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Research Article

Spatial Analysis of Malaria on The Geo-Additive Bayesian Model

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Abstract

One of the major public health issues in Ethiopia is malaria. From the total population about 4-5 million Ethiopians affected each year. The objective of this study is to identify the dependence of malaria situation on spatial factors and socio-economic, demographic and geographic variables. The investigation in this study uses the household cluster malaria survey which was conducted from December 2006 to January 2007. Geo-additive Bayesian model using *Kebele* as the geographic unit of the study was used. From the investigation, it can be seen that households in the SNNP region were found to be at more risk than Amhara and Oromiya regions. Households with better facilities including bed nets have less chance to be infected by malaria. The study also suggested that including spatial variability is essential to understand and plan the most suitable policies to decrease the threat of malaria. Semi-parametric models were used to modeling the effects of socio-economic, demographic and geographic covariates and spatial effects on malaria distribution in Ethiopia. The results recommend the strong positive relations between malaria rapid diagnosis test and socio-economic, demographic and geographic factors. The spatial variability showed important spatial patterns of malaria.

Keywords: *Malaria, Rapid Diagnostic Test, Spatial Statistics, Bayesian Model, MCMC, Geo-additive*

Introduction

The relationship between malaria and socio-economic status in Ethiopia dictated the use of a spatial model to identify the risks. About 4-5 million people are affected by malaria because most (75%) of Ethiopia is malarious during the rainy season. Currently, strong associations between malaria and climate; and demographic, geographic and socio-economic factors have been found. A further significantly positively correlated relationship between the number of malaria cases, temperature and rainfall was documented by Pemola and Jauhari in 2006 [1-3].

A number of researchers examining the same topic indicated that factors other than climate may explain the distribution of malaria [4-6]. For instance, Ayele, Zewotir and Mwambi (2012, 2013, 2014. 2015) noted high rates of malaria morbidity could result from poor access to socio-economic services. Consequently, the problems are associated with key socio-economic, demographic and geographic factors, and in particular, with poverty levels of households [7-11]. In addition to this, environmental factors, population growth, limited access to healthcare systems, and lack of unsuccessful malaria control measures contribute to malaria transmission [12].

In previous studies malaria risk factors were examined using spatial statistics analysis and semiparametric methods separately [13,14]. But, the factors affecting malaria RDT result might have both spatial variability and nonlinear relationships with malaria RDT result. These effects were not done previously. Therefore, in this study, a geo-additive model is suggested to identify the risk factors of malaria on spatial effects and socio-economic, demographic and geographic factors in three regions of Ethiopia. The method incorporates both the spatial variability and the nonlinear relationships between covariates and response variables.

Methods

Study area

Ethiopia's land size is estimated to be about 1.1 million square kilometers. The country is the Federal Democratic Republic divided into nine national regional states. These are: Tigray, Afar, Amhara, Oromia, Somali, Benishangul-Gumuz, Southern Nations Nationalities and People Region (SNNPR), Gambella and Harari and two administrative regions (Addis Ababa City administration and Dire Dawa City Council). From these eleven regions, Amhara, Oromiya and SNNP regions constitute more than 58% of the total size of Ethiopia. The Amhara region is found in the north western and north central part of Ethiopia. This region has ten administrative zones, one special zone, 105 woredas, and 78 urban centres. The region is divided into the highlands and lowlands. The highlands (northern and eastern parts of the region) are 1500 meters above sea level and are characterized by chains of mountains and plateaus. The region of Oromiya covers the biggest portion of the country. This region has of twelve administrative zones and 180 woredas. The landscape of the region includes tall and rocky mountains. The region is located 500 meters above sea level to high ranges that culminate into more than 4000 meters. But the altitude of over 1500 meters is dominant in the region. The region of Southern Nations, Nationalities and Peoples' comprises 10% of the total area of the country. The region is divided in to nine zones, 72 woredas and five special woredas. The region lies in the southern part of the country and has an elevation range from 376 to 4, 207 meter above sea level. About 56 % of the total area is

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found below 1,500m. The remaining 44% is temperate in climate. These three regions were selected for this study.

Data description

The aim of the study was to identify the problem of malaria on aspects, such as socio-economic, demographic and geographic variables and spatial correlated and uncorrelated spatial effects in three regions of Ethiopia. Baseline household survey was conducted from December 2006 to January 2007 by The Carter Center (TCC). In the survey, *Kebele* (smallest administrative unit) was considered as the sampling frame in each of the rural populations of Amhara, Oromiya and SNNP regions. From the three regions, 5,708 households located in 224 clusters were selected, i.e, 4,101 (71.85%) for Amhara, 809 (14.17%) for Oromiya and 798 (13.98%) for SNNP. From each *Kebele*, twelve even numbered households were selected for malaria tests.

