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Thierno Souleymane Barry (barry.thiernosouleymane@gmail.com)
Pan African University Institute for basic Sciences, Technology and Innovation (PAUISTI)
Oscar Ngesa
Taita Taveta University, Voi
Nelson Owuor Onyango
University of Nairobi
Henry Mwambi
University of KwaZulu-Natal

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RESEARCH

Bayesian Spatial Modeling of Anemia among children under 5 years in Guinea

Thierno S. Barry[1*], Oscar Ngesa[2], Nelson Owuor Onyango[3] and Henry Mwambi[4]

Abstract

Bacground: Anemia is a major public health problem in Africa with an increasing number of children under 5 years getting infected. Guinea is one of the most affected countries. In 2018, the prevalence rate was 75% in children under 5 years. This study sought to identify the factors associated with anemia and to map spatial variation of anemia across the eight (8) regions in Guinea for children under 5 years, which can provide guidance for control programs for the reduction of the disease.

Methods: Data from the Guinea Multiple Indicator Cluster Survey (MICS5) 2016 was used for this study. A total of 2609 children under 5 years who had full covariate information were used in the analysis. Spatial binomial logistic regression methodology was undertaken via Bayesian estimation based on Markov chain Monte Carlo (McMC) using WinBUGS software version 1.4.

Results: Our findings revealed that 77% of children under 5 years in Guinea had anemia and the prevalence in the regions ranged from 70.32% (Conakry) to 83.60% (N'Zerekore) across the country. After adjusting for non spatial and spatial random effects in the model, older children (48–59 months) (OR: 0.47, CI [0.29 0.70]) were less likely to be anemic compared to those who are younger (0-11 months). Children whose mothers have completed secondary education or more had a reduced chance of anemia infection by 33% (OR: 0.67, CI [0.49 0.90]) and Children from household heads from Kissi ethnic group are less likely to have anemia than their counterparts whose leader is from Soussou (OR: 0.48, CI [0.22 0.91]).

Conclusion: The spatial analysis allowed the identification of high-risk areas as well as the identification of socio-economic and demographic factors associated with anemia among children under 5 years. Such an analysis is important in helping policy makers and health practitioners in developing programs geared towards control and management of anemia among children under 5 years in the country.

Keywords: Anemia; Children; Guinea; Bayesian; Region; Spatial

Background

Anemia is a global public health problem affecting both developing and developed countries with major consequences for human health as well as social and economic development [1]. Most seriously affected are young children and women [2]. In 2011, the global prevalence of anemia in the world was 43% among children less than 5 years of age, and 67% in sub-Saharan Africa [3]. The worrying aspect of anemia in children is the fact that the incidence (well on the rise) and also the mortality rate is already the highest. According to Brabin et al [4], the highest estimates of deaths attributed to anemia are for India and then sub-Saharan Africa. Health specialists note that recurrent diseases in a country are both due to poverty and a cause of poverty. The level of economic development has an influence on the level of endemicity [5]. Guinea, West African country with over 12 million inhabitants [6] is not on the fringes of the impacts of anemia. Despite the efforts made by the Guinean Government and development partners to reduce prevalence among children, the rate is quite high. According to the Guinea DHS report in 2018, the prevalence rate was 75% in children under 5 years and it varies widely from one geographical location to another, from 69% (Boke) to 78% (Faranah). Since 2012, the prevalence of anemia in children 6-59 months did not vary significantly, from 77% to 75% in 2018 [7].

In the medical manifest, it is pointed out that anemia in children is when the hemoglobin level in the blood

*Correspondence: barry.thiernosouleymane@gmail.com
[1]Mathematics (Statistics option) Program, Pan African University Institute for basic Sciences, Technology and Innovation (PAUISTI), Nairobi, Kenya
Full list of author information is available at the end of the article

is lower than 110g/L due to iron deficiency [8]. It is characterized by signs which include pallor, abnormal tiredness or repeated infections. Anemia during childhood has short and long-term effects on health. The former include an increased risk of morbidity due to infectious diseases [9, 10]. In addition, anemia in children seriously affect the growth and mental development [11]. Thus the consequences of anemia in children are multiple and harmful. They are reflected in human development (absences from class, school grade, repetitions and poorer school performance), morbidity (bone disease, heart murmur, liver and spleen enlargement) and mortality (significant death)[12, 13].

In the context of health policy, mapping of disease incidence and prevalence is very important. Mainly, its aim is to smooth and predict certain health outcomes over a geographic domain of interest.
Spatial data analysis has a role to play in supporting the search for scientific explanation. It also has a role to play in more general problem solving because observations in geographic space are more than often correlated[14]. Within the framework of the development of decisions on the allocation of public health resources, the analysis helps decision makers in setting priorities.

A number of articles have demonstrated the various risk factors associated with anemia among children. For example, a multivariable hierarchical Bayesian geoadditive model which included a spatial effect for district of child's residence was applied to examine the association of demographic, socio-economic and environmental factors in four Sub-Saharan African countries [15]. Another study was done on spatial pattern and determinants of anemia in Ethiopia. In that study, multilevel analysis was used and spatial dependence is tested using Moran's I statistic [16].
Despite the studies that have been carried out, there is limited literature on anemia in Guinea. Therefore, it is important to understand the risk factors of anemia in such a country. Thus although overall the models are structurally similar, country specific applications, help to understand the spatial distribution of a disease in much more detail with results directly applicable to health policy formulation.

Methods

Study data

The Guinea Multiple Indicator Cluster Survey (MICS5) was carried out in 2016 by National Institute of Statistics in collaboration with the National Malaria Control Program and the National Institute of Public Health, as part of round five of the MICS global survey program. Technical support was provided by the United Nations International Children's Emergency Fund (UNICEF) and International Coach Federation (ICF) for testing for malaria and anemia in children under 5 years. Also, UNICEF, USAID, the Global Fund / CRS, UNFPA and UNDP provided financial support to the project alongside the Government. The objective of the survey was to provide valuable information for monitoring the progress made in Guinea for their international commitments.

