on discrete spatial data obliterates local variation across states. However, estimates of spatial effects in non-residential areas may not be useful, because they say nothing about individuals. We have shown that people in northern Nigeria are more affected by comorbidities among these three diseases than those in the south. Petri et al. (2008) and Bhutta et al. (2008) explained that frequent diarrheal episodes in a child increase the risk of stunting, which could explain the relationship between the spatial distributions of these two diseases considered individually. Amare et al. (2018) showed that children in northern Nigeria are twice as likely to be stunted as those in the south, confirming the north-south contrast we highlighted. Akinyemi and Morakinyo (2018b) attributed this to socioeconomic and environmental differences. Not only do northern states have higher rates of illiteracy (71% in the northwest and 68% in the northeast against 15% in the southwest and 17% in the southeast) and poverty than in the south (77% in the northwest and 78% in the northeast against 49% in the southwest and 58% in the southeast), but they also have lower coverage of vaccination for whooping cough, measles, tetanus, and poliomyelitis (Jaiyeola and Choga, 2020; Obanewa and Newell, 2020). There is also the problem of parents who have little knowledge of how to control diarrhea and consider it to be due to teething (Odunrinde et al., 2012).

Adesanya et al. (2017) and Akinyemi and Morakinyo (2018b) linked the prevalence of acute respiratory infections and whooping cough (pertussis) (Darrow et al., 2014) in most of northern Nigeria to dust storms (7.5 meters per second (Oyewole and Aro, 2018)), which occur in the dry season. This may explain the higher estimates of odds ratios for the localities of Adamawa, Taraba, and Bauchi in northeastern Nigeria. Children in the southern states of Rivers, Akwa Ibom, Bayelsa, and Delta also suffer from environmental conditions such as air pollution from oil spills, caused mainly by pipeline corrosion, and gas flaring from industrial activities on oil rigs and in refineries located in southern Nigeria (Ologunorisa and Tamuno, 2003).

Breastfed children were less likely to suffer from any comorbidity among the three diseases. Nutrients, antioxidants, hormones, and antibodies needed for child development are contained in breast milk (Ballard and Morrow, 2013). Adewuyi and Adefemi (2016) for the year 2013 across Nigeria reported an increase in the average duration of breastfeeding, although exclusive breastfeeding is increasingly rare (the mean duration of breastfeeding across Nigeria increased from 10 months in 1979 to 13 months in 2014). Children of working mothers are more likely to suffer from the co-occurrence of the three diseases. Gayawan, Adebayo, and Chitekwe (2014) explained that the country's difficult economic situation forces working women to return to work soon after birth, leaving their children with not necessarily as conscientious caregivers. Half of Nigerian women are engaged in the labor force (Gonzale et al., 2015) , which makes breastfeeding become a population problem. Breastfeeding should be facilitated either in the workplace or extended paid maternity leave.

Education promotes health (Zajacova and Lawrence, 2018). Mothers with little or no education are often dependent on their spouse or on older women in the extended family, but these are not necessarily educated (Gayawan and Turra, 2015). Children of educated mothers are half (53%) as likely to suffer from these diseases, as we showed by their lower probabilities of having these diseases. Women's education therefore remains at the heart of health policies. Children whose mothers watch television at least once a week are less at risk as well. These women receive health-related television messages. Girls are less likely to suffer from stunting, diarrhea, and acute respiratory infection, except for a comorbidity between the two latter diseases. Children benefiting from protected water are less likely to catch any of these diseases, but we found, somewhat surprisingly, that improving the toilet did not have a significant effect. Safe drinking water and good sanitation reduce the risk of exposure to infant morbidity and mortality (Adebayo and Fahrmeir, 2005). Black et al. (2003) established a link between diarrheal diseases and unsafe water, poor sanitation, and poor hygiene (Bonneuil and Fursa, 2017). Improving access to drinking water, sanitation and better hygiene has helped reduce 56% the number of deaths from diarrhea in children between 2000 and 2015 (World Health Organization, 2018). According to Babalola and Fatusi (2009), older mothers are more experienced in caring for children. For Quigley et al. (2016), early weaning, irregular breastfeeding and missed vaccination for whooping cough, measles, tetanus, and poliomyelitis increase the risk of diarrhea in children under one year of age, but this risk decreases in older children.