Socioeconomic, demographic and geographic factors of interest

Outcome variable: For this study, the malaria rapid diagnosis test (RDT) result (binary) was considered as an outcome variable. RDT is a method which helps to the diagnosis of malaria. RDT are used instead of microscopy if there are no good quality services.

Predictor variables: The predictor variables or covariates were the baseline socioeconomic status, demographic and geographic variables. These variables are described in the following table (Table 1).

Model construction

In previous studies, assuming that socioeconomic, demographic and geographic variables were assumed to have a nonlinear effect on malaria rapid diagnosis test [15-17]. Because age, household size, number of rooms per person, number of nets per person, altitude and number of months the room sprayed are continuous variables, the relationship with malaria rapid diagnosis test might be nonlinear [14]. In addition to nonlinear effects, there was spatial variability was found in the previous study [13]. Therefore, using the algorithm described in [18], Generalized Additive Mixed Model (GAMM) with spatial covariance structure [19] was suggested to investigate the effect of malaria rapid diagnosis test on socioeconomic, demographic and geographic variables.

Table 1: The description of predictor variable used in the model.

Variables	Levels and coding
Region	1 = Amhara , 2 = Oromiya, 3 = SNNP
Main source of drinking water	1= Unprotected, 2 = protected, 3 = Tap water
Time to collect water	1=<30 minutes, 2 = 30 to 40 minutes, 3 = 40 – 90 minutes, 4 = >90 minutes
Toilet facilities	1 = No facility, 2 = pit latrine, 3 = toilet with flush
Availability of electricity	1 = yes, 2 = no
Availability of radio	1 = yes, 2 = no
Availability of television	1 = yes, 2 = no
Main material of the room's wall	1 = cement block, 2 = mud block/stick/wood, 3 = corrugated metal
Main material of the room's roof	1 = thatch, 2 = stick and mud, 3 = corrugate
Main material of the room's floor	1 = earth/Local dung plaster, 2 = wood, 3 = cement
Use of indoor residual spray in the past twelve months	1 = yes, 2 = no
Use of mosquito nets	1 = yes, 2 = no
Rapid Diagnosis test (RDT)	0 = Negative, 1= Positive
Age	Continuous predictor
Family size	Continuous predictor
Altitude	Continuous predictor
Total number of rooms	Continuous predictor
Total number of nets	Continuous predictor
Number of months room sprayed	Continuous predictor

$$\eta_{ij} = \beta_0 + \beta_1 G_i + \beta_2 R_{it} + \beta_3 W_i + \beta_4 TW_i + \beta_5 TF_i + \beta_6 E_i + \beta_7 TV_i + \beta_8 RD_i + \beta_9 RF_i + \beta_{10} RW_i + \beta_{11} RR_i + \beta_{12} AM_i + \beta_{13} NU_i + \beta_{14} G*W_i + \beta_{15} G*E_i + \beta_{16} G*RW_i + f_1(AGE_i) + f_2(ALT_i) + f_3(FSIZE_i) + f_4(TR_i) + f_5(TN_i) + f_6(MS_i) + \in_{ij} \quad (1)$$

Where η_{it} is the predictor of malaria RDT, age $_{it}$ is age, ALT $_{it}$ is altitude, $FSIZE_{it}$ is Family size and TR $_{it}$ is total room, TN $_{it}$ total number of nets and MS $_{it}$ is months the room sprayed with indoor residual spray. G $_{it}$,R $_{it}$,W $_{it}$,TW $_{it}$,TF $_{it}$,E $_{it}$,TV $_{it}$,RD $_{it}$,RF $_{it}$ RW $_{it}$,RR $_{it}$,AM $_{it}$ and NU $_{it}$ are gender, region, source of drinking water, time to get water, toilet facility, availability of electricity, availability of television, availability of radio, material of room's floor, material of room's wall, material of room's roof, indoor residual spray and use of nets respectively. $f_1 \ldots, f_6$ are unidentified nonlinear smooth functions of the predictors. The $\beta_i \ (i = 1,...,16)$ are the regression coefficient of the linear effects. $\beta_0 i$ is the intercept and $\in_{it} i$ is the error term [14] .