The data were collected on 8081 households in the eight (8) regions of the country, including the capital Conakry, with a response rate of 99%. The survey targeted men and women aged 15 to 49 and children. Four sets of questionnaires were used in the survey, based on the standard MICS round 5 questionnaires developed by UNICEF and the standard questionnaires for MIS surveys developed by ICF Macro within the framework of the international DHS program. These standard questionnaires were adapted to Guinean context. The types of questionnaires are: a household questionnaire which was used to collect demographic information on all members of the de jure household, the household and the dwelling, an individual woman questionnaire administered in each household to all women aged 15-49 years, an individual questionnaire for children under 5 years administered to mothers for children under 5 living in the household. It is in this questionnaire that the biomarker module (anemia and malaria test) was administered and a verbal autopsy questionnaire administered to mothers for all children under 5 who died during the past 3 years. The household, child and woman questionnaires were used to extract information on anemia in children under five, the characteristics of the household and those of the mothers of the children[17].
In total, 2609 children under 5 years who had full covariate information were used in the current analysis.

Variables of interest

Response variable

The dependent variable of the study is the status of anemia in children under five. In our study, this disease was detected by screening, via an anemia test. The procedure consisted of collecting a drop of blood of the child in a microcuvette and then introducing it into the HemoCue photometer that showed hemoglobin level. All results are recorded in the child questionnaire in the section for biomarker testing. The response variable has two status: the positive status (the child has anemia) and the negative status (the child does not have anemia).

Independent variables

The independent variables used for the analysis are contextual, socio-economic and demographic variables.

The contextual covariates were: natural region, administrative region and place of residence. The socioeconomic and demographic variables: sex of the child, age of the child, sex of the household head, mosquito net observed in the house, status of mosquito net, mother's education level, wealth index, ethnicity of the household head, religion of the household head, potable water source, household size, treatment of drinking water, access to electricity, own radio, own TV, main material of roof, main material of floor, wall exterior main material and type of toilet.

Statistical analyses

This present study aims to contribute to improving knowledge of anemia in children under five in Guinea in order to help the Government and its partners to better reorient and strengthen control strategies. To this end, three analysis approaches will be used: descriptive analysis (the description of the study population which will include a univariate (unadjusted) analysis or crude odds ratio), multivariable analysis (binary logistic regression) and spatial analysis to describe heterogeneity of anemia in children in the space. Bayesian methodology, using Markov chain Monte Carlo (McMC) methods, was used for parameter estimation in the models.

Statistical modeling

spatial model

Let Y_{ij} be disease status of child i in region j, $j = 1, 2, \ldots, 8$ and $i = 1, 2, \ldots, n_j$, where n_j is the number of children in region j. We have binary responses, such that:

$$Y_{ij} = \begin{cases} 1, & \text{if child } i \text{ in region } j \text{ is anemia positive} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

This study assumes that the dependent variable Y_{ij} is Bernoulli distributed i.e $Y_{ij}|p_{ij} \sim$ Bernoulli (p_{ij}) with an unknown mean $\mathrm{E}(Y_{ij}) = p_{ij}$, being related to the independent variables as follows:

$$\begin{aligned} g\left(E\left(Y_{ij}\right)\right) &= \log\left(\frac{P\left(Y_{ij}=1 \mid x, u_j, v_j\right)}{1-P\left(Y_{ij}=1 \mid x, u_j, v_j\right)}\right) \\ &= X^T\beta + u_j + v_j, \quad i = 1, \ldots, n_j, \\ \textit{and} \quad j &= 1, \ldots, 8. \end{aligned} \tag{2}$$

In equation 2, X^T is a k- dimensional row-vector of covariates with β the corresponding vector of regression coefficients, u_j is spatial random effect and v_j is non-spatial (region-specific) random effect (normal).
Regarding the non-spatial component, the vector v follows a priori normal distribution with a vector of mean 0, and a variance-covariance matrix $\sigma^2\mathrm{I}$ (with I being identity matrix and $\sigma^2 > 0$ unknown). Concerning the spatial component u, we assume that the prior is represented by a Markov Gaussian field or conditional Gaussian autoregressive model[18].
In this case, let u_{-j} denotes the vector of effects excluding that of the j-th region, then we assume that:

$$\boldsymbol{u}_j \mid \boldsymbol{u}_{-j} \sim \boldsymbol{N}\left(\sum_{r \neq j} c_{jr}\boldsymbol{u}_r, \boldsymbol{\sigma}_j^2\right)$$

where c_{jr} and σ_j are defined in terms of the precision matrix. We assume inverse gamma hyperpriors for the variance of the normal priors.

Parameter estimation

Bayesian McMC simulation entails estimating the posterior distribution of all parameters by combining prior information on them with the likelihood for the respective model, and sampling each parameter sequentially from its conditional distribution.
The posterior distribution is factorized as follows:

$$\begin{aligned} \pi(u, v, \tau^2, \sigma^2, \beta \mid \mathrm{y_1}, \cdots, \mathrm{y_{n_j}}) \propto & \left[\prod_{j=1}^{8}\prod_{i=1}^{n_j} L(Y_{ij}, u, v, \beta)\right] \\ & \times \left[\prod_{j=1}^{8} \pi(v_j \mid \sigma^2)\pi(\sigma^2)\right] \\ & \times \left[\prod_{j=1}^{8} \pi(u_j \mid u_{-j}, \tau^2)\pi(\tau^2)\right] \\ & \times \left[\prod_{h=1}^{k} \pi(\beta_h)\right] \end{aligned} \tag{3}$$

The conditional distributions is generically denoted by $\pi(\mathrm{o} \mid \mathrm{y})$, and the contribution to likelihood of the i-th unit in the j-th area by L_{ij}, $\mathrm{i} = 1, \ldots n_j$ (where n_j represents the number of observations in the j-th region). Prior distributions for fixed and random effects and hyperpriors are mutually independent.

Diagnostics of model

The Deviance Information Criterion (DIC) was used to compare models as suggested by Spiegelhalter et al [19]. DIC value is given by:

$$\mathrm{DIC} = \mathrm{Dbar} + \mathrm{pD} = \mathrm{Dhat} + 2\mathrm{pD}. \tag{4}$$

Dbar is the posterior mean of the deviance, which is a measure of goodness of fit statistic for a statistical model and pD=Dbar-Dhat is the effective number of parameters.
The model with the smallest DIC is the best fitting model. According to the authors, by comparing the models, a difference in DIC of 3 or less between two models cannot be distinguished while for a difference of between 3 and 7 the two models can be weakly differentiated [19, 20].