Among the limitations of our work, prevalence measurements are based on statements rather than on a physician's diagnosis. Recalling the memory of caregivers over the last two weeks preceding the survey to report episodes of diarrhea and acute respiratory infection introduces a recall bias (Dunn et al., 2020) . Third, we are dependent on the month of the year the survey was conducted, in this case between August and December for the 2018 Demographic Health Survey, while acute respiratory infections and diarrhea occurring during the raining season (July-November) (Fagbule, Parakoyi, and Spiegel, 1994). We used cross-sectional survey data from the 2018 Nigeria Demographic and Health Survey and the causal effects cannot be inferred. Disease mapping is one way to highlight disparities and target interventions. For Nigeria, we found high prevalence locations for diarrhea, acute respiratory infections, and stunting, and spatial variations of these prevalence values.

Table 1: Odds ratio for the fixed effects estimates with their 95% credible intervals

Variables	Acute respiratory infection and diarrhea		Acute respiratory infection and stunting		Diarrhea and stunting		The three diseases	
	Odds ratio	95% credible interval	Odds ratio	95% credible interval	Odds ratio	95% credible interval	Odds ratio	95% credible interval
Urban residence	1.11	0.96, 1.27	0.91	0.82, 1.01	0.94	0.85, 1.03	0.97	0.88, 1.06
Cleansed water	0.73	0.64, 0.83	0.78	0.71, 0.87	0.88	0.80, 0.96	0.80	0.73, 0.87
Toilet facility								
Improved	0.93	0.83, 1.05	0.96	0.87, 1.04	0.95	0.88, 1.03	0.94	0.87, 1.02
Newspaper	0.93	0.77, 1.12	0.96	0.83, 1.11	0.97	0.85, 1.11	0.96	0.85, 1.09
Radio	1.09	0.97, 1.22	0.97	0.88, 1.06	0.99	0.91, 1.08	1.01	0.93, 1.09
Television	0.99	0.87, 1.15	0.80	0.72, 0.89	0.82	0.74, 0.90	0.86	0.78, 0.94
Mother's education:								
No education	1	reference	1	reference	1	reference	1	reference
Primary	1.03	0.88, 1.20	0.91	0.81, 1.03	0.87	0.78, 0.97	0.92	0.83, 1.02
Secondary	0.96	0.81, 1.13	0.68	0.60, 0.77	0.69	0.61, 0.77	0.74	0.66, 0.82
Higher	0.69	0.53, 0.90	0.43	0.35, 0.53	0.41	0.34, 0.50	0.47	0.39, 0.56
Working status:								
Working	1.14	1.02, 1.27	1.07	0.98, 1.17	1.11	1.02, 1.20	1.10	1.02, 1.18
Mother's age, in years:								
15 to 19	1	reference	1	reference	1	reference	1	reference
20 to 29	0.76	0.62, 0.93	0.58	0.49, 0.69	0.65	0.55, 0.76	0.64	0.55, 0.74
30 to 39	0.65	0.51, 0.83	0.48	0.40, 0.59	0.53	0.44, 0.64	0.54	0.45, 0.63
40 to 49	0.63	0.47, 0.84	0.46	0.36, 0.58	0.51	0.41, 0.63	0.51	0.42, 0.62
Child birth order:								
1^{st}	1	reference	1	reference	1	reference	1	reference
2^{nd} or 3^{rd}	0.98	0.85, 1.14	1.05	0.93, 1.18	1.03	0.93, 1.15	1.02	0.93, 1.13
4^{th} and higher	1.04	0.88, 1.23	1.20	1.05, 1.38	1.21	1.07, 1.37	1.16	1.03, 1.30
Female	0.98	0.89, 1.08	0.79	0.73, 0.85	0.82	0.76, 0.88	0.84	0.79, 0.90
Breastfeeding	0.67	0.60, 0.75	0.87	0.80, 0.94	0.91	0.85, 0.99	0.84	0.78, 0.90
Child's age, in months								
0 to 11	1	reference	1	reference	1	reference	1	reference
12 to 23	1.01	0.88, 1.14	1.99	1.76, 2.24	1.96	1.76, 2.19	1.66	1.51, 1.83
24 to 35	0.61	0.52, 0.72	2.50	2.19, 2.84	2.20	1.95, 2.47	1.69	1.52, 1.88
36 to 59	0.38	0.33, 0.44	1.80	1.61, 2.02	1.41	1.27, 1.56	1.14	1.03, 1.25