The purpose of equation (1) was to assess the socioeconomic, demographic and geographic effects that are highly related with malaria RDT in three regions of Ethiopia. In this study, spatial variability was not included. As an extension of study conducted by Ayele, Zewotir and Mwambi (2014), the GAMM in equation (1) is Substituted by a geo-additive model by accommodating the spatial variability as follows.

$$\eta_{ij} = \beta_0 + \beta_1 G_i + \beta_2 R_{it} + \beta_3 W_i + \beta_4 TW_i + \beta_5 TF_i + \beta_6 E_i + \beta_7 TV_i + \beta_8 RD_i + \beta_9 RF_i + \beta_{10} RW_i + \beta_{11} RR_i + \beta_{12} AM_i + \beta_{13} NU_i + \beta_{14} G*W_i + \beta_{15} G*E_i + \beta_{16} G*RW_i + f_1(AGE_i) + f_2(ALT_i) + f_3(FSIZE_i) + f_4(TR_i) + f_5(TN_i) + f_6(MS_i) + f_{spat}(k_i) + \in_{ij} \quad (2)$$

In equation 2, $f_1 \ldots, f_6$ are nonlinear smooth functions of the continuous predictor variables and f_{spat} the influence of the spatial predictor for *kebele* i . The spatial effect f_{spat} can be divided into two parts, i.e., correlated/structured and uncorrelated/unstructured effects. The spatial effects can be expressed as follows.

$$f_{spat}(k_i) = f_{str}(k_i) + f_{unstr}(k_i) \quad (3)$$

Here, spatial variability is usually contained many unobserved influences exist only locally [26-31,33]. Therefore, equation (2) can be written as

$$\eta_{ij} = \beta_0 + \beta_1 G_i + \beta_2 R_{it} + \beta_3 W_i + \beta_4 TW_i + \beta_5 TF_i + \beta_6 E_i + \beta_7 TV_i + \beta_8 RD_i + \beta_9 RF_i + \beta_{10} RW_i + \beta_{11} RR_i + \beta_{12} AM_i + \beta_{13} NU_i + \beta_{14} G*W_i + \beta_{15} G*E_i + \beta_{16} G*RW_i + f_1(AGE_i) + f_2(ALT_i) + f_3(FSIZE_i) + f_4(TR_i) + f_5(TN_i) + f_6(MS_i) + f_{str}(k_i) + f_{unstr}(k_i) + \in_{ij} \quad (4)$$

The assumption for geo-additive model states that the nonlinear variabilities are similar for all *kebeles*.

Prior assumptions and inference

For the case of Bayesian inference, the unidentified functions

$\ldots, f_6$ in equation (4), the vector of the linear factors parameter β_i are considered as the random factor. They are also accompanied by prior assumptions. Diffuse priors are the suitable alternative for fixed effects parameters if there is no any prior knowledge [19-21].

For smooth, a second order random walk prior is selected. To define f , take the case of predictor x with equally spread out observations x_i , $i = 1,...m.$ Let $x_{(1)} < ... < x_{(t)} < ... < x_{(m)}$ is an orderly sequence of distinct values where define $f_{(t)}$ as $f(x_{(t)})$ Furthermore, the second order random walk is given by

$$f(t) = 2f(t-1) - f(t-2) + u(t) \quad (5)$$

where $u(t) \sim N(0, \tau^2)$ is Gaussian errors. The diffuse priors can be given as $f(1) \propto c^{st}$ and $f(2) \propto c^{st}$, for first values. A

second order random walk penalizes deviations from the linear trend $2f(t-1)-f(t-2)$. Hence, Markov random field prior is chosen for the spatially correlated effect f_{str} [22-25]. This prior indicates spatial neighborhood relationship which shows prior spatial neighborhood relationship. Accordingly, a spatial extension of the random walk model gives the conditional spatially autoregressive description [21,26-32]. This equation is given as follows.

$$f_{str}(k)/f_{str}(k'),k'\neq k,\tau_{str}^2 \sim N\left(\frac{1}{N_S}\sum_{K'\in\delta k} f_{str}(k'),\frac{\tau_{str}^2}{N_s}\right) \quad (6)$$

where N_s is the number of neighboring *kebele* and $k'\in k$ represents that *kebele* k' is a neighbor of *kebele* k. Here, the assumption is that the influence of *kebele* k is conditionally Gaussian with expectation equals to the mean of the influence of neighboring *kebele* and a variance that is inversely proportional to the number of its neighbors N_s [33]. The conditional mean of $f_{str}(k)$ is an unweighted average of function evaluations of neighboring *kebele*. For the spatially uncorrelatated/unstructured effect, f_{unstr} as the common assumptions of Gaussian, are assumed to be *i.i.d* [27,30,32,34], i.e,

$$f_{unstr}/\tau_{unstr}^2 \sim N(0,\tau_{unstr}^2).$$

Flexibility and smoothness of the trade-off is controlled by the variance parameter τ_j^2, $j=1,...,6$, *str*, *unstr* [22,26]. The values are unidentified and estimated with corresponding unidentified functions f_j. For the variance τ_j^2, inverse Gamma hyper-prior $\tau_j^2 \sim IG(a_j,b_j)$ are allocated to τ_j^2. Hence, the probability density function can be presented as

$$p(\tau_j^2) \propto (\tau_j^2)^{-a_{j-1}} \exp\left(-\frac{b_j}{\tau_j^2}\right)$$