Results

Descriptive analysis

Table 1 shows that 77% of the children are positive for anemia and about 15% for malaria.
Analysis by sex showed that there were more male children (51.36%) and more male headed households (85.17%) than female. The distribution of children by place of residence shows that 71.18% are in rural areas and only 28.82% live in urban areas. However, children who are in big cities and those in secondary cities are almost equal, (14.64%) and (14.18%) respectively. Regarding the analysis by Administrative region, the majority of children are in the region of Boke (17.90%) followed by N'zerekore (16.67%) and the region of Mamou has the lowest percentage (8.78 %). In terms of Natural region, 24.76 % of children lived in Maritime Guinea, 22.35% in Middle Guinea, 22.08% in Upper Guinea, 20.54% in Forested Guinea and 10.27% in Conakry. The highest percentage of children (29.86%) were between 48 and 59 months and the lowest (6.52%) were between 0 and 11 months. According to the socio-economic status of the household (Wealth index), 24.68% had a disadvantaged standard of living (poor level) and 12.04% of households had a good level (rich level). 74.74% of the mothers of the children and 66.73% of heads of household have not attended formal education. In the majority of households (98.93%) mosquito nets were hung up and 98.43% of the nets observed were in good condition. The ethnic distribution of the household heads shows that 36.80% were Peul, 25.49% were Malinke, 16.67% were Soussou, 7.17% were Guerze or Kono or Mano, 5.98% were Kissi, 2.38% were Toma and 5.52% other ethnicity. It is the household heads of the Muslim religion who are more represented (84.44%). In terms of potable water source in the households, 78.42% of them had improved water sources. Thus, 66.73% did not treat drinking water. The analysis of the number of people in the household shows that households with 1-5 people are 40.17%, 36.14% are between 6-8 and 23.69% had 9 and more. 27.06% of households have access to electricity. The household heads who had their own radio and television were 48.41% and 25.53% respectively.

Table 1 socio-economic and demographic characteristics of the respondents

Variables	N	Percentage
Status of anemia		
Negative	600	23.00
Positive	2,009	77.00
Status of malaria		
Negative	2214	84.86
Positive	395	15.14
Sex of child		
Male	1340	51.36
Female	1269	48.64
Place of residence		
Big city	382	14.64
Secondary city	370	14.18
Rural	1857	71.18
Place of residence		
Urban	752	28.82
Rural	1857	71.18
Administrative Region		
Boke	467	17.90
Conakry	268	10.27
Faranah	369	14.14
Kankan	308	11.81
Kindia	288	11.04
Labe	245	9.39
Mamou	229	8.78
N'Zerekore	435	16.67
Natural Region		
Maritime Guinea	646	24.76
Middle Guinea	583	22.35
Upper Guinea	576	22.08
Forested Guinea	536	20.54
Conakry	268	10.27
Age of Child (months)		
$0-11$	170	6.52
12-23	427	16.37
$24-35$	523	20.05
$36-47$	710	27.21
$48-59$	779	29.86
Sex of the household head		
Male	2,222	85.17
Female	387	14.83
Education level of household head		
None	1741	66.73
Primary	288	11.04
Secondary and more	580	22.23
Mosquito net observed in the house		
Observed hanging	2581	98.93
Observed not hanging	28	1.07
Status of mosquito net		
Good	2568	98.43
Bad	41	1.57
Education level of mother		
None	1950	74.74
Primary	329	12.61
Secondary and more	330	12.65
Ethnicity of household head		
Soussou	435	16.67
Peul	960	36.80
Malinke	665	25.49
Kissi	156	5.98
Toma	62	2.38
Guerzé/Kono/Mano	187	7.17
Other	144	5.52

The main materials most used as roof, wall exterior and floor were metal sheet (74.01%), Cement or stone with lime cement or brick or cement block (70.18%)

Table 1 continued

Variables	N	Percentage
Religion of household head		
Muslim	2203	84.44
Christian	353	13.53
others(Animist, no religion)	53	2.03
Wealth index		
Poorest	644	24.68
Second	671	25.72
Middle	522	20.01
Fourth	458	17.55
Richest	314	12.04
Potable water source		
improved water source	2046	78.42
Non-improved water source	563	21.58
Total member in the house		
$1-5$	1048	40.17
$6-8$	943	36.14
9 and more	618	23.69
Treatment of drinking water		
Yes	868	33.27
No	1741	66.73
Access to Electricity		
Yes	706	27.06
No	1903	72.94
Own Radio		
Yes	1263	48.41
No	1346	51.59
Own TV		
Yes	666	25.53
No	1943	74.47

and Cement or grout or carpet (51.59%) respectively. Table 2 shows that the prevalence of anemia among children varies according to the region of residence. Indeed, it is in the region of N'zerekore (85.29%) where the prevalence was highest. On the other hand, in Labe region, this prevalence was lowest (69.39%).

Table 3 presents the factors associated with anemia status among children in the eight (8) region in Guinea. All the interpretations of the models were done using the odds ratio and corresponding 95% credible intervals.

In view of the results, we noticed that the variables associated with the status of anemia in children are: place of residence, administrative region, natural region, age of the child, standard of living of the household, mother's level of education, head of the household's ethnicity, religion of household head, household's access to electricity and the fact that if the household head has his own television.

Indeed, children from rural areas were more likely to be anemic (OR: 1.59, CI [1.31 1.93]) when compared to those from urban areas. Same observation by comparing children from rural areas and those from big cities. Rural children were more likely to have anemia (OR: 1.59, CI [1.24 2.03]). The results also indicate that children in the region of N'zerekore were more likely to have anemia (OR: 1.54, CI [1.09 2.18]) compared to those from Boke region. It appears that children from Conakry were less likely to be anemic (OR: 0.61, CI [0.44 0.84]) than those of Maritime Guinea. In addition, children in the age group of 48–59 months were less likely to be anemic (OR: 0.51, CI [0.34 0.78]) than children in the 0-11 months age group. Regarding education level of mother, the analysis shows that the children of mothers in advanced level (secondary and more) were less likely to have anemia (OR: 0.61, CI [0.47 0.79]) compared to the children of mothers that do not have formal education. As for the standard of living of the household, children from rich households were less likely to be anemic compared to their counterparts in poor households (OR: 0.52, CI [0.38 0.71]). Children whose head of household is of the Peul ethnic group were less likely to have anemia (OR: 0.66, CI [0.50 0.86]) compared to the children whose head is Soussou. Results also indicate that children whose household head is animist or no religion were less likely to be anemic (OR: 0.80, CI [0.61 1.04]) compared to the children whose head is Muslim. If the household did not have electricity, children in the household were more likely to have anemia (OR: 1.50, CI [1.23 1.83]) than those in the household with electricity. Children whose households do not own a television are more likely to have anemia (OR: 1.51, CI [1.23 1.84]) compared to those whose households own a television.