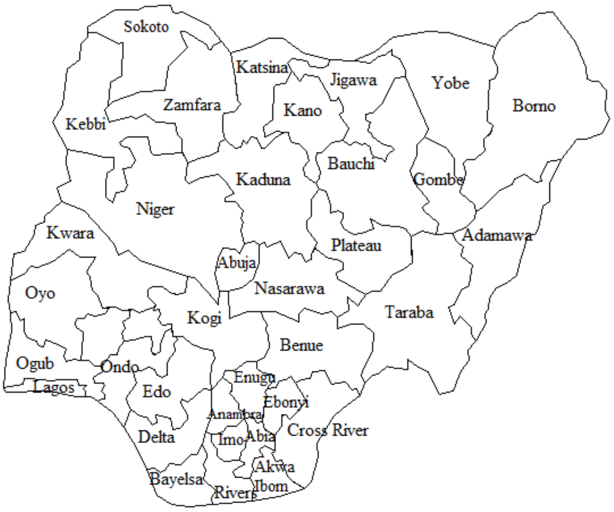


Figure 1: The 36 states of Nigeria with the Federal Capital Territory, Abuja

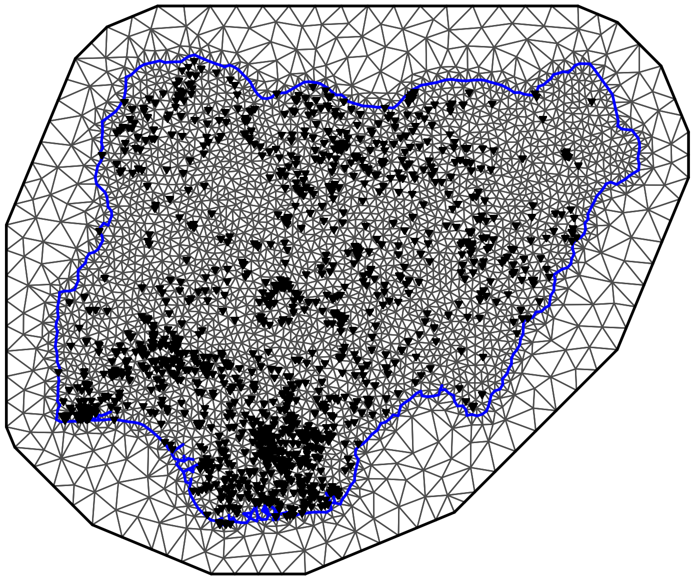
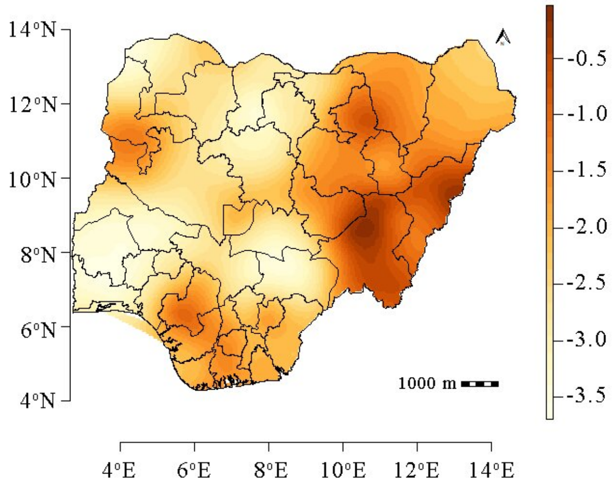
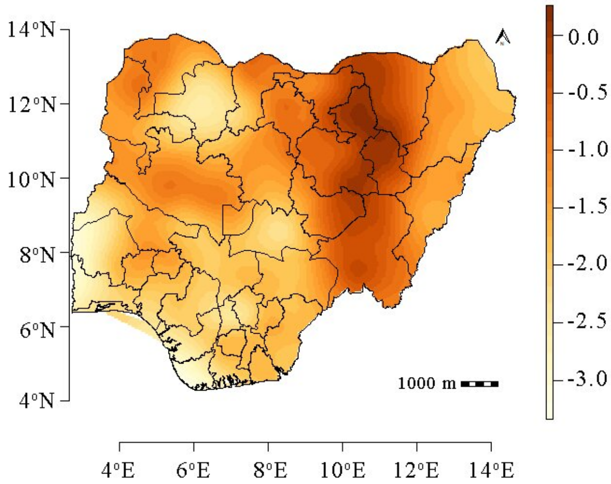


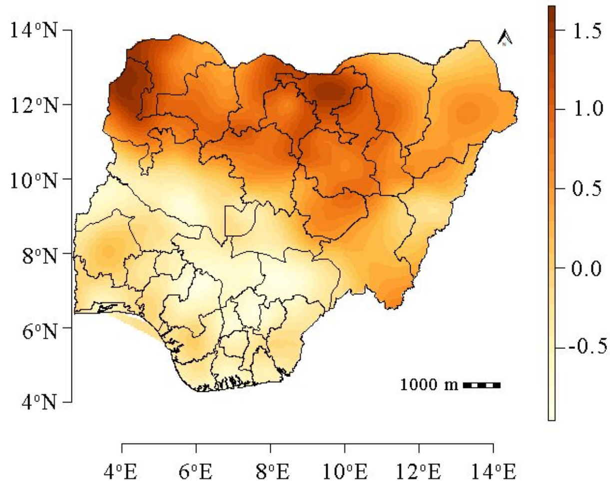
Figure 2: A triangulation of Nigeria based on 3660 vertices. The locations where the samples were collected are marked with points. The internal and external triangulation of the domain is necessary to form the model of the stochastic partial differential Eq. (4).