The bayesian inference is established on the posterior of the model. The analysis is investigated using MCMC simulation techniques. Therefore, equation (4), the predictor γ denotes the vector of all unidentified parameters. The conditional independence assumptions, the posterior of the model is presented as

$$p(\gamma/y) \propto \prod_{i=1}^{n} L_i(y_i,\eta_i)\prod_{i=1}^{6}\{p(f_i/\tau_j^2)p(\tau_j^2)\}\prod_{i=0}^{5} p(\alpha_i)p(f_{str}/)p(f_{unstr}/\tau_{unstr}^2) \quad (7)$$

where, $f_j, j=1,...,6$, f_{str}, f_{unstr} are multivariate Gaussian. The MCMC simulation is implemented for consecutive draw of $f_1,...,f_4$, f_{str}, f_{unstr}, $\tau_j^2, j=1,...,6$ from the full conditionals [27,30,31,34]. BayesX was used for the analysis. This software is public domain software for Bayesian inference in structured Additive Regression Models [35].

Results and discussion

The objective of the study is to analyze the burden of malaria RDT result on covariates, such as socioeconomic, demographic, geographic covariates and spatial effects both correlated and uncorrelated in three regions of Ethiopia. The estimate for the linear effects parameters is presented in Table 2. As the value indicates, region (Amhara, Oromiya), source of drinking water (tap water), time to collect water (less than 30 minutes, between 30 and 40, between 40 and 90), toilet facility (pit latrine, toilet with flush), use of electricity (yes), use of radio (yes), material used for walls (mud blocks, corrugated), material used for floor (wood, cement) and use of indoor residual spray (yes) have a negative posterior mean. Therefore, these variables have negative relationship with malaria RDT result. In contrast, the rest variables, i.e., source of drinking water (unprotected), availability of television, material for floor (thatch, stick and mud) have a positive means. These variables are positively related to malaria RDT result. In general, Table 2 shows that gender, source of drinking water, time to collect water, toilet facility, availability of television and radio, main roof material, main floor material and use of indoor residual spray have significant effects on malaria RDT result.

In Figure 1 the nonlinear factors of the model with 95% confidence interval is presented. Figure 1(A) indicates that malaria incidence in a given age, positive RDT result is increased for the first five years of life and then progressively decreased subsequently. Figure 1(B) displays the estimated smooth function for altitude. As can be seen from the figure, the malaria RDT result is increasing for the first 3000 meters then starts to decline. Similarly, from the result, it was found that family size had the significant effect on malaria RDT test result. Figure 1(C) presented the estimated smooth function. The figure

Table 2: Estimate of the linear effects parameters using geo-additive models.

Parameter	Mean	OR	95% C.I.	
			Lower	Upper
Region (Ref. SNNP)				
Amhara	-2.2778	0.1025	0.1875	1.2903
Oromia	-1.1952	0.3026	0.3125	1.4346
Gender (Ref Male)				
Female	-2.1391	0.1178	0.0704	0.4962
Source of drinking water (Ref. Protected water)				
Unprotected	1.4133	4.1095	4.0075	5.1115
Tap water	-2.0848	0.1243	0.1024	0.1944
Time to collect water (Ref. Greater than 90 minutes)				
Less than 30 minutes	-5.2918	0.0050	0.0037	0.0261
Between 30 and 40 minutes	-0.3973	0.6721	0.0419	0.9466
Between 40 and 90 minutes	-0.6631	0.5153	0.5154	1.6151
Toilet Facility (Ref. No facility)				
Pit Latrine	-1.2573	0.2844	0.1046	0.5947
Toilet with flush	-0.9087	0.4030	0.3028	0.9133
Availability of electricity (Ref. No)				
Yes	-0.8251	0.4382	0.2807	0.6835
Availability of television (Ref. No)				
Yes	0.4655	1.5928	0.6219	1.9215
Availability of radio (Ref. No)				
Yes	-0.8655	0.4208	0.3167	0.7208
Main wall material (Ref. Cement)				
Mud Blocks	-0.3558	0.7006	0.4281	1.4409
Corrugated	-0.5665	0.5675	0.3674	0.8676
Main roof material (Ref. Corrugated)				
Thatch	1.9228	6.8401	2.5169	8.7183
Sticks and mud	0.7713	2.1626	1.8859	6.4886
Main floor material floor (Ref. Earth/local gung plaster)				
Wood	-0.7898	0.4539	0.3598	0.7541
Cement	-0.6216	0.5371	0.4309	0.6537
Use of indoor residual spraying (ref. no)				
Yes	-0.7121	0.4906	0.2844	0.9882
Structured	2.2854		2.0852	3.2856
Unstructured	2.8002		2.2002	3.7801