Multivariable analysis

The multivariable analysis presents only the variables that were significantly associated with anemia infection in the bivariate analysis. The analysis (model M1) also confirms that the variables administrative region, age of the child, education level of mother and the ethnicity of household head are significantly associated with the status of anemia in children. Therefore, children in the region of Labe were less likely to have anemia (OR: 0.65, CI [0.44 0.96]) than their counterparts in the Boke region. According to the child's age, children in the age group 48-59 months were less likely to be anemic (OR: 0.46, CI [0.30 0.71]) than those in the 0-11 months group. In addition, children of mothers with secondary education and above were less likely to be anemic (OR: 0.67, CI [0.50 0.91]) than those of mothers with no educational attainment. Finally, comparing the level of risk of children according to the ethnicity of their household head shows that, children who are under the responsibility of household head from Kissi ethnic group were less likely to be anemic (OR: 0.45, CI [0.22 0.92]) than those under the responsibility of Soussou ethnic group.

Model assessment and comparison

Four models are provided which are M1, M2, M3 and M4. M1 is the binary logistic regression, M2 is the non-spatial (region- specific) model, M3 is the structured model and M4 is the convolution model. The

Table 1 continued

Variables	N	Percentage
Main material of roof		
Palm leaf/Palm/Bamboo/wood/wooden planks/Cardboard	239	9.16
Grass	367	14.07
Metal sheet	1931	74.01
Other(Roof tiles/Concrete/Cement/Mat/ shingles, no roof)	72	2.76
Main material of floor		
Earth/Sand/Cow dung	998	38.25
Plank of wood/bamboo(Plank of wood, palm/bamboo/Other)	56	2.15
Floor tile(floor tile/ waxed wood/vinyl/asphalt)	209	8.01
Cement/grout/Carpet	1346	51.59
Wall exterior main material		
Clods of earth	547	20.97
Bamboo with Mud	100	3.83
Stone with mud	83	3.18
Cement/Stone with lime cement/Brick/Cement block	1831	70.18
Wood(stick/trunk/plywood/cardboard/salvage wood/wood planks	11	0.42
Other(no wall/adobe/ covered/Adobe not covered	37	1.42
Type of toilet		
Improved toilet	1687	64.66
Non-improved toilet	922	35.34

DIC values were used to compare the goodness of fit of these four separately models M1, M2, M3 and M4 in explaining variations of children anemia. Model with a small DIC value provides a better fit. By comparing their DICs, models two (M2) and four (M4) are the preferred models. They have the same and the smaller DIC (2721.9). Indeed, extension of model M1, to Model M2 by including non-spatial random effects and model M4 by including both non-spatial and spatial random effects improved the goodness of fit of the final model. Note that the three models (M2, M3 and M4) are not significantly different form each other as the difference in DIC is less than 3. So the three models have the same covariates which provoke different responses across space.

Table 2 Prevalence of anemia by region

	Prevalence N(%)	Predicted prevalence of spatial model (%)
Total	2609 (77.00)	-
Boke	467 (79.01)	77.98
Conakry	268 (70.52)	70.32
Faranah	369 (77.24)	77.71
Kankan	308 (75.65)	77.30
Kindia	288 (80.56)	78.96
Labe	245 (69.39)	72.23
Mamou	229 (69.87)	71.40
N'zerekore	435 (85.29)	83.60

Factors associated with anemia prevalence from the non-spatial, spatial and convolution models

In the table 4, we have the multivariable analysis of the factors associated with anemia infection in Guinea after controlling for the non-spatial random effects, spatial random effects and both non-spatial and spatial random effects. These results were implemented in WinBUGS version 1.4.

Significant risk factors from the non-spatial random effects model were included in the binary logistic model. For example, in the model (M1), children aged 48-59 months (OR: 0.46, CI [0.30 0.71]) were less likely to have anemia compared to those who are younger (0-11 months). Adjustment for non-spatial random effects have provided a protective effect against anemia infection for this age group, which reduces the odds of being anemic by 53% (OR: 0.47, CI [0.29 0.70]). Children whose mothers attained secondary or above in education had reduced chance of being anemia positive compared to children of mothers who did not have formal education, 33% (OR: 0.67, CI [0.49 0.90]). Children who are under the responsibility of household head from Peul ethnic group after controlling for non-spatial random effects were associated with anemia infection among children as well. They are less likely to have anemia than their counterpart whose leader is Soussou (OR: 0.57, CI [0.41 0.78]). Figure 1 illustrates areas perceived as high and low prevalence of anemia infection among children. It is the region of N'Zerekore (yellow color) which has the highest prevalence and Conakry region (gray color) as the lowest. But, seeing these prevalences, all areas are considered as having a high anemia prevalence among children. This map was achieved from the Bayesian analysis results.

Table 5 presents the posterior means and standard deviation (sd) for non-spatial random, spatial random and both. The map of the posterior means for non-spatial random effects based on the best fitting model is given (figure 2), which shows that the mean was much higher in the region of N'zerekore (yelow color) than the other regions. Then, the posterior standard deviations of the non-spatial random effects show that