(a)



(b)



(c)

Figure 3: Non-shared spatial components for Nigeria for (a) acute respiratory infection, (b) diarrhea, and (c) stunting.

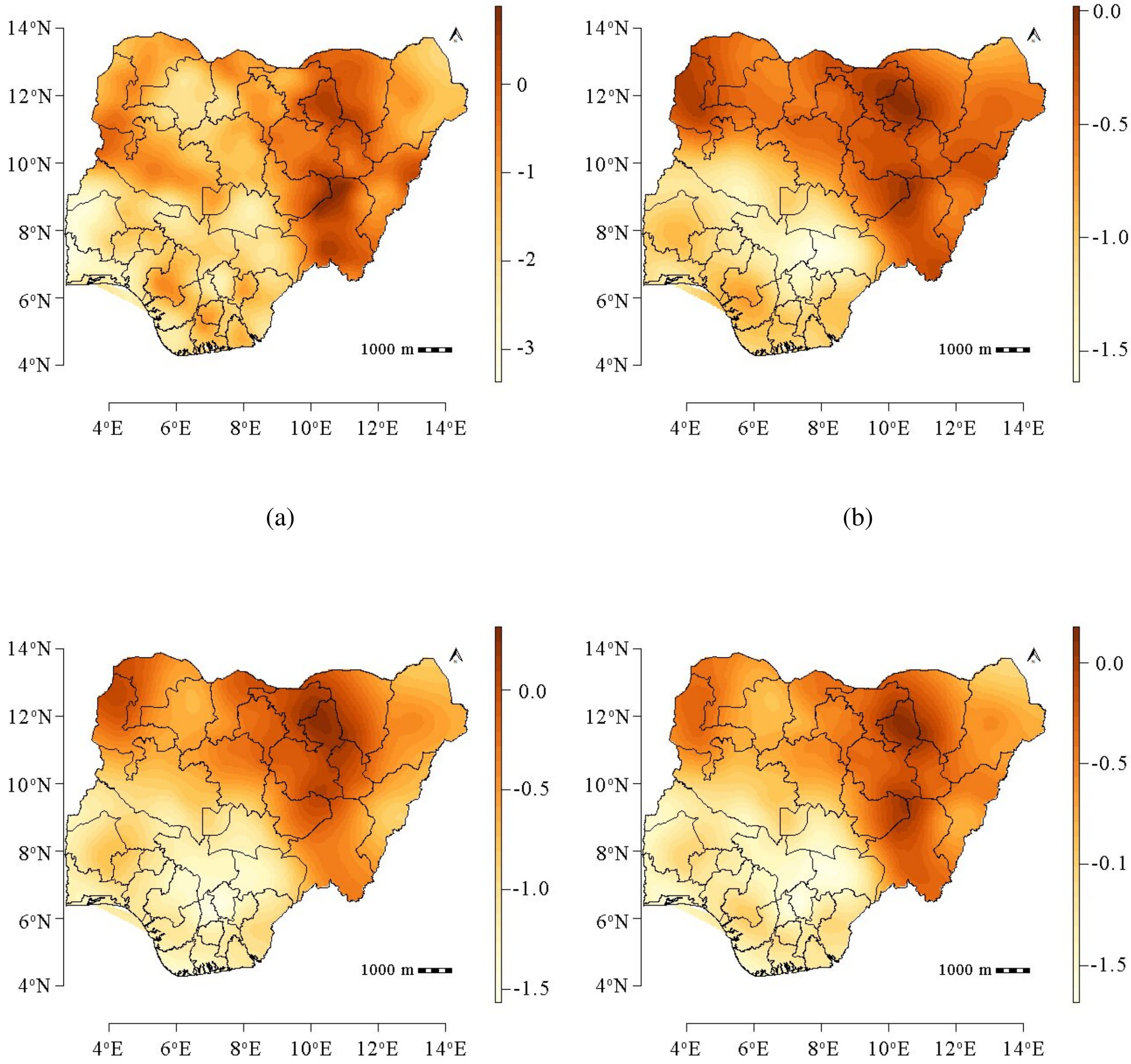


Figure 4: Shared spatial field components for Nigeria for (a) acute respiratory infection and diarrhea, (b) acute respiratory infection and stunting, (c) diarrhea and stunting, and (d) these three diseases.

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