suggested that household size is not linearly related with malaria RDT test result. In addition, total number of nets found to be nonlinearly related to malaria RDT result.

Figure 2 presents the posterior mean estimated values of the structured smooth spatial component and the unstructured which is also known random component maps of Amhara, Oromiya and SNNP regions of Ethiopia. The map for both structured and unstructured posterior mean estimates, the SNNP region is most affected by malaria followed by Amhara and Oromiya regions. In order to have a closer look at each region with regard to the distribution of malaria, Figures 2,34 and 4 are given to show the posterior mean estimates of the structured smooth spatial and the unstructured component for Amhara, Oromiya and SNNP regions of Ethiopia respectively.

Figure 3 presents the posterior mean estimates of the structured and unstructured component for Amhara region. It is clearly seen that there is a similar trend for structured and unstructured components; however, three zones (North Gondor, South Gondor and North Shewa) seem to exhibit different patterns between structured and unstructured components. As the figure indicates, the highest malaria is present in northern and southern Gondor. One of the reasons for this might be that the high-level population density in these zones. The other high risk exists in the southern, western and eastern parts of the Amhara region. For the unstructured component, however, the highest risk is seen in Northern Gondor followed by Southern Gondor. The smallest is in the northern Shewa zone of the Amhara region.

Figure 4 depicts the posterior mean estimates of the structured and unstructured (random) component for Oromia region. The map shows the similar trend for structured and unstructured components, but some zones seem to present different patterns between structured and unstructured components. According to the figure, the highest malaria is present in the southern and eastern part of Oromoiya (Borena and East Harergie). The next highest malaria risk area is found at the central and Northern part of Oromiya region. In contrast, for the unstructured component, the highest risk is present in Borena, East Hagegrie and East Shewa zone of the Oromiya region.

Figure 5 displays the posterior mean estimates of the structured and unstructured component for SNNP region. The map shows the similar trend for structured and unstructured components, but some zones seem to present different patterns between structured and unstructured components. As the figure indicates, the highest malaria is present in the south eastern part of the SNNP region (Burji) followed by the central and southern parts of the regions. The lowest malaria risk area is present at the western part of SNNP region (Northern Omo). But, for the unstructured component, the highest risk is present in the central part of the SNNP region.

A clearer understanding of the presence of these differences is required concerning the highest malaria risks between zones of the Amhara, Oromiya and SNNP regions of Ethiopia. The produced maps from this work could be used for targeting Zones of the high risk of malaria with a view to initiating control policy.

Conclusion

Normally, malaria is referred to be disease of poverty [36] because it influences the poor who have limited access to health care [37]. Socioeconomic covariates are related to poverty. Therefore, it is significant to recognize the linkages between malaria and poverty. The result will be valuable to guide government policy-makers into creating and implementing more effective policies to tackle the disease [10,11].

In this study, semi-parametric models with spatial variations were implemented to model the effects of socioeconomic, demographic and geographic covariates and spatial effects on malaria distribution. The spatial analysis was implemented using geo-additive model where *kebele* was used as the geographic unit. In the analysis the spatial effect was divided into smooth structured and unstructured components. Statistical inference was made using bayesian method, and the analysis was based on Markov chain Monte Carlo techniques. The effect of socioeconomic, demographic and geographic covariates and the effects of other spatial determinants were estimated simultaneously.

This study identified the relationship between socioeconomic, demographic and geographic factors and malaria problems. The results reveal that malaria can be considered as a disease of poverty i.e., households who can have enough money to have proper toilet facilities, more number of rooms in the house, clean drinking water, and well built houses were found to be less affected by malaria. Moreover, our findings implied that households with more bed nets and sleeping rooms have good chance to reduce malaria. Women and children are also unprotected to mosquito bites while they are travelling long ways to get water. The study suggests that wealthier households were found to be less vulnerable to malaria than the poor households. Therefore, creating better living surroundings for the societies could be one way of reaching the malaria control goals set by the government.