Table 3 Factors associated with anemia in the eight (8) regions in Guinea

	Crude odds ratio (95% credible interval)	Adjusted odds ratio (95% credible interval) M1
Place of residence		
Urban	1	1
Rural	1.59 [1.31 1.93]	1.35 [0.96 1.90]
Place of residence		
Big city	1	-
Secondary city	0.99 [0.73 1.36]	-
Rural	1.59 [1.24 2.03]	-
Administrative Region		
Boke	1	1
Conakry	0.64 [0.45 0.90]	0.94 [0.62 1.42]
Faranah	0.90 [0.65 1.25]	0.82 [0.56 1.20]
Kankan	0.83 [0.59 1.16]	0.73 [0.47 1.13]
Kindia	1.10 [0.76 1.59]	1.05 [0.71 1.56]
Labe	0.60 [0.42 0.86]	0.65 [0.44 0.96]
Mamou	0.62 [0.43 0.88]	0.73 [0.49 1.08]
Nzerekore	1.54 [1.09 2.18]	1.25 [0.77 2.04]
Natural Region		
Maritime Guinea	1	-
Middle Guinea	0.63 [0.49 0.82]	-
Upper Guinea	0.87 [0.66 1.15]	-
Forested Guinea	1.21 [0.90 1.63]	-
Conakry	0.61 [0.44 0.84]	-
Age of Child (months)		
0-11	1	1
12-23	1.26 [0.79 2.03]	1.26 [0.78 2.04]
24-35	1.03 [0.66 1.62]	0.99 [0.63 1.57]
36-47	0.68 [0.44 1.03]	0.62 [0.40 0.95]
48-59	0.51 [0.34 0.78]	0.46 [0.30 0.71]
Wealth index		
Poorest	1	1
Second	1.02 [0.77 1.34]	0.88 [0.66 1.17]
Middle	0.75 [0.57 0.99]	0.75 [0.55 1.00]
Fourth	0.67 [0.50 0.89]	0.68 [0.41 1.14]
Richest	0.52 [0.38 0.71]	0.57 [0.30 1.11]
Education level of mother		
None	1	1
Primary	1.08 [0.81 1.44]	1.05 [0.77 1.42]
Secondary and more	0.61 [0.47 0.79]	0.67 [0.50 0.91]
Ethnicity of household head		
Soussou	1	1
Peul	0.66 [0.50 0.86]	0.65 [0.47 0.90]
Malinke	0.84 [0.62 1.13]	0.90 [0.61 1.34]
Kissi	0.97 [0.61 1.53]	0.45 [0.22 0.92]
Toma	2.33 [0.97 5.59]	1.35 [0.44 4.13]
Guerze/Kono/Mano	1.42 [0.89 2.26]	0.89 [0.39 2.01]
Other	0.99 [0.61 1.59]	0.88 [0.54 1.46]
Religion of household head		
Muslim	1	1
Christian	0.82 [0.63 1.06]	1.60 [0.85 3.04]
Others(Animist, no religion)	0.80 [0.61 1.04]	0.72 [0.27 1.97]
Own TV		
Yes	1	1
No	1.51 [1.23 1.84]	1.05 [0.70 1.59]
Access to electricity		
Yes	1	1
No	1.50 [1.23 1.83]	0.88 [0.58 1.34]
Deviance information criterion (DIC)		2724.9

the region of N'zerekore tend to be higher than the other regions. This means the within-region variation of anemia tends to be higher than the rest of the regions after accounting for all the covariate effects. The map of the posterior means for spatial random effects also shows that the regions of N'zerekore, Boke, Kindia and Conakry (green color) had the highest means (figure 3).

Discussion

The results of this study show that the association between some variables (place of residence, own TV and access to electricity) were significant in the bivari-

Table 4 Factors associated with anemia from the non-spatial, spatial and convolution models

	Odds ratio (95% credible interval), non-spatial model M2	Odds ratio (95% credible interval), spatial model M3	Odds ratio (95% credible interval), convolution model M4
Place of residence			
Urban	1	1	1
Rural	1.31 [0.92 1.82]	1.31 [0.93 1.80]	1.32 [0.93 1.82]
Age of Child (months)			
0-11	1	1	1
12-23	1.31 [0.78 2.06]	1.32 [0.78 2.06]	1.30 [0.77 2.04]
24-35	1.02 [0.62 1.57]	1.03 [0.62 1.57]	1.02 [0.62 1.56]
36-47	0.63 [0.39 0.95]	0.63 [0.39 0.95]	0.63 [0.39 0.93]
48-59	0.47 [0.29 0.70]	0.47 [0.30 0.70]	0.47 [0.29 0.70]
Wealth index			
Poorest	1	1	1
Second	0.89 [0.66 1.17]	0.89 [0.66 1.17]	0.89 [0.66 1.17]
Middle	0.75 [0.55 1.01]	0.75 [0.55 1.00]	0.75 [0.55 1.00]
Fourth	0.72 [0.42 1.16]	0.72 [0.42 1.15]	0.71 [0.42 1.15]
Richest	0.63 [0.31 1.13]	0.62 [0.31 1.11]	
Education level of mother			
None	1	1	1
Primary	1.06 [0.78 1.43]	1.06 [0.78 1.43]	1.06 [0.78 1.43]
Secondary and more	0.67 [0.49 0.90]	0.67 [0.49 0.90]	0.67 [0.49 0.90]
Ethnicity of household head			
Soussou	1	1	1
Peul	0.57 [0.41 0.78]	0.56 [0.41 0.76]	0.58 [0.42 0.79]
Malinke	0.84 [0.59 1.17]	0.83 [0.58 1.17]	0.86 [0.59 1.21]
Kissi	0.48 [0.22 0.91]	0.48 [0.22 0.91]	0.48 [0.23 0.92]
Toma	1.86 [0.52 5.11]	1.87 [0.53 5.13]	1.84 [0.52 4.99]
Guerze/Kono/Mano	1.06 [0.44 2.17]	1.07 [0.44 2.19]	1.05 [0.44 2.16]
Other	0.89 [0.53 1.43]	0.88 [0.53 1.41]	0.89 [0.53 1.43]
Religion of household head			
Muslim	1	1	1
Christian	1.81 [0.90 3.30]	1.83 [0.91 3.33]	1.79 [0.90 3.24]
Others(Animist, no religion)	0.95 [0.31 2.32]	0.96 [0.31 2.34]	0.93 [0.30 2.28]
Own TV			
Yes	1	1	1
No	1.10 [0.71 1.62]	1.10 [0.71 1.62]	1.09 [0.71 1.61]
Access to electricity			
Yes	1	1	1
No	0.91 [0.59 1.34]	0.91 [0.59 1.33]	0.91 [0.59 1.35]
Deviance information criterion (DIC)	2721.9	2722.9	2721.9

ate analysis but non-significant in the multivariable analysis. Note that also, only the region of Labe was significantly associated with anemia in the multivariable model (M1). Efforts to control infection among children under 5 years should focus on factors such as the age of the child, the mother's level of education and the ethnicity of the household head. The results obtained are consistent not only within country context but what has been shown in previous studies. The authors have showed that the child's late age and his mother's high-level education were negatively associated to childhood anemia [21, 22]. The variation in the child's age determines the hemoglobin requirements of red blood cells for physical and psychomotor functioning as well as cognitive development in children in their early years of life [23]. In addition, Flores et al [24] have attributed the ethnicity of the parents as an important factor on children diseases. The very different lifestyles of the various ethnic groups and the geographical setting in which an ethnic group resides could strongly influence the health of the child.