Significant spatial patterns of malaria that are associated with socioeconomic, demographic, geographic and the spatial effects were identified in this study. High-rate malaria affected areas can be identified using spatial statistics analysis. This method is appropriate in monitoring and identifying malaria affected parts of the country. Using this result, policy makers can implement preventative strategies to eliminate the problem of malaria. Therefore, studies which account spatial variability are essential for planning the most suitable methodology for corrective action to decrease the danger of malaria in Ethiopia.

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Conflicts of Interest

The authors declare that they have no competing interests.

Authors' contributions

DGA acquired the data, design the research, performed the analysis and drafted the manuscript. TTZ and HGM designed the research. All authors discussed the results and implications and commented on the manuscript at all stages. All authors contributed extensively to the work presented in this paper.

Ethical clearance

The ethical protocol received approval from the Emory University Institutional Review Board (IRB 1816) and Amhara, Oromiya and SNNPR regional health bureaux. Informed consent was sought in accordance with the tenets of the declaration of Helsinki.

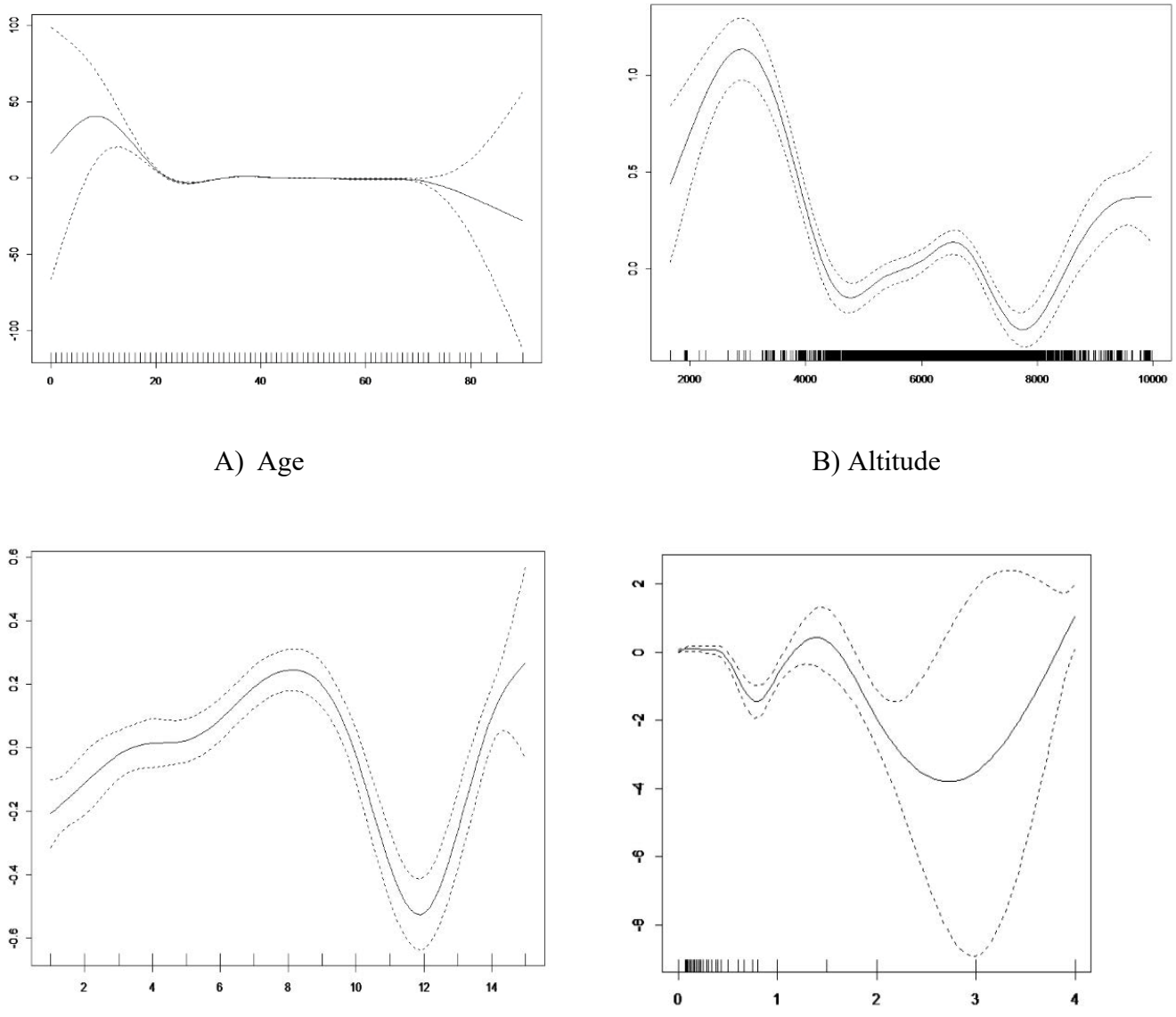

Figure 1: Nonlinear effects of the continuous covariates, with 95% confidence interval

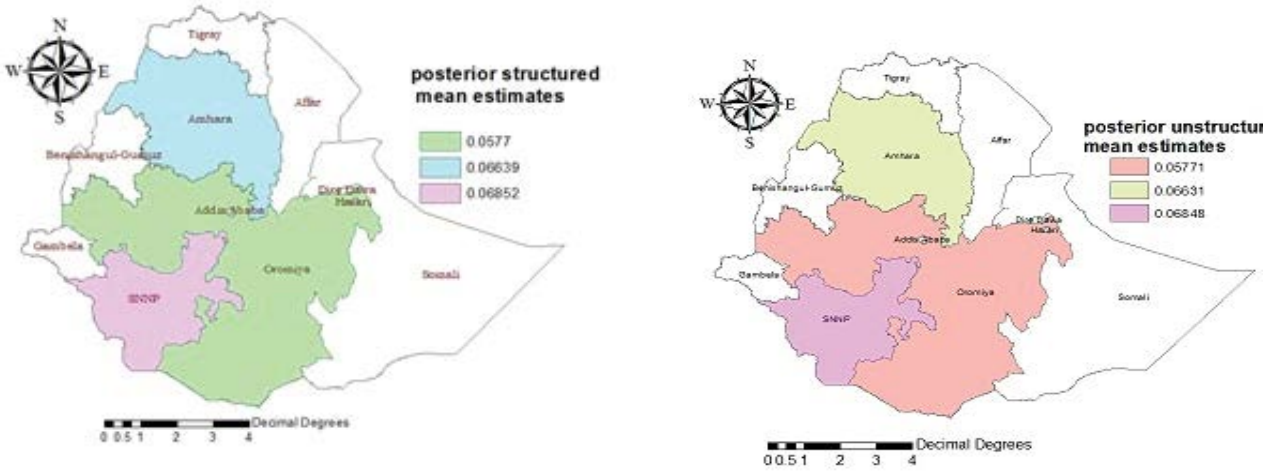

Figure 2: The posterior mean estimates of the structured smooth spatial component and the unstructured (ran¬dom) component.

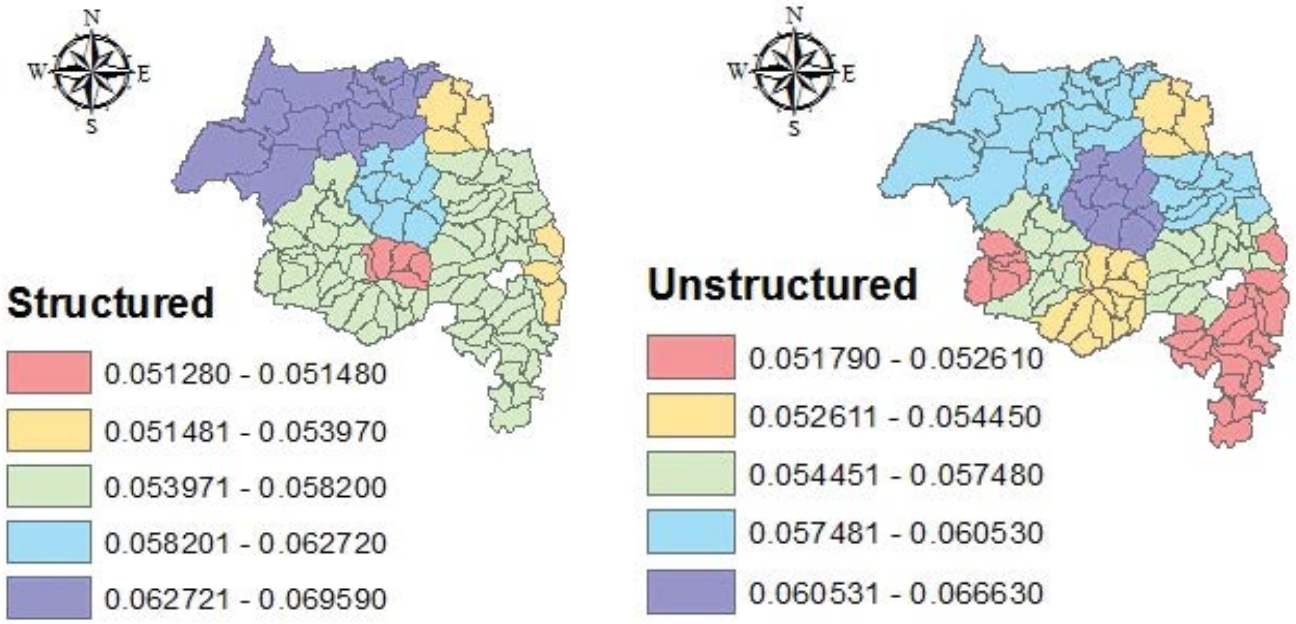

Figure 3: The posterior mean estimates of the structured smooth spatial component and the unstructured component for Amhara region.