In our study, a Bayesian spatial analysis was applied that allowed for understanding of disease factors and variations in different regions. The results also confirmed the significant association between age of the child, mother's level of education, ethnicity of the household head and increased likelihood of being infected with anemia. The incorporation of random effects helped to avoid underestimating the standard errors of model parameters, thereby avoiding wrong statistical significance of covariates since their credible intervals would be deceptively narrower [25]. For example, in the case of ethnicity of household head factor, Kissi ethnic category coefficient had lower disease odds, 55% (OR:0.45, CI [0.22 0.92] in model M1 where non-spatial random effects were not incorporated. However, this coefficient has increased (OR:0.48, CI [0.22 0.91] in Models M2, M3 and M4 when the non-spatial random, spatial random and both, respectively were included in the models (Table 4), the chance of having anemia is reduced by approximately 52%. In addition, the analysis showed a het-

Table 5 Summary of models fit

Non-spatial random effects	Mean	Standard deviation (sd)
V[1] Boke	0.06	0.10
V[2]Conakry	0.01	0.11
V[3] Faranah	-0.02	0.10
V[4] Kankan	-0.07	0.12
V[5] Kindia	0.07	0.11
V[6] Labe	-0.10	0.12
V[7] Mamou	-0.05	0.11
V[8] N'Zerekore	0.11	0.14
Spatial random effects		
U[1] Boke	0.05	0.08
U[2]Conakry	0.03	0.11
U[3] Faranah	-0.03	0.07
U[4] Kankan	-0.05	0.10
U[5] Kindia	0.04	0.08
U[6] Labe	-0.06	0.09
U[7] Mamou	-0.04	0.09
U[8] N'Zerekore	0.07	0.12
Non-spatial and spatial random effects		
V[1] Boke	0.05	0.11
V[2]Conakry	0.01	0.11
V[3] Faranah	-0.02	0.10
V[4] Kankan	-0.06	0.12
V[5] Kindia	0.06	0.11
V[6] Labe	-0.09	0.13
V[7] Mamou	-0.04	0.11
V[8] N'Zerekore	0.09	0.13
U[1] Boke	0.03	0.09
U[2]Conakry	0.02	0.11
U[3] Faranah	-0.02	0.07
U[4] Kankan	-0.03	0.10
U[5] Kindia	0.02	0.08
U[6] Labe	-0.04	0.09
U[7] Mamou	-0.03	0.08
U[8] N'Zerekore	0.05	0.12

erogeneity of the spatial distribution of anemia among children. The regions of N'zerekore is identified as a high prevalence region, which should raise concerns to policy-makers.

This study has some limitations, anemia in children could also take into account the association with biological factors. For example, anemia among children is frequently associated with many aspects such as mothers received iron supplementation during pregnancy [26]. But, the current study used only demographic and socio-economic factors. Then, other socio-economic factors were not included in the models. The relationship was also statistical association, not causal between investigated factors and anemia. MICS data is a cross-sectional study, this could neither establish temporality nor causality of the observed associations with the anemia of children. Moreover, the results could be influenced by sample error. In terms of methodology, the Bayesian computational approach we adopted enables us to provide estimates of parameters in an otherwise too complex model. It also allows us to refrain from the assumption of mutual independence between areas usually imposed in multilevel statistical models [27].

Despite the limitations above, this study contributes to the literature and the model can be replicated in other countries with other factors that the study did not capture. These results could be relevant information for control programs aimed at reducing the prevalence of anemia in Guinea, specifically in the regions with high prevalence.

Conclusions

In conclusion, this study applied a Bayesian methodology using McMC methods. The objective was to identify the factors associated with anemia and to map their possible spatial effects on anemia among children under 5 years. The analysis revealed that children in Guinea, who had a lower age are at a higher risk of anemia. The analysis also showed that anemia of children is influenced by the education level of mothers. The children of mothers with higher level of education were more protected against anemia. Children who are under the responsibility of a Kissi and Peul ethnic head of household were less likely to have anemia than their counterpart whose leader is Soussou. The findings from spatial analysis also highlighted that N'zerekore region had the higher prevalence of anemia among children. The results may help policy makers to identify regions that require more attention to reduce prevalence of anemia in Guinea.

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Abbreviations

PAUISTI: Pan African University Institute for basic Sciences, Technology and Innovation; CI: Credibility Intervals; DIC: Deviance Information Criterion; OR: Odds ratio; McMC: Markov chain Monte Carlo; MICS: Multiple Indicator Cluster Survey; DHS: Demographic and Health Survey; WinBUGS: Windows Version of Bayesian Inference Using Gibbs Sampling.

Availability of data and materials

The datasets used and/or analysed during the current study are available from the link http://mics.unicef.org/surveys.

Ethics approval and consent to participate

Not applicable.

Competing interests

The authors declare that they have no competing interests.

Consent for publication

Not applicable.

Authors' contributions

Thierno Souleymane Barry developed the method, wrote the WinBUGS code, analysed the data and wrote the draft manuscript.
Dr. Oscar Ngesa, Dr. Nelson Owuor Onyango and Prof. Henry Mwambi gave some strategic advise and made critical revisions of the paper. All authors read and approved the final manuscript.

Authors' information

Dr. Oscar Ngesa, Department of Mathematics and Physical Sciences, Taita Taveta University, voi, Kenya.
Dr. Nelson Owuor Onyango, School of Mathematics, College of Biology and Physical Science, University of Nairobi, Nairobi, Kenya.
and Prof. Henry Mwambi, School of Mathematics, Statistics and Computer Science, University of KwaZulu-Natal, Durban, South Africa.