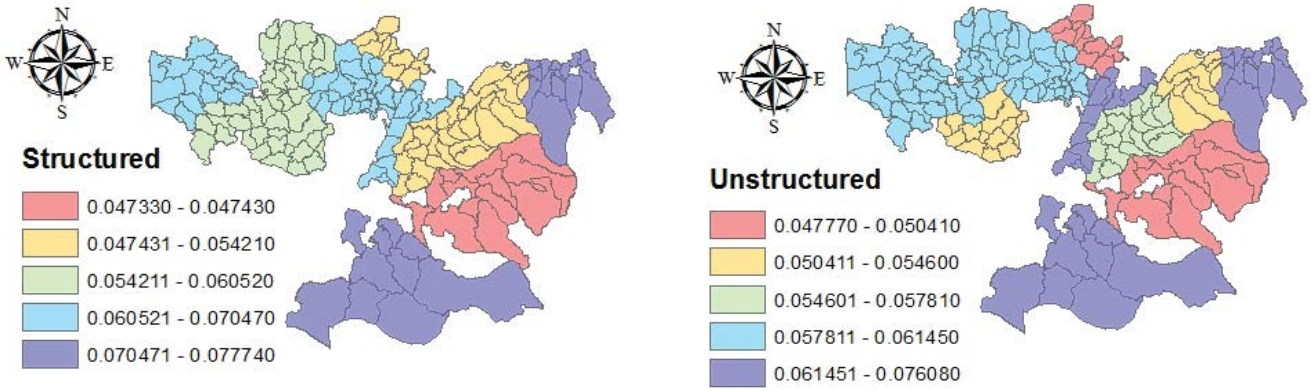

Figure 4: The posterior mean estimates of the structured smooth spatial component and the unstructured component for Oromiya region.

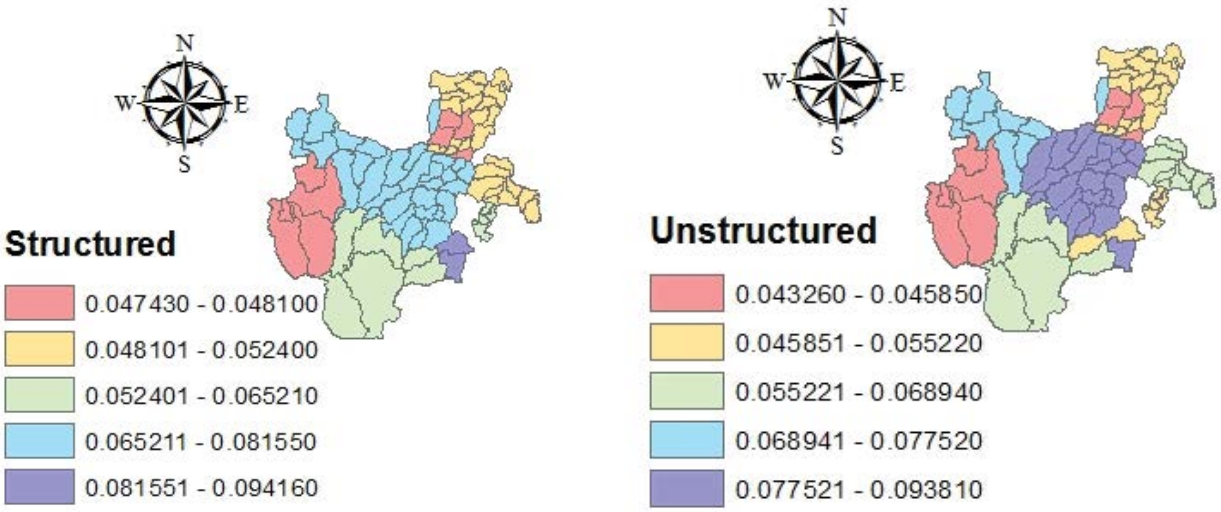

Figure 5: The posterior mean estimates of the structured smooth spatial component and the unstructured component for SNNP region.

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