Author details

[1]Mathematics (Statistics option) Program, Pan African University Institute for basic Sciences, Technology and Innovation (PAUISTI), Nairobi, Kenya. [2]Department of Mathematics and Physical Sciences, Taita Taveta University, Voi, Kenya. [3]School of Mathematics, College of Biology and Pysical Science, University of Nairobi, Nairobi, Kenya. [4]School of Mathematics, Statistics and Computer Science, University of KwaZulu-Natal, Durban, South Africa.

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Figures

Figure 1 Prevalence categories of anemia

Figure 2 (samples) means for v

Figure 3 (samples) means for u

Tables

Table 1 socio-economic and demographic characteristics of the respondents

Table 1 continued

Table 1 continued

Table 2 Prevalence of anemia by region

Table 3 Factors associated with anemia in the eight (8) regions in Guinea

Table 4 Factors associated with anemia from the non-spatial, spatial and convolution models

Table 5 Summary of models fit

Additional Files
Additional file 1 — Winbugs codes used in the analysis
Additional file descriptions text (word format).

Figures

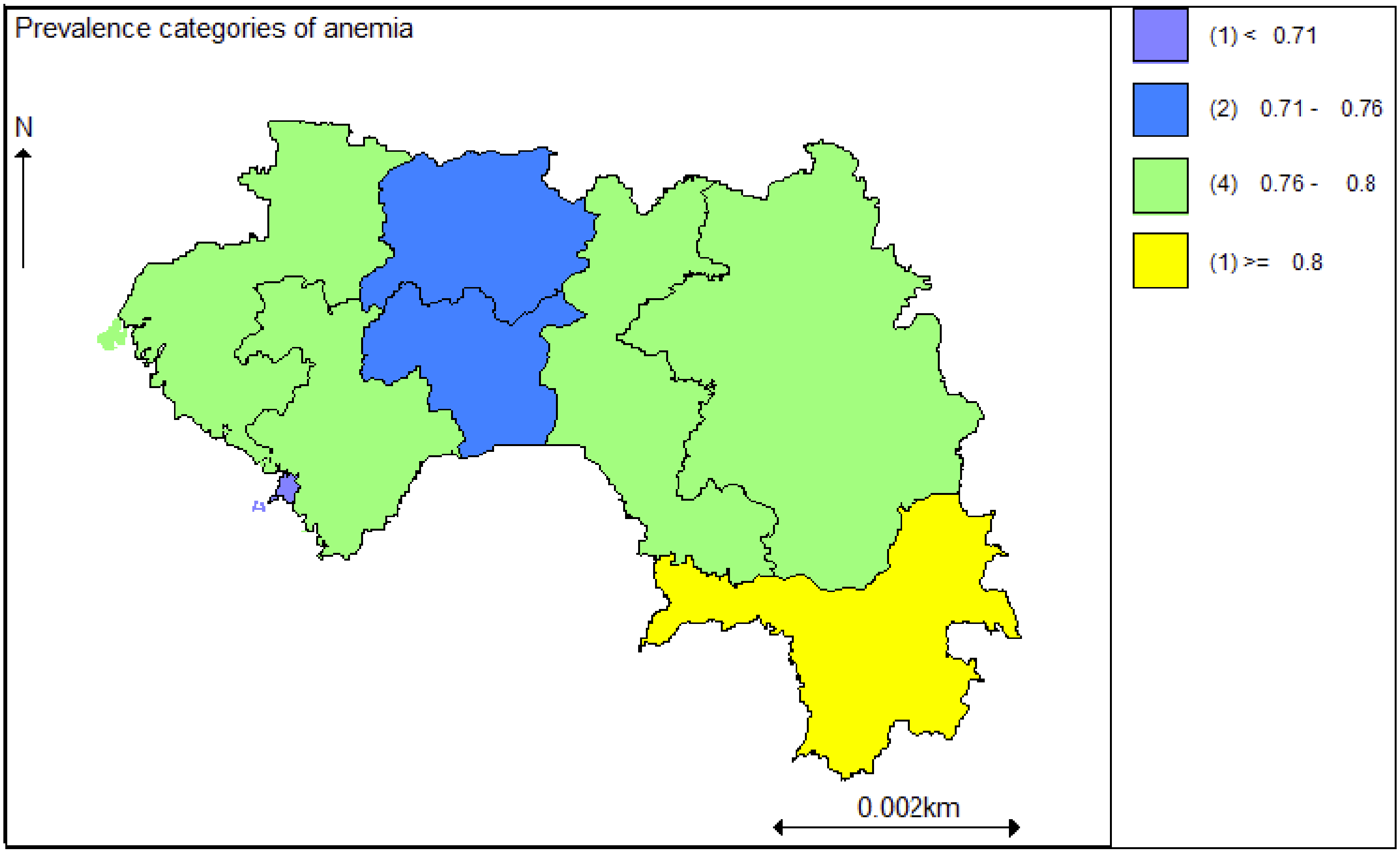

Figure 1

Prevalence categories of anemia

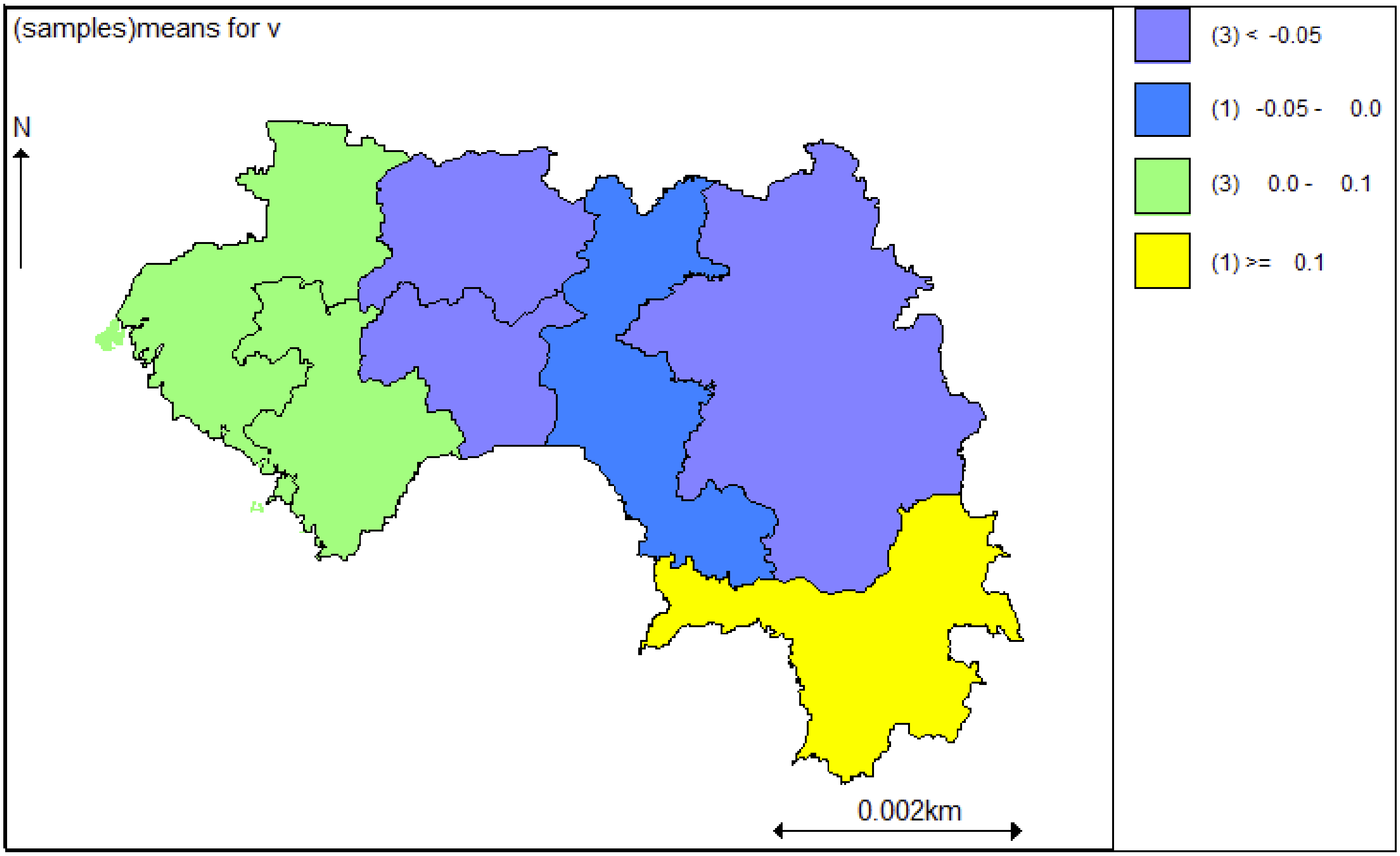

Figure 2

(samples) means for v

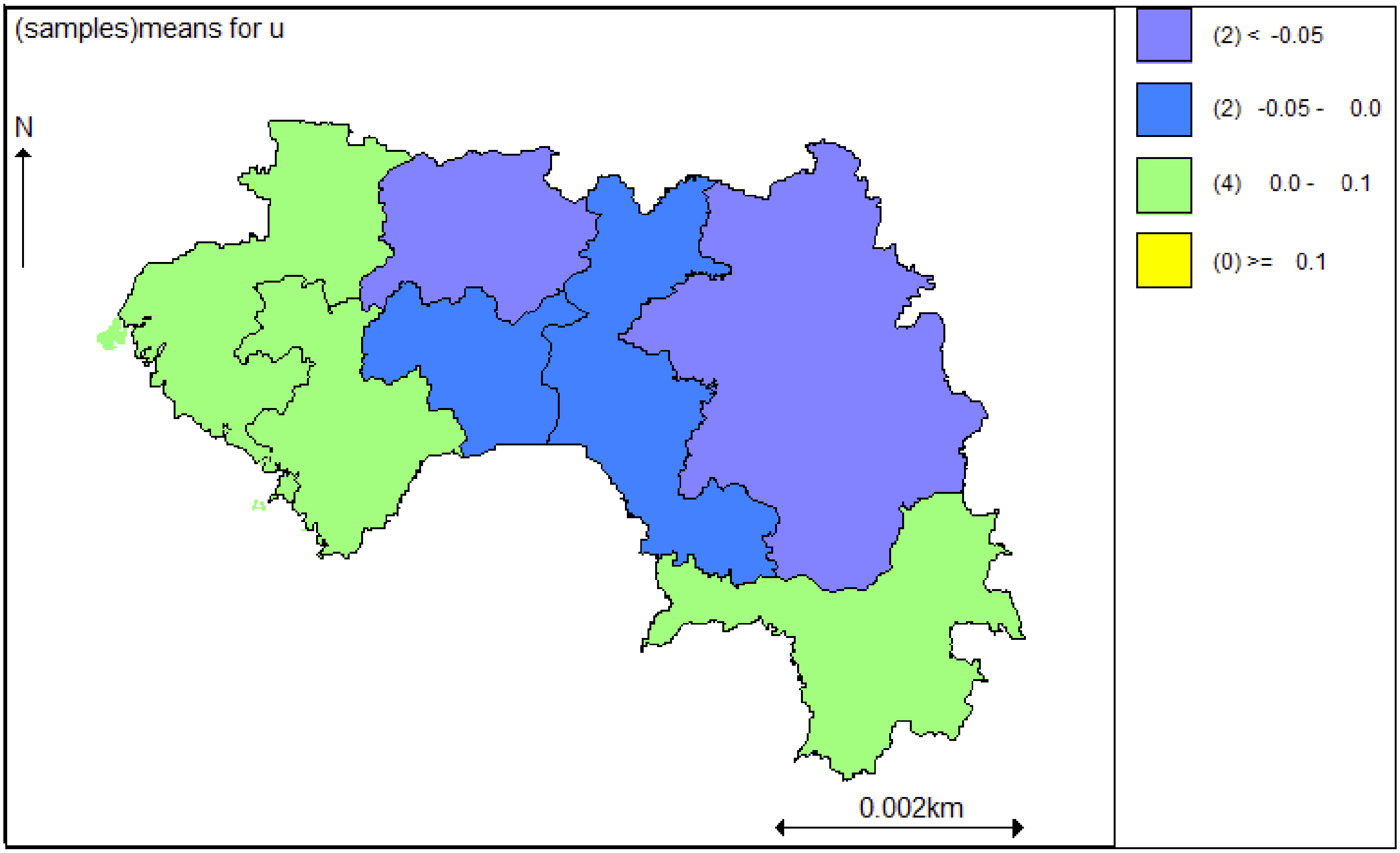

Figure 3

(samples) means for u